Three Essays on Wage Inequality in Germany: the Impact of Automation, Migration and the Minimum Wage

Dissertation to obtain the doctoral degree of Economic Sciences (Dr. oec.)

Faculty of Business, Economics and Social Sciences

University of Hohenheim

Institute of Economics

Submitted by

Ramona Elisabeth Schmid

from Bietigheim-Bissingen

2023

Date of Oral Examination: November 06, 2023

Dean: Prof. Dr. Jörg Schiller
Examination Chair: Prof. Dr. Alfonso Sousa-Poza
Supervisor and First Reviewer: Prof. Dr. Thomas Beißinger
Second Reviewer: Prof. Dr. Klaus Prettner

Acknowledgements

First and foremost, I would like to thank Prof. Dr. Thomas Beißinger, my supervisor and first mentor, for all his teaching and encouragement as well as guidance and valuable comments throughout the last years. His enthusiasm for labour economics motivated me in my dissertation as well as working together was much inspiring and supportive, both on the professional but also personal level. I consider it a great privilege that I was given the opportunity to write a doctoral thesis and also that I had the freedom to focus on my own research interests. For that, I am forever grateful to him.

I would also like to thank Prof. Dr. Klaus Prettner for being my second mentor during my doctorate phase and second supervisor of my doctoral thesis. I am extremely grateful for all valuable comments to my research papers and to the intermediate evaluation of the doctoral programme as well as for taking the time to assess my work.

Further, I am indebted to Dr. Martyna Marczak for not only being my third mentor but especially for being my dear colleague during the last years. With her input and always being ready to help in any kind of matter, she was a great support.

I am grateful to my dear colleague and co-author Franziska Brall. Starting at the same time as PhD-students and working together on our first research project, we experienced and mastered the typical ups and downs of academic research. This mutual support and input provided me a productive working atmosphere during my doctorate phase.

I am also thankful to Anita Bott, not only for her support in all administrative matters but also as a dear colleague of our team.

I am extremely thankful to Dr. Angelo Martelli and Dr. Vassilis Monastiriotis for my stay as a visiting research student in European studies at the European Institute of the London School of Economics and Political Science. For providing me the opportunity to expand my knowledge at the LSE as well as for all productive conversations and valuable comments, I cannot thank you enough. Of course, also many thanks to the PhD-students of the European Institute for their warm welcome into their community and inspiring exchanges during my research stay.

Moreover, I am grateful to all my dear colleagues of the Humboldt reloaded team with special thanks to PD Dr. Joanna Fietz and Dr. Natascha Selje-Aßmann for inspiring team meetings and exchanges to the concept of research-based learning during the last two years of my doctoral project.

Further, I am very grateful and honoured to have received a scholarship from the Ministry of Science, Research and Arts Baden-Württemberg (Landesgraduiertenförderung) during the first two years of my doctoral project.

Finally, I am deeply grateful to my family, in particular my parents and grandparents. I am aware that there are no words to describe how grateful I am to my parents, but I would still like to emphasise their constant support with unconditional belief in me and their unwavering encouragement not only during my doctoral project but also throughout my whole life.

Mama and Papa, thank you!

Ramona Schmid

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Economic inequality has increased in the majority of countries worldwide and in almost all advanced economies over the last three decades (see e.g. Katz and Autor, 1999; OECD, 2009, 2011; Salverda and Checchi, 2015).[1] This phenomenon of unequal distribution of resources, incomes and opportunities among individuals of a society is thus widely present in public discussion, political debate and scientific research. With on the one hand rising poverty and on the other hand increases in extreme wealth, economic inequality is a considerable and persistent issue of today's world. Since economic disparities can impact the life of individuals in different ways, it is of special importance to develop profound related knowledge that covers various aspects. Unequal distribution of salaries and incomes is closely related to the individual's well-being and involvement in society (see e.g. Buttrick et al., 2017; Coccia, 2018; Van de Werfhorst and Salverda, 2012). Ultimately, economic inequality may have impact on the cohesion of society, the voting behaviour and thus on the political as well as social stability of a country (see e.g. Champernowne and Cowell, 1998; Tavits and Potter, 2015; Vergolini, 2011).

Since differentials in pay are a decisive element of economic inequality (see e.g. Biewen and Juhasz, 2012; Drechsel-Grau et al., 2022), this thesis focuses on this field of research.[2] In this context, developments in wage inequality in Germany over the last decades represent an extensive and interesting area of analysis. Since the mid-1990s, wage inequality

[1] Besides economic inequality, there are several other types and dimensions of inequality that can be observed, for example inequality in legal and social rights as well as inequality in education and health (see e.g. Carter and Reardon, 2014).

[2] Other elements of economic inequality are for example income inequality as a whole, inequality in wealth or inequality in opportunity (see e.g. Atkinson and Morelli, 2014).

in Germany considerably increased with distinct rises in lower tail wage inequality (see e.g. Antonczyk et al., 2010; Card et al., 2013; Dustmann et al., 2009). After 2010, the literature provides evidence that wage inequality not further increased or even declined (see e.g. Baumgarten et al., 2020; Möller, 2016). While it is not only necessary to reveal changes in the development of wage differentials, it is also essential to identify driving forces behind observed developments in wage inequalities. Thus, there is a vast literature on factors that impact the wage distribution. The observed ageing of the population and the trend towards higher educated individuals significantly impact the population structure in Germany and thus are often analysed as traditional factors in the context of wage inequality (see e.g. Baumgarten et al., 2020; Biewen and Seckler, 2019). Another highly discussed factor is the role of technological progress and its possibly biased impact on different skill groups among workers (see e.g. Antonczyk et al., 2018; Spitz-Oener, 2006). Further, studies show that the structure of labour market institutions, such as the level of the minimum wage and the degree of unionization, (see e.g. Bossler and Schank, 2020; Dustmann et al., 2009) but also international trade (see e.g. Felbermayr et al., 2014) affect the distribution of wages. Moreover, wage differentials between specific groups of workers, such as gender, peripheral-urban and immigrant-native wage gaps, are a pivotal component in analysing overall wage dispersion (see e.g. Antonczyk et al., 2010; Brixy et al., 2022; Ingwersen and Thomsen, 2021). Due to the large number and complexity of driving forces behind changes in wage inequality, this thesis focuses on three challenges of the German labour market in relation to unequal remuneration[3], resulting in the following research questions:

- How do automation and robotization impact wage inequality among workers of the manufacturing sector in Germany?
- How does the immigrant-native wage gap evolve over time in different economic regions in Germany?
- To which extent does the introduced minimum wage affect the development of gender wage gaps in the East and West of Germany?

[3]Besides the considered aspects, there are certainly further challenges that affect today's labour market, such as an aging population, shortage of skilled workers, the COVID-19 crisis and digitisation.

These research questions address different aspects of inequality research. The first question analyses the effect of technological progress on the wage structure and composition of the workforce in the manufacturing labour market. The second study deals with between-group wage inequality of German and Non-German workers in the context of increasing migration and regional-specific differences. The final research issue aims in assessing the impact of an introduced policy instrument in relation to changes in wage differentials between men and women.

In particular, the first study addresses technological progress, which is seen as one of the most challenging developments in the world of work in recent decades. Considerable advances in the use of robot technology, artificial intelligence as well as machine learning lead to new possibilities of substituting human labour by machines within the production process. With significant impact on labour markets and the nature of work, the economics of automation is a crucial subject of labour market research (see e.g. Acemoglu and Restrepo, 2018; Arntz et al., 2016; Dauth et al., 2021). On the one hand, new automation technologies affect employment by automating specific jobs, possibly increasing demand for other jobs as well as impact the composition of tasks within occupations (see e.g. Acemoglu and Restrepo, 2020; Frey and Osborne, 2017; Graetz and Michaels, 2018). On the other hand, technological progress impacts the wage structure and thus the wage distribution of labour markets. In this context, the concept of skill-biased technological change is regarded as one of the driving factors behind increases in wage inequality in many countries during recent decades. Arguing that automation technologies disproportionately raise productivity of high-skilled workers to the detriment of low-skilled workers, this development is seen to contribute to a widening of the wage distribution (see e.g. Acemoglu and Restrepo, 2020; Autor and Dorn, 2013; Lankisch et al., 2019).

The second part of this thesis deals with wage differentials in regards to international migration. In 2019, the number of international migrants in the world nearly reached 272 million people, where Europe hosted with 82 million the largest number of the migrant population (United Nations, 2019). At the same time, the circumstances of an aging population and a relating thereto shrinking labour force as well as a significant lack of specialists pose considerable challenges to contemporary labour markets (see e.g. Mergener and Maier, 2019; Serban, 2012). In the case of Germany, opening up the job market and promoting qualified immigration are seen as one of the factors to counteract these developments (OECD, 2018). In that respect, an efficient integration of Non-German workers in the labour market has to be facilitated (see e.g. Brunow and Jost, 2022; Ingwersen and Thomsen, 2021). Therefore, in order to define necessary measures of action and to provide appropriate conditions to include foreign workers into the labour market, existing wage gaps and characteristics of prevalent workers have to be revealed. Analysing immigrant-native wage differentials over time and their respective driving forces are thus essential and provide information for the socio-economic integration of immigrants.

The last part of this thesis is linked to the introduction of the minimum wage in Germany. With potentially considerable effects on the wage structure and employment, wage floors have always been subject of international controversial discussions among economists and policymakers (see e.g. Card et al., 1994; Machin and Manning, 1997; Neumark and Wascher, 1994). Following traditional standard models, an introduced or increased minimum wage will lead to job losses especially among low-skilled workers (Neumark and Wascher, 2015). However, recent studies provide evidence to contradict this prediction (see e.g. Bossler and Gerner, 2020; de Linde Leonard et al., 2014; Dustmann et al., 2022). Being confronted with a low-wage sector of considerable extent (see e.g. Grabka and Schröder, 2019) and a long-lasting rise in wage inequality (see e.g. Card et al., 2013), a national binding minimum wage of €8.50 per hour was introduced in January 2015 in Germany. With the primary aim of raising hourly wages at the lowest level of the wage distribution, around 11% of all jobs were directly affected by the introduced wage floor (Destatis, 2016). In that context, the observed impact on different groups of employed persons is highly varied. Marginal and part-time employment relationships as well as workers in the East of Germany and with fixed-term contracts are especially affected. Apart from that, there are also considerable gender-specific differences in the extent to be affected by the minimum wage (Amlinger et al., 2016).

The above mentioned research questions all have one feature in common: applying decomposition methods, it is possible to answer them. With the seminal estimation procedure in this context, that is extended with state-of-the-art modifications, the aforementioned challenges of the labour market are analysed. Providing new evidence in all of these three areas, this thesis not only contributes to the current understanding of wage inequality and its driving forces in Germany but also identifies channels through which policymakers may address these issues. Chapter 2 examines the contribution of automation and robotization on wage inequality by implementing a new measure of automation threat in which the information about occupation- and requirement-specific automation probabilities with sector-specific robot densities are combined. In Chapter 3 changes in wage differentials between German and Non-German workers and the relating thereto explaining factors are analysed over time. In doing so, new evidence on regional-specific differences between metropolitan and non-metropolitan areas are identified. Chapter 4 reveals the impact of the introduced national binding minimum wage in 2015 on the observed gender wage gap, where new evidence on various group-specific responses is provided.

In order to identify explanatory factors that drive wage inequality between groups or over time, applied economists use decomposition methods. The seminal papers of Oaxaca (1973) and Blinder (1973) provide a method that is now the standard tool in the toolkit of inequality research and are among the most heavily cited studies in labour economics (Fortin et al., 2011). This standard approach distinguishes between explained effects, due to differences in observable characteristics, and unexplained effects, due to differences in coefficients.[4] Further, various explanatory variables can be considered, which leads to a better understanding of driving factors behind wage differentials and changes in wage inequality. Apart from the analysis of mean wage gaps, there are several methodological modifications that extend the basic decomposition strategy with other distributional parameters (see e.g. Chernozhukov et al., 2013; Juhn et al., 1993; Machado and Mata, 2005). In this thesis, the extension of the Oaxaca-Blinder decomposition using the recentered influence function regressions approach introduced by Firpo et al. (2018) is applied in different contexts. This procedure allows detailed decomposition results based on per-

[4] In the following, the terms explained effect and composition effect as well as unexplained effect and wage structure effect are used interchangeably.

centiles and percentile differences as well as on other inequality measures such as the Gini coefficient and the variance. Further, the reweighting approach introduced by DiNardo et al. (1996) is combined with the above mentioned estimation procedures in various ways in order to address the respective research questions.

The first research project in Chapter 2 (joint work with Franziska Brall) addresses the question to which extent automation and robotization impact wage inequality in the manufacturing sector in West Germany between 1996 and 2017. The rise in automation technologies is recently discussed as a potential explanatory factor for changes in economic inequality. However, until now existing empirical literature on the impact of technological progress on wage inequality using data on industrial robots is scarce. Since the early 1990s automation has entered virtually every area in the economy. The production sector uses widely automated processes that on the one hand increase the productivity of labour but on the other hand also enable the substitution of it (see e.g. Acemoglu and Restrepo, 2020; Autor, 2015; Dauth et al., 2021; Dengler et al., 2014; Frey and Osborne, 2017). Having one of the highest robot densities worldwide, Germany is in this context an interesting field of research. This study is the first to implement a measure of automation and robotization in a decomposition analysis in order to disentangle the relative importance of automation technologies for wage inequality in the German manufacturing sector. The proposed measure of automation threat combines occupation- and requirement-specific scores of automation risk with yearly sector-specific robot densities. Using rich linked employer-employee data and information on industrial robots from the International Federation of Robotics, it is possible to account for a variety of different worker and plant characteristics as well as disentangle their relative contributions to changes in German wage dispersion. The empirical strategy is based on the Oaxaca-Blinder decomposition using recentered influence function regressions on several inequality indices (see Fortin et al., 2011). During the time period between 1996 and 2010 the most important factors that are associated with an increase in wage inequality are compositional changes in educational levels and the age structure of workers, reflecting an observed shift towards older and higher educated workers in the underlying data. In addition, it is revealed that the automation-related explained effect plays a significant non-negligible role in the overall composition effect. This effect is explained by the observable trend towards occupations with medium automation threat, accompanied by decreasing shares of occupations with high and low automation threat. Due to the fact that within-group wage inequality is the lowest in the group with the highest automation threat, those compositional changes contribute to an increase in wage inequality. In addition, the decomposition analyses provide evidence of a growing wage dispersion between occupations with low automation threat (especially related to non-routine tasks) and occupations with high automation threat (especially related to routine tasks). Following these results, there is rising wage inequality as predicted by routine-biased technological change, where progressing technology increases the relative demand and consequently the relative wages for non-routine tasks in comparison to routine tasks (see e.g. Acemoglu and Autor 2011). In the more recent time period until 2017, compositional changes in automation threat are the major factor that contributes to wage inequality through the composition effect. However, the overall positive aggregate composition effect is compensated by negative wage structure effects, leading to a rather constant development of wage inequality in this period.

In Chapter 3 (single authored) new evidence on immigrant-native wage differentials in consideration of regional differences between metropolitan and non-metropolitan areas between 2000 and 2019 for West Germany is presented. As a result of recent migration developments, studies analysing wage differentials between immigrant and native-born workers and the related driving forces attracted special interest during the last years (see e.g. Aldashev et al., 2012; Ingwersen and Thomsen, 2021). Building up on standard literature that covers effects of immigration on labour market outcomes of the host-country's workforce (see e.g. Borjas, 2014; Ottaviano and Peri, 2012) as well as on studies dealing with ethnic clustering in larger cities (see e.g. Glitz, 2014; Schaffner and Treude, 2014), this study adds to current literature evidence on developments of immigrant-native wage differentials with a special focus on regional differences between German metropolitan and non-metropolitan areas. Further, it contributes not only new evidence for the years after the beginning of the refugee crisis in 2014/15, but also presents analyses over time and thus shows how effects of various explanatory factors on wage differentials evolve. Using linked employer-employee-data, unconditional quantile regression models are estimated in order to assess the degree of labour market integration of foreign workers along the whole wage distribution. Applying the extended version of the Oaxaca-Blinder decomposition method, the results provide evidence on driving factors behind wage gaps (see Fortin et al., 2011). Aggregate decompositions identify considerable differences in the size of wage gaps along the wage distribution, where in all cases the majority can be explained by differences in observed characteristics. Further, detailed decomposition analyses present insights in explanatory factors behind wage differentials between German and Non-German workers. It is revealed that there are not only changes in the relative importance of explanatory variables over time, but also the driving factors of wage disadvantages of foreign workers shift along the wage distribution. Whereas the impact due to differences in educational attainment decreases, there are significant sector-specific effects in the lower half of the wage distribution and occupation-specific effects for higher wages. Differentiating between various areas in Germany, on average, larger wage gaps are revealed in metropolitan areas with at the same time a higher presence of foreign population. Increasing tendencies in wage differentials due to immigration are especially identified at lower wage levels, providing evidence of a widening of the wage distribution between native and foreign workers. As a consequence of these results, several policy-related implications can be defined that address current issues in Germany, such as employers' insecurity about immigrants' lack of work experience in the German labour market as well as general problems related to the shortage of skilled labour and an aging population.

The third research project in Chapter 4 (single authored) evaluates the effect of the introduced national minimum wage on the gender wage gap in Germany. Being one of the most discussed issues in labour economics, the national minimum wage was introduced in 2015 after many years of debate. The vast amount of international empirical studies provides evidence of possible effects of an introduced wage floor on labour market outcomes such as employment and wages but also working hours, prices and productivity (see e.g. Coviello et al., 2022; Dolton et al., 2015; Lemos, 2008; Stewart and Swaffield, 2008). Analysing Germany is a particularly interesting case. First of all, it is a rare example of a large developed country that introduces a national binding minimum wage (Bruttel, 2019). Further, Germany has a distinct low-wage sector that significantly increased during the last two decades and affects a considerably larger share of women compared to men (Grabka and Schröder, 2019). At the same time, there is one of the highest observed unadjusted gender wage gaps in the European Union with significant constant values over time (Eurostat, 2022). In this context, this study contributes to the exiting literature by providing first evidence on the impact of the introduced national binding minimum wage in 2015 on observed wage differences between men and women in Germany. The separate analyses of the East and West of Germany moreover not only identify regional-specific differences before the introduction of the minimum wage but also reveal varied responses of gender wage gaps. Lastly and most important, the applied method provides a strategy to analyse how decreases in wage differentials can be separated into an effect due to changes in the observed characteristics and into an impact resulting from the wage floor. Using administrative data, a difference-in-differences framework is applied, where counterfactual wage distributions introduced by DiNardo et al. (1996) are estimated. For the years around the minimum wage introduction, a significant drop in the size of wage differentials in the lower half of the wage distribution is revealed. At the same time, estimated minimum wage bites show that there are significant differences regarding gender and location of residence regarding the magnitude of impact, with higher values for women and workers in the East of Germany. Further, the estimated gender wage gap is on average significantly larger in the West of Germany. However, the minimum wage induced reduction of pay gaps is on average higher in the East of Germany. This confirms the hypothesis of a significant decrease in gender wage gaps in regions, where workers are strongly affected by the minimum wage introduction. Overall, the majority of decreases at lowest wage levels in the West and East of Germany are explainable by the wage structure effect that results from the wage floor and only smaller impact is identified due to changes in observed characteristics. The estimates of the counterfactual decomposition analyses additionally support the effectiveness of the policy measure.

Finally, after the detailed presentation of the three empirical studies, Chapter 5 concludes the thesis.

References

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, volume 4, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6):2188–2244.

Aldashev, A., Gernandt, J., and Thomsen, S. L. (2012). The Immigrant-Native Wage Gap in Germany. *Jahrbücher für Nationalökonomie und Statistik*, 232(5):490–517.

Amlinger, M., Bispinck, R., and Schulten, T. (2016). Ein Jahr Mindestlohn in Deutschland: Erfahrungen und Perspektiven. Technical report, WSI Report.

Antonczyk, D., DeLeire, T., and Fitzenberger, B. (2018). Polarization and rising wage inequality: comparing the US and Germany. *Econometrics*, 6(2):20.

Antonczyk, D., Fitzenberger, B., and Sommerfeld, K. (2010). Rising wage inequality, the decline of collective bargaining, and the gender wage gap. *Labour Economics*, 17(5):835–847.

Arntz, M., Gregory, T., and Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. *OECD Social, Employment and Migration Working Papers*, (No. 189).

Atkinson, A. B. and Morelli, S. (2014). Chartbook of Economic Inequality. *ECINEQ WP*, 324.

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3):3–30.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5):1553–97.

Baumgarten, D., Felbermayr, G., and Lehwald, S. (2020). Dissecting Between-Plant and Within-Plant Wage Dispersion: Evidence from Germany. *Industrial Relations: A Journal of Economy and Society*, 59(1):85–122.

Biewen, M. and Juhasz, A. (2012). Understanding Rising Income Inequality in Germany, 1999/2000–2005/2006. *Review of Income and Wealth*, 58(4):622–647.

Biewen, M. and Seckler, M. (2019). Unions, internationalization, tasks, firms, and worker characteristics: A detailed decomposition analysis of rising wage inequality in Germany. *The Journal of Economic Inequality*, 17:461–498.

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

Borjas, G. J. (2014). *Immigration economics*. Harvard University Press.

Bossler, M. and Gerner, H.-D. (2020). Employment effects of the new German minimum wage: Evidence from establishment-level microdata. *ILR Review*, 73(5):1070–1094.

Bossler, M. and Schank, T. (2020). Wage inequality in Germany after the minimum wage introduction. *IZA Discussion Paper*.

Brixy, U., Brunow, S., and Ochsen, C. (2022). On the peripheral-urban wage gap in Germany. *Applied Geography*, 139:102647.

Brunow, S. and Jost, O. (2022). Wages of Skilled Migrant and Native Employees in Germany: New Light on an Old Issue. *International Migration Review*, 56(2):410–432.

Bruttel, O. (2019). The effects of the new statutory minimum wage in Germany: a first assessment of the evidence. *Journal for Labour Market Research*, 53(1):1–13.

Buttrick, N. R., Heintzelman, S. J., and Oishi, S. (2017). Inequality and well-being. *Current Opinion in Psychology*, 18:15–20.

Card, D., Heining, J., and Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics*, 128(3):967–1015.

Card, D., Katz, L. F., and Krueger, A. B. (1994). Comment on David Neumark and William Wascher,"Employment effects of minimum and subminimum wages: Panel data on state minimum wage laws". *ILR Review*, 47(3):487–497.

Carter, P. L. and Reardon, S. F. (2014). *Inequality matters*. William T. Grant Foundation New York, NY.

Champernowne, D. G. and Cowell, F. A. (1998). *Economic inequality and income distribution*. Cambridge University Press.

Chernozhukov, V., Fernández-Val, I., and Melly, B. (2013). Inference on counterfactual distributions. *Econometrica*, 81(6):2205–2268.

Coccia, M. (2018). Economic inequality can generate unhappiness that leads to violent crime in society. *International Journal Happiness and Development*, 4(1):1–24.

Coviello, D., Deserranno, E., and Persico, N. (2022). Minimum wage and individual worker productivity: Evidence from a large US retailer. *Journal of Political Economy*, 130(9):2315–2360.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6):3104–3153.

de Linde Leonard, M., Stanley, T., and Doucouliagos, H. (2014). Does the UK minimum wage reduce employment? A meta-regression analysis. *British Journal of Industrial Relations*, 52(3):499–520.

Dengler, K., Matthes, B., and Paulus, W. (2014). Occupational Tasks in the German Labour Market. IAB-Forschungsbericht 12/2014, Nürnberg.

Destatis (2016). 4 Millionen Jobs vom Mindestlohn betroffen. *Statistisches Bundesamt Press Release, no. 121.*

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64(5):1001–1044.

Dolton, P., Bondibene, C. R., and Stops, M. (2015). Identifying the employment effect of invoking and changing the minimum wage: A spatial analysis of the UK. *Labour Economics*, 37:54–76.

Drechsel-Grau, M., Peichl, A., Schmid, K. D., Schmieder, J. F., Walz, H., and Wolter, S. (2022). Inequality and income dynamics in Germany. *Quantitative Economics*, 13(4):1593–1635.

Dustmann, C., Lindner, A., Schönberg, U., Umkehrer, M., and Vom Berge, P. (2022). Reallocation effects of the minimum wage. *The Quarterly Journal of Economics*, 137(1):267–328.

Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the German wage structure. *The Quarterly Journal of Economics*, 124(2):843–881.

Eurostat (2022). Gender pay gap statistics https://ec.europa.eu/eurostat/statistics-explained (access on 13-01-2023). *Statistics Explained.*

Felbermayr, G., Baumgarten, D., and Lehwald, S. (2014). Increasing Wage Inequality in Germany: What Role Does Global Trade Play? *Docbase - Publication Database of the CESifo Group, Bertelsmann Stiftung, Gütersloh.*

Firpo, S. P., Fortin, N. M., and Lemieux, T. (2018). Decomposing Wage Distributions Using Recentered Influence Function Regressions. *Econometrics*, 6(2):1–40.

Fortin, N., Lemieux, T., and Firpo, S. (2011). Decomposition Methods in Economics. In *Handbook of Labor Economics*, volume 4, pages 1–102. Elsevier.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254–280.

Glitz, A. (2014). Ethnic segregation in Germany. *Labour Economics*, 29:28–40.

Grabka, M. M. and Schröder, C. (2019). The low-wage sector in Germany is larger than previously assumed. DIW Weekly Report 14, Berlin.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768.

Ingwersen, K. and Thomsen, S. L. (2021). The immigrant-native wage gap in Germany revisited. *The Journal of Economic Inequality*, 19(4):825–854.

Juhn, C., Murphy, K. M., and Pierce, B. (1993). Wage inequality and the rise in returns to skill. *Journal of Political Economy*, 101(3):410–442.

Katz, L. F. and Autor, D. H. (1999). Changes in the Wage Structure and Earnings Inequality. In *Handbook of Labor Economics*, volume 3, pages 1463–1555. Elsevier.

Lankisch, C., Prettner, K., and Prskawetz, A. (2019). How can robots affect wage inequality? *Economic Modelling*, 81:161–169.

Lemos, S. (2008). A Survey of the Effects of the Minimum Wage on Prices. *Journal of Economic Surveys*, 22(1):187–212.

Machado, J. A. F. and Mata, J. (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics*, 20(4):445–465.

Machin, S. and Manning, A. (1997). Minimum wages and economic outcomes in Europe. *European Economic Review*, 41(3):733–742. Paper and Proceedings of the Eleventh Annual Congress of the European Economic Association.

Mergener, A. and Maier, T. (2019). Immigrants' chances of being hired at times of skill shortages: results from a factorial survey experiment among German employers. *Journal of International Migration and Integration*, 20(1):155–177.

Möller, J. (2016). Lohnungleichheit–Gibt es eine Trendwende? *Wirtschaftsdienst*, 96(1):38–44.

Neumark, D. and Wascher, W. (1994). Employment effects of minimum and subminimum wages: Reply to Card, Katz, and Krueger. *ILR Review*, 47(3):497–512.

Neumark, D. and Wascher, W. (2015). The effects of minimum wages on employment. *FRBSF Economic Letter*, 37:2015.

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

OECD (2009). Growing unequal. Income distribution and poverty in OECD countries. *OECD Publishing, Paris.*

OECD (2011). Divided We Stand: Why Inequality Keeps Rising. *OECD Publishing, Paris.*

OECD (2018). Germany Policy Brief - Migration: using migraton to meet skill shortages. *OECD Publishing, Paris.*

Ottaviano, G. I. P. and Peri, G. (2012). Rethinking the Effect of Immigration on Wages. *Journal of the European Economic Association*, 10(1):152–197.

Salverda, W. and Checchi, D. (2015). Labor Market Institutions and the Dispersion of Wage Earnings. In *Handbook of Income Distribution*, volume 2, pages 1535–1727. Elsevier.

Schaffner, S. and Treude, B. (2014). The effect of ethnic clustering on migrant integration in Germany. *Ruhr Economic Papers.*

Serban, A. C. (2012). Aging population and effects on labour market. *Procedia Economics and Finance*, 1:356–364.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, 24(2):235–270.

Stewart, M. B. and Swaffield, J. K. (2008). The other margin: do minimum wages cause working hours adjustments for low-wage workers? *Economica*, 75(297):148–167.

Tavits, M. and Potter, J. D. (2015). The effect of inequality and social identity on party strategies. *American Journal of Political Science*, 59(3):744–758.

United Nations (2019). International Migrant Stock 2019. *United Nations / Department of Economic and Social Affairs / Population Division.*

Van de Werfhorst, H. G. and Salverda, W. (2012). Consequences of economic inequality: Introduction to a special issue. *Research in Social Stratification and Mobility*, 30(4):377–387.

Vergolini, L. (2011). Social cohesion in Europe: How do the different dimensions of inequality affect social cohesion? *International Journal of Comparative Sociology*, 52(3):197–214.

Automation, Robots and Wage Inequality in Germany: A Decomposition Analysis

Authors: Franziska Brall and Ramona Schmid

Abstract. We conduct a decomposition analysis based on recentered influence function (RIF) regressions to disentangle the relative importance of automation and robotization for wage inequality in the manufacturing sector in Germany between 1996 and 2017. Our measure of automation threat combines occupation-specific scores of automation risk with sector-specific robot densities. We find that besides changes in the composition of individual characteristics, structural shifts among different automation threat groups are a non-negligible factor associated with wage inequality between 1996 and 2017. Moreover, the increase in wage dispersion among the different automation threat groups has contributed significantly to higher wage inequality in the 1990s and 2000s.

Status: Published - Brall, F. & Schmid, R. (2023) Automation, robots and wage inequality in Germany: A decomposition analysis. LABOUR, 37(1), 33– 95. Available from: `https://doi.org/10.1111/labr.12236`. Published in an earlier version in Hohenheim Discussion Papers in Business, Economics and Social Sciences.

JEL classification: J31, C21, O33

Keywords: Automation, Decomposition Method, Linked Employer–Employee Data, RIF-Regressions, Robots, Wage Inequality

Acknowledgments: We would like to thank Thomas Beißinger for his guidance throughout this project and his helpful suggestions. We thank Martyna Marczak and Klaus Prettner for their constructive comments. Further, we are grateful for valuable remarks from participants of the 13th Workshop on Labour Economics of the IAAEU at Trier University (March, 2021).

Chapter 2

Automation, Robots and Wage Inequality in Germany: A Decomposition Analysis

2.1 Introduction

During the last decades, Germany experienced increasing wage inequality like many other industrialised countries all over the world. The considerable rise in German wage dispersion since the 1990s is well documented by a vast literature (see e.g. Antonczyk et al., 2018; Card et al., 2013; Dustmann et al., 2009). At the same time, automation technologies have entered virtually every area in the economy. The manufacturing sector uses widely automated processes that on the one hand increase the productivity of labour but on the other hand also enable the substitution of labour.

Although there is a lot of current research analysing the impact of automation on labour market outcomes (see e.g. Acemoglu and Restrepo, 2020; Dauth et al., 2021; De Vries et al., 2020; Kariel, 2021), we are one of the first who examine the relative contribution of automation and robotization on wage inequality using a decomposition analysis. In order to measure the contribution of automation and robotization, we implement a new measure of automation threat in which we combine the information about occupation- and requirement-specific automation probabilities with sector-specific robot densities. This allows us to take into account, that on the one hand working in a sector with lower robot density is associated with a lower automation threat than working in a sector with higher robot density, regardless of the occupation. On the other hand, working in the same sector but in different occupations or requirement levels naturally leads to a different threat of automation.

In addition, we enlarge the covered time period of the existing literature by considering wage inequality developments in the German manufacturing sector from 1996 to 2017. We find that the recent time period exhibits steady or even declining wage inequality developments. Nevertheless, even in this more recent period, we find evidence of an inequality-increasing contribution due to compositional changes in automation threat structures. Using the administrative linked employer–employee data provided by the German Institute for Employment Research (IAB), we are able to evaluate the importance of further individual-, firm- and industry-specific explanatory factors on German wage inequality. We apply the extended Oaxaca-Blinder decomposition method based on recentered influence function (RIF) regressions introduced by Firpo et al. (2018). Using this empirical estimation strategy, we are able to disentangle the relative contribution of several covariates on different inequality measures. Moreover, we are able to distinguish between composition and wage structure effects. It is important to note that the decomposition analysis enables us to identify sources that contribute to wage inequality, however, our results cannot be interpreted as causal effects.

We reveal that besides the commonly used demographic factors, our measure of automation threat contributes significantly to wage inequality in the German manufacturing sector. We identify compositional effects due to automation threat as a non-negligible factor associated with changes in wage inequality in Germany. There is an observable trend towards occupations with medium automation threat, accompanied by a decreasing share of occupations with high and low automation threat. Due to the fact that within-group wage inequality is the lowest in occupations with the highest automation threat, those compositional changes are associated with an increase in overall wage inequality.

Moreover, we find evidence that there is growing wage dispersion between workers in occupations with high and low automation threat that contributes to rising overall wage inequality between 1996 and 2010. This result is supported by the predictions of routine-biased technological change (RBTC), where technology is replacing labour in routine tasks and complements labour in non-routine tasks (see e.g. Acemoglu and Autor, 2011; Autor et al., 2003; Goos and Manning, 2007). An increase in technology would increase the relative demand for non-routine tasks compared to routine tasks, which leads to an increase in the relative wage returns of workers performing the former tasks. Our proposed automation threat variable captures different automation probabilities in occupations based on a task-based approach. Due to this, we can link the changes in relative wages between workers in occupations with high and low automation threat to RBTC, where the relative wage of non-routine tasks that are typically at low risk of automation is increasing compared to routine tasks that are usually faced with higher risk of automation, leading to a rise in wage dispersion between those two groups.

Regarding the general empirical approach and the applied data, this paper is related to Antonczyk et al. (2010), Biewen and Seckler (2019), Felbermayr et al. (2014) and Baumgarten et al. (2020), who have implemented decomposition analyses of the wage distribution in Germany using linked employer-employee data. Antonczyk et al. (2010) and Biewen and Seckler (2019) analyse the increase in wage inequality in West Germany and show that firm effects, bargaining effects and personal characteristics mainly account for the rise in wage dispersion. Felbermayr et al. (2014) restrict the sample to the manufacturing sector and focus on the contribution of investment in new technologies and international trade to the increase in wage inequality from 1996 to 2010. Their results show that the change in the wage distribution can be explained to a large extent by composition effects, where the traditional factors such as age, education and collective bargaining agreements play the most important roles. Investment in new technologies as well as international trade had no significant influence on wage dispersion. More recently, Baumgarten et al. (2020) enlarge the covered time period up to 2014 and show that overall wage inequality in Germany has been rising up to 2010 before decreasing slightly thereafter.

There is a variety of theoretical and empirical literature that supports the implementation of automation threat as a factor of rising wage inequality. The endogenous growth models presented by Acemoglu and Restrepo (2018), Hémous and Olsen (2022) and Prettner and Strulik (2019) analyse labour-saving innovation and their impact on economic growth and inequality. While Acemoglu and Restrepo (2018) and Hémous and Olsen (2022) focus on the production sector in order to analyse under which conditions (low-skilled) workers could gain from automation, Prettner and Strulik (2019) endogenise education decisions of households in order to capture the race between education and technology. Beside conceptual differences, in all three endogenous growth models automation tends to increase wage inequality. Lankisch et al. (2019) present a variant of the Solow (1956) model with high-skill workers, low-skill workers and automation capital. In this simpler model, an increase in automation leads as well to a rise in the skill premium.

Turning to empirical literature, Autor et al. (2003) show that an increase in computerisation goes along with a relative shift in labour demand towards college-educated workers. Furthermore, Acemoglu and Restrepo (2020) find evidence that a rise in robot exposure reduces employment and wages between 1990 and 2007 in the USA. In a similar way Dauth et al. (2021) analyse the effect of robot exposure in Germany and show that a rise in robot exposure decreases employment of workers in the manufacturing industry. They provide evidence that the negative employment effect is offset by an increase in employment in the service sector. In addition, they show that robot exposure increases inequality within the manufacturing sector, because those who remain by their original employer experienced higher wages, while those who are forced to leave their original firm are faced with wage losses. Kariel (2021) introduces a new measure of automation that captures the regional exposure to automation innovation and finds evidence that automation has a negative impact on manufacturing employment in the UK, while it increases employment in other industries such as services. De Vries et al. (2020) analyse the impact of industrial robots on occupational shifts by task content and find evidence that the increased use of robots rise the employment share of especially non-routine analytic jobs, while it decreases the share of routine manual jobs. Aksoy et al. (2021) examine the impact of robots on the gender wage gap in European countries and find evidence that while both men and women receive an increase in earnings due to robotization, men at medium- and high-skill occupations benefit disproportionately. Kaltenberg and Foster-McGregor (2020) present related decomposition analyses on wage distributions in 10 European countries, where

Germany is not included, and focus on the impact of automation risk of occupations between 2002 and 2014. They find evidence that the composition effect contributes to a large extent to automation related wage dispersion in all countries, while the wage effect explains automation related inequality in half of the countries.

The remainder of this paper proceeds as follows: Section 2.2 describes the different data sets used in our empirical analysis. In Section 2.3 we outline our empirical approach and define our variable quantifying automation threat. Descriptive evidence on the development of wage inequality and automation as well as descriptive statistics of our explanatory variables are revealed in Section 2.4. Finally, we present our empirical results in Section 2.5 before we conclude in Section 2.6.

2.2 Data

Labour market data. We use German linked employer-employee data (LIAB), provided by the Research Data Centre of the Institute for Employment Research (IAB).[1] The data set combines information on the yearly representative employer survey (IAB Establishment Panel) with the corresponding establishment and individual data, drawn from labour administration and social security. The IAB Establishment Panel has been conducted since 1993 in West Germany as well as since 1996 in East Germany and contains establishments with at least one employee subject to social security. The sample size of the IAB Establishment panel increased from roughly 4,000 establishments in 1993 to more than 16,000 establishments in 2017. Due to the fact that larger establishments are overrepresented, the IAB provides appropriate weights to ensure a representative sample. This sample of establishments is matched with the social security data of workers who were employed in those establishments on 30th June of each year. Therefore, workers that do not contribute to social security are not included in the panel.

The main advantage of the LIAB data is the wide set of information of the work-

[1] In more detail, this study uses the LIAB cross-sectional model 2, version 1993-2017, of the Linked-Employer-Employee Data (LIAB) from the IAB. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access. DOI: 10.5164/IAB.LIABQM29317.de.en.v1. For detailed data description see Schmidtlein et al. (2019).

ers characteristics and of the particular establishment in which they are employed. The data contains personal information of the workers such as gender, year of birth, nationality, vocational training, education and place of residence as well as information on their employment like daily wage, occupation, task level and number of days in employment. Moreover, the data set provides information on the establishments such as the classification of economic activities, total number of employees and region.

We restrict the data to male full-time workers in the manufacturing sector in their main employment between 18 and 65 years, who earned more than 10 Euros per day and consider the time period between 1996 and 2017.[2] Following the common literature on wage inequality in Germany, we restrict our analysis to West Germany, due to the fact that East and West of Germany are still faced with significantly different labour market and wage structures (see e.g. Baumgarten et al., 2020; Biewen and Seckler, 2019; Dustmann et al., 2009). The wage earnings recorded by social security are right-censored at the contribution assessment ceiling of the social security system. To account for this problem, we use imputed wages following the approach by Gartner (2005).[3] Non-censored and imputed wages are converted into constant 2015 Euros with the Consumer Price Index provided by the German Federal Statistical Office.

Robot data. The data on industrial robots is obtained from the International Federation of Robotics (IFR), which is commonly used in recent analyses (see e.g. Acemoglu and Restrepo, 2020; Anelli et al., 2021; Dauth et al., 2021). The data contain the stock of industrial robots for 50 countries broken down at the industry level, where data availability differs across countries. German robot data is available from 1993 to 2017. An industrial robot is defined as “an automatically controlled, reprogrammable, multipurpose [machine]” (International Federation of Robotics, 2018).[4] The data rely on primary and

[2]Due to the fact that the data do not contain any information on the number of working hours, we decide to consider only men working full-time. We are aware of this strong restriction, nevertheless it reduces noise and increases consistency in the analysis.

[3]In order to circumvent estimations that are driven by the imputation procedure, the analysis provides results including only the uncensored part of the wage distribution represented by the inter-percentile ranges up to the 85th percentile.

[4]We consider only industrial robots in the analysis. Data on service robots is also available since 2002. However, the data is not available at the industry level during the considered time period.

secondary data sources. The primary source are yearly surveys of worldwide industrial robot suppliers that report their stock of industrial robots to the IFR. Additionally, the IFR uses secondary data collected by national robot associations to validate the survey data. Before 2004, the data on German industrial robots rely solely on collected data by national robot associations.

The industry classifications in the IFR data are very coarse and differ between the manufacturing and non-manufacturing sector, which is one of the main disadvantages of the data. Away from the manufacturing sector, industries are aggregated to very broad groups, while among the manufacturing sector the data are more disaggregated. Thus, our analysis focuses on the manufacturing sector in Germany due to better data availability and the predominant role of automation in this sector. Industrial robot data reported by the IFR is mainly based on the International Standard Industrial Classification of All Economic Activities (ISIC) Rev. 4.[5] In total, we focus on 8 different manufacturing sectors: 10-12 food products, beverages and tobacco products, 13-15 textiles, wearing apparel, leather and related products, 16-18 wood (including furniture) and paper products, printing and reproduction of recorded media, 19-23 coke and refined petroleum products, chemical products, pharmaceutical products, rubber and plastics products, and other non-metallic mineral products, 24-25 basic metals and fabricated metal products, 26-27 computer, electronic and optical products, electrical equipment, 28 industrial machinery and equipment n.e.c., 29-30 automotive and other vehicles.[6] The IFR data can be matched with the LIAB data without any crosswalk, for further information see Appendix 2.A.

Automation risk data. We use an occupation- and requirement-specific score of automation risk. In contrast to the commonly used measure provided by Frey and Osborne (2017), we relate to specific estimations for occupations in Germany based on the task-based approach by Dengler and Matthes (2015). The resulting advantages are presented in Appendix 2.A. Dengler et al. (2014) calculate the task composition for different occu-

[5] Within the manufacturing sector there is one exception at the 2-digit level. The IFR classification uses the 2-digit code 16-wood and furniture. This industry contains the ISIC Rev. 4 code 16 and 31.

[6] As Dauth et al. (2021) and Graetz and Michaels (2018), we exclude *All other manufacturing branches*, since it covers only 6.8% of the robot stock in the manufacturing sector in 1996 and the share declines to 1.7% in 2017.

pations, based on BERUFENET Expert Database of the German Federal Employment Agency. The data set contains information of around 3,900 single occupations, such as the tasks to be performed in the respective occupation, the equipment or the working conditions. The so called requirement matrices classify 8,000 different requirements to each single occupation. Dengler et al. (2014) assign to each requirement one task type (analytical non-routine tasks, interactive non-routine tasks, cognitive routine tasks, manual routine tasks and manual non-routine tasks). The central criterion whether the task is routine or non-routine is the substitutability of computers or computer-controlled machines, based on the available technology in 2013.[7]

On the basis of this data, Dengler and Matthes (2015) estimate the share of routine tasks to non-routine tasks for each single occupation, by dividing the core requirements, that are essential for the occupation, in each single occupation that have been assigned to a routine task by the total number of core requirements in the respective single occupation.[8] Next, they aggregate the shares of routine tasks for each single occupation into different occupation aggregates, using weights based on employment numbers from 2012. The weights ensure that single occupations with high employment are taken more into consideration, when determining the substitution potential at the aggregated occupational level. The share of routine activities is used to determine the substitution potential of the occupation.

The data is available in the 2-digit Classification of Occupations 2010 (Klassifizierung der Berufe 2010, KldB 2010). In addition, they distinguish for each 2-digit KldB 2010 code four different requirement levels.[9] In total, they estimate substitution potentials for 131 occupation-requirement level combinations. The LIAB data contains occupation codes and requirement levels in the KldB 2010 classification.[10] Therefore, merging both

[7]There are already updated versions of the automation probabilities based on the available technology in 2016, see Dengler and Matthes (2018), and 2019, see Dengler and Matthes (2021). Due to the fact that the considered time period in our analysis begins in 1996, we use the automation probabilities calculated on the basis of the available technology in 2013.

[8]For example, if one single occupation contains three different core requirements, and one requirement is assigned to a routine task, then the share would be 1/3.

[9]The requirement levels correspond to the 5th digit KldB 2010 classification: 1-unskilled activities, 2-specialist activities, 3-complex activities, 4-highly complex activities.

[10]The occupational information before 2011 was reported using the occupation code KldB 1988. This older classification is less detailed than the occupation code KldB 2010, which leads to inaccuracies.

data sets is possible without any crosswalk.

2.3 Empirical Approach

2.3.1 Method

Oaxaca-Blinder decomposition. The standard Oaxaca-Blinder (OB) decomposition divides the overall mean wage gap, $\hat{\Delta}_O^\mu$, between two defined groups, in our case two points in time ($t = 0, 1$) (Firpo et al., 2018; Oaxaca, 1973). Assuming a linear wage equation, where w_t denotes the log wage and X is a vector of covariates, the following holds true:

$$\begin{aligned}\hat{\Delta}_O^\mu &= \bar{X}_1(\hat{\beta}_1 - \hat{\beta}_0) + (\bar{X}_1 - \bar{X}_0)\hat{\beta}_0 \\ &= \hat{\Delta}_S^\mu + \hat{\Delta}_X^\mu.\end{aligned} \tag{2.1}$$

The first part of equation (2.1) denotes the wage structure effect, $\hat{\Delta}_S^\mu$, which is the result of holding the distribution of covariates constant and only modifying the conditional wage structure.[11] Thus, in other words this effect represents the differences in the estimated coefficients between the two groups and shows the way the specific characteristics are valued in the labour market. The second part is the composition effect, $\hat{\Delta}_X^\mu$, where the conditional wage structure is held constant and the distribution of covariates varies according to the observed changes between the two points in time (Fortin et al., 2011). In other words, this effect presents the differences in the distribution of the explanatory factors between the two points in time.

RIF-regressions approach. The recentered influence function (RIF) regressions approach allows to quantify the impact of each covariate, conditional on all other factors, on the change in wage inequality measures, such as percentile wage gaps, the variance or the Gini coefficient (Firpo et al., 2018). Thus, the dependent variable, w, is replaced by the recentered influence function of the statistic of interest. The influence function,

[11] Using categorical variables in a detailed decomposition, the estimated wage structure effect depends on the defined base group. Therefore, the effect of changes in the returns have to be interpreted based on this omitted group (Fortin et al., 2011).

$IF(w;v)$, of an observed wage w for the distributional statistic $v(F_w)$, that is dependent on the wage distribution F_w, shows the influence of each observation on this distributional statistic. The conditional expectation of the $RIF(w;v)$ can be estimated using a linear function of the explanatory variables, i.e. $E[RIF(w;v)|X] = X\gamma$, where the parameters γ can be estimated by OLS (Fortin et al., 2011).

When it comes to quantiles, the estimated coefficients are interpreted as unconditional (quantile) partial effects (UQPE) of small location shifts in the covariates (Firpo et al., 2009). Using the RIF-regressions approach it is possible to identify the effect of a changing explanatory variable on the τth quantile of the unconditional distribution of w. This procedure is different to the commonly used conditional quantile regressions.

With the estimated coefficients of the unconditional quantile regressions, $\hat{\gamma}_{t,\tau}$, for each group of $t = 0, 1$ the OB decomposition can be written as:

$$\begin{aligned} \hat{\Delta}_O^\tau &= \bar{X}_1(\hat{\gamma}_{1,\tau} - \hat{\gamma}_{0,\tau}) + (\bar{X}_1 - \bar{X}_0)\hat{\gamma}_{0,\tau} \\ &= \hat{\Delta}_S^\tau + \hat{\Delta}_X^\tau, \end{aligned} \tag{2.2}$$

where $\hat{\Delta}_O^\tau$ defines the wage gap at the τth unconditional quantile. The first term of equation (2.2) corresponds to the wage structure effect that is obtained by holding the distribution of the covariates constant and only modifying the conditional wage structure represented by the RIF coefficients. The second term represents the composition effect, which is the result of holding the conditional wage structure constant and changing the distribution of the covariates according to the observed change between the points in time $t = 0$ and $t = 1$. The detailed decomposition can be computed similarly as in the case of the mean (Fortin et al., 2011).

However, as in the standard OB decomposition it could be the case that the linearity assumption does not hold.[12] Therefore, the two step procedure proposed by Firpo et al. (2018) is used in order to avoid this problem. In a first step, a counterfactual sample, which is defined by point in time $t = 01$, is estimated applying the reweighting function introduced by DiNardo et al. (1996). Using the reweighting function, the hypothetical

[12] As discussed by Barsky et al. (2002), if the linearity assumption does not hold, the estimated counterfactual mean wage would not be equal to $\bar{X}_1\hat{\beta}_0$ in the case of the standard OB decomposition.

sample makes the characteristics of point in time $t = 0$ similar to those of point in time $t = 1$. In a second step, two OB decompositions are specified by using the three different samples.

The first OB decomposition uses the sample $t = 0$ and the counterfactual sample $t = 01$ to estimate the reweighted composition effect, $\hat{\Delta}^{\tau}_{X,R}$, as follows:

$$\begin{aligned} \hat{\Delta}^{\tau}_{X,R} &= (\bar{X}_{01} - \bar{X}_0)\hat{\gamma}_{0,\tau} + \bar{X}_{01}(\hat{\gamma}_{01,\tau} - \hat{\gamma}_{0,\tau}) \\ &= \hat{\Delta}^{\tau}_{X,p} + \hat{\Delta}^{\tau}_{X,e}, \end{aligned} \tag{2.3}$$

where the first part of the right-hand side of equation (2.3) corresponds to the pure composition effect, while the second part represents the specification error.

The wage structure effect is estimated in a similar way using the sample $t = 1$ and the counterfactual sample $t = 01$:

$$\begin{aligned} \hat{\Delta}^{\tau}_{S,R} &= \bar{X}_1(\hat{\gamma}_{1,\tau} - \hat{\gamma}_{01,\tau}) + (\bar{X}_1 - \bar{X}_{01})\hat{\gamma}_{01,\tau} \\ &= \hat{\Delta}^{\tau}_{S,p} + \hat{\Delta}^{\tau}_{S,e}, \end{aligned} \tag{2.4}$$

where the first term of the right-hand side of equation (2.4) defines the pure wage structure effect and the second part denotes the reweighting error. Since the counterfactual sample $t = 01$ is used to imitate the sample of point in time $t = 1$, in large samples it should be $plim(\bar{X}_{01}) = plim(\bar{X}_1)$.

The description of the RIF-regressions based OB decomposition is limited to specific percentiles of the wage distribution. In order to estimate effects on percentile wage gaps, the difference between the respective estimated coefficients of the corresponding percentiles has to be computed. Regarding other distributional statistics, like the variance or the Gini coefficient, the RIF-regressions have to be adjusted accordingly (see Firpo et al., 2018).

The following analysis is based on different inequality measures. Depending on which index is used, a specific part of the wage distribution is taken into focus. The commonly used Gini coefficient is one of the standard indices and measures inequality considering the whole wage distribution. However, it has to be taken into account that the Gini index is more sensitive to changes in the middle of wage distribution and less sensitive to changes at the top and the bottom of wage distribution (Atkinson, 1970). That is why we use in addition percentile wage gaps not only between the highest and the lowest wages (85th-15th wage gap) but also in relation to the median wages (50th-15th and 85th-50th wage gaps). Thus, it is also possible to observe changes separately for the lower and upper half of the wage distribution. Further results of the variance are presented in order to have comparative values for estimates of the whole distribution.

The fact that the method uses simple regressions that are easy to interpret provides a straightforward way of a detailed decomposition. Compared to the sequential decomposition introduced by DiNardo et al. (1996) (DFL-method), the RIF-regressions based detailed decomposition does not suffer from path dependence. However, the RIF-regressions assume the invariance of the conditional distribution and therefore does not take general equilibrium effects into account (Fortin et al., 2011). Moreover, this decomposition method ascribes the change in wage inequality completely to the considered covariates. Thus, the sum of all composition effects and wage structure effects defines the overall change in wage inequality over time.

2.3.2 Model Specification

The decomposition analyses consider a wide range of covariates that are determinants to changes in the wage distribution. Besides the commonly used personal and plant characteristics, we propose a measure of automation threat that is described in more detail below. The personal characteristics include the individual's age (five categories)[13]; education (three categories)[14]; tenure (five categories)[15]; and a dummy variable capturing German or foreign citizenship. Furthermore, we consider the following two plant characteristics: plant size (six categories)[16]; and the bargaining regime (three categories)[17].

[13](1) 18-25 years; (2) 26-35 years; (3) 36-45 years; (4) 46-55 years; (5) 56-65 years.

[14](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.

[15](1) 0-2 years; (2) 2-4 years; (3) 4-8 years; (4) 8-16 years; (5) >16 years.

[16](1) 1-9 employees; (2) 10-49 employees; (3) 50-199 employees; (4) 200-999 employees; (5) 1000-4999 employees; (6) $\geq$5000 employees.

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

In addition, we control for fixed effects of 8 different manufacturing sectors and include federal state dummies to capture regional shifts.[18]

The main factor of interest is our new introduced measure of automation threat, which captures two dimensions of automation. On the one hand, we take the various evolution of the sectoral robot density into account, which is often used as an approximation of automation exposure. On the other hand, we consider the different automation risk of workers due to the task content of their occupation. Therefore, we merge data on the substitution potential of an occupation provided by Dengler and Matthes (2015), which we interpret as a proxy variable for the automation probability of an occupation, with the IFR robot data. This procedure combines the occupational information about the automation probability with the time varying sectoral information about the number of robots per 1,000 workers:[19]

$$automation\ threat_{j,s,t} = \theta_j * \frac{Robots_{s,t}}{emp_{s,1995}}, \tag{2.5}$$

where θ_j is the automation probability of occupation j, $Robots_{s,t}$ is the stock of operational robots in sector s in year t and $emp_{s,1995}$ is the number of employees in thousands in the corresponding sector s in the base year 1995.[20] Thus, each individual working in occupation j and sector s is confronted with the corresponding automation probability of its occupation and a specific sectoral robot density of a given year t.

For our decomposition analysis we have to define three groups of different automation

[18] The base category is a medium-skilled worker between 26 and 35 years, with 0-2 years of tenure, with German citizenship and is exposed to low automation threat. Further, the worker is employed in an establishment with 200-999 employees, which has no collective bargaining agreement, belongs to the basic metals and fabricated metal products sector and is located in North Rhine-Westphalia.

[19] In a familiar way, this approach is used in Anelli et al. (2019) to capture the individual exposure to automation. In a first step, a multinomial logit model is estimated using all available covariates to predict the probability of an individual being in a certain occupation. This probability is multiplied with the corresponding automation probability in that occupation to obtain an individual vulnerability to automation. In a last step, the individual vulnerability is multiplied with the national percentage change in total operational robots in a country. Due to the characteristics of our estimation strategy it is not possible to implement this kind of automation threat variable.

[20] The data on sectoral employment in 1995 is provided by EU KLEMS database, see Stehrer et al. (2019).

threat in order to ensure the common support assumption.[21] In a first step we have a look at the total number of all combinations of the occupation specific automation probabilities with the sector specific robot densities in a specific year sorted by size. Then we define cut-off points in a way that the number of combinations in a specific year is divided into three groups.[22] As a consequence, we are able to assign every individual to either low, middle or high automation threat. This procedure is done separately for each year.

The estimation strategy of this variable is reasoned by the following considerations. First of all, since the automation probabilities are time constant, adding yearly information about the stock of robots in a given sector adds a time dimension to our proposed automation variable. Due to this, the significant increase in the use of robots is represented and considered in our subsequent analysis. Second, the sector specific robot densities influence the relative degree of automation threat, since there are substantial differences between economic sectors. In other words, the automation probability of an occupation exhibits a different importance depending on the specific sector.

The necessity of the combination between automation probabilities and sector specific robots densities is shown in Table 2.B.1 in Appendix 2.B. Here the distribution of the different economic sectors within the three groups of automation threat is compared to the shares of economic sectors within the groups based on the automation probabilities by Dengler and Matthes (2015).[23] The first thing that becomes apparent is the fact that in the medium and especially in the high automation threat group not all economic sectors are represented. Looking at the robot densities reveals that the missing sectors (textiles and wood, furniture and paper) indeed exhibit the lowest values. The low robot density

[21]The common support assumption is one of the main conditions proposed by Fortin et al. (2011) that ensures a successful estimation of the decomposition. This assumption imposes the condition of common support on the covariates and makes sure that no observation can serve to identify the assignment into one specific group (Fortin et al., 2011). Due to this condition it is not possible to use a continuous variable measuring automation threat. The considerable increase over time would lead to exclusively present values in points in time $t = 0$ and $t = 1$, which contradicts this assumption.

[22]For example, if there are in total 300 possible occupation-sector combinations in one year, the first group includes the lowest 100 combinations, the second group the 100 combinations in the middle and the third group the 100 highest combinations. There are two cut-off points, namely the values of the 100th and the 200th combination. Of course, the values of these cut-off points increase over time as the values of the automation threat variable increases as well.

[23]The group of low automation risk is given if a maximum of 30% of the occupation could be performed by computers. The medium automation risk captures those occupations, which are substitutable by automation between 30% and a maximum of 70% and high automation risk exists if more than 70% of the occupation could be performed by computers.

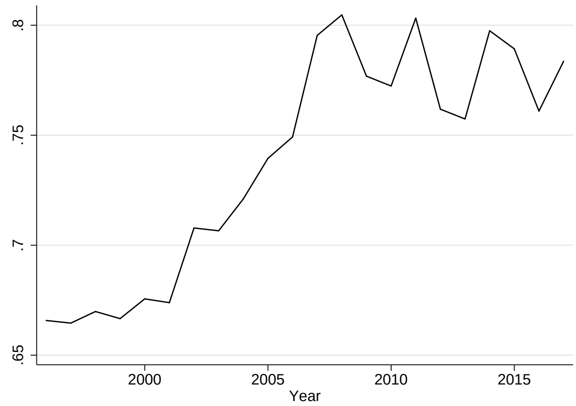
weights the automation probability down, which leads to the result that no employee within this sector is faced with a high (or even medium) automation threat. Another striking feature is the relatively low share in the low and medium automation threat group within the automotive sector. This is due to the fact that the automotive sector is faced with a very high robot density which leads to an upweight of the automation probabilities. This takes into account that working in a sector with higher robot density is associated with a higher automation threat than working in a sector with lower robot density, regardless of the occupation. These findings validate the combination of automation probabilities of occupations and sector specific robot densities. Further descriptive information about our proposed variable is presented in the following.

2.4 Descriptive Evidence

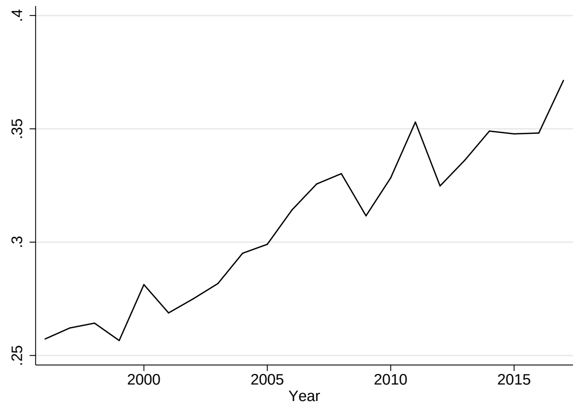
Developments in wage inequality. The development of wage inequality in the German manufacturing sector defined by the difference between the 85th and 15th percentiles of log real daily wages for men working full-time is displayed in Panel (a) of Figure 2.1. Starting with a short period of moderate increase in wage inequality, a significant rise in the wage gap is observable between 2001 and 2008. In the subsequent years, wage inequality shows an alternating behaviour but is not subjected to major increases as before. A similar pattern is observable by having a look at the development of the Gini coefficient, which measures the normalised average absolute difference between all wage pairs in the workforce. As a result of these observations, we divide our overall period of observation into two subperiods, 1996 to 2010 in which wage inequality is overall increasing and 2012 to 2017 in which wage inequality more or less stagnates.[24]

Since the 85-15 percentile wage gap only takes the top and bottom percentiles into account, developments in the middle of the distribution are omitted. Therefore, the wage gaps between the 50th and 15th percentiles as well as between the 85th and 50th per-

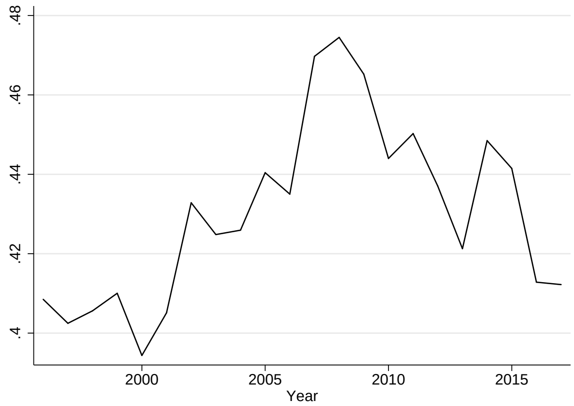
[24]Baumgarten et al. (2020) consider similar time periods: 1996 to 2010 and 2010 to 2014. Due to a change in the reporting procedure of the social security agency, a considerable increase in the number of missing values occurs in the year 2011. In order to circumvent this possible source of misleading estimation results, we define 2012 as our starting point of the second period of observation. For more information see Schmidtlein et al. (2019).



(a) 85-15 percentile wage gap



(b) 50-15 percentile wage gap



(c) 85-50 percentile wage gap

Figure 2.1: The evolution of the 85-15, 50-15 and 85-50 percentile wage gaps between 1996 and 2017

Source: LIAB QM2 9317, own calculations.
Note: The figure presents the evolution of the 85-15, 50-15 and 85-50 percentile wage gaps between 1996 and 2017 for men working full-time in the manufacturing sector in Germany. The results are based on imputed real daily wages. Sampling weights are employed.

centiles are presented to account on the one hand for developments at the lower half and on the other hand for developments at the upper half of the wage distribution. The results presented in Panel (b) of Figure 2.1 suggest that in the manufacturing sector a significant increase in inequality at the lower part of the wage distribution is observable. This development is seen throughout the whole period of observation. Regarding the findings of the wage gap in the upper half of the distribution a different pattern is identified. Panel (c) of Figure 2.1 shows a noticeable increase between 2000 and 2008. However, in the following years inequality at the upper part of the wage distribution decreased significantly and ends up in 2017 almost at the same level as in 1996. These trends result in the consistent increase of the overall wage inequality until 2008. Thereafter, the observed developments in wage inequality at the lower and upper parts of the wage distribution balance each other out.

The rise of automation. At the same time, automation technology accelerated since the 1990s. This increase is also captured by our automation threat variable, despite sectoral differences. Figure 2.C.1 in Appendix 2.C illustrates the estimated automation threat variable in equation (2.5) summarised over all occupations in each manufacturing sector in Germany from 1996 to 2017. While most sectors experienced an increase in automation threat, the wood, furniture and paper sector and the textiles sector have seen a slight decrease in automation threat. It is striking that the automotive and other vehicles sector was faced with an extraordinary increase compared to the other sectors. Automation threat in the automotive and other vehicles sector was eight times higher in 1996 compared to the average of automation threat in the other manufacturing sectors. In 2017 automation threat was even almost twelve times higher than in the other sectors.

Descriptive statistics of explanatory variables. Since one important part of the OB decomposition are changes in the composition of workers, we present in Table 2.1 the descriptive statistics of our considered explanatory variables for the years 1996, 2010, 2012 and 2017. The first column of each year gives the mean of the respective variable, whereas in the second column the corresponding standard deviation is listed. Looking at the first row, a clear trend towards higher real daily wages becomes apparent, where between 1996 and 2010 an increase by 9% and between 2012 and 2017 an increase by 7% is observed. The demographic factors regarding age and education reflect the often described trend in the literature towards an older and more educated workforce. The share of highly skilled workers increased in our sample from 9% in 1996 to more than 15% in 2017, whereas at the same time the low skilled group is halved, from 12% to 6%. In addition, workers tend to have a higher tenure. The group of workers with more than 16 years of employment increased by more than 16 percentage points over the whole period of observation, whereas all other groups decreased in size over time. Workers are denoted as foreigners or natives based on their nationality. During the observed time span the amount of workers with a foreign nationality decreased, which is presumably the result of a change in the German nationality law.

Table 2.1: Descriptive statistics

	1996		2010		2012		2017	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Real daily wage	126.42	(51.31)	137.52	(69.71)	137.19	(67.78)	147.33	(70.32)
Age: 18-25 years	7.39	(26.17)	5.73	(23.25)	6.65	(24.92)	5.84	(23.45)
Age: 26-35 years	32.19	(46.71)	18.04	(38.45)	18.77	(39.05)	20.17	(40.13)
Age: 36-45 years	28.62	(45.19)	30.87	(46.19)	26.58	(44.18)	22.49	(41.75)
Age: 46-55 years	22.29	(41.62)	33.88	(47.33)	34.04	(47.38)	33.68	(47.26)
Age: $\geq$ 56 years	9.51	(29.33)	11.48	(31.87)	13.96	(34.65)	17.81	(38.26)
Education: low	12.21	(32.73)	8.65	(28.10)	7.22	(25.89)	6.03	(23.80)
Education: middle	78.55	(41.04)	77.64	(41.66)	78.25	(41.25)	78.49	(41.09)
Education: high	9.23	(28.96)	13.71	(34.39)	14.53	(35.24)	15.48	(36.17)
Tenure: 0-2 years	5.11	(22.02)	2.45	(15.47)	3.24	(17.70)	2.61	(15.95)
Tenure: 2-4 years	5.33	(22.46)	3.38	(18.06)	3.78	(19.07)	3.95	(19.48)
Tenure: 4-8 years	16.94	(37.50)	9.03	(28.65)	9.48	(29.29)	9.35	(29.10)
Tenure: 8-16 years	25.32	(43.48)	22.15	(41.52)	21.18	(40.86)	20.10	(40.07)
Tenure: $\geq$ 16 years	47.30	(49.93)	62.99	(48.28)	62.32	(48.45)	63.99	(48.00)
Nationality	11.32	(31.69)	8.74	(27.91)	9.25	(28.97)	8.92	(28.50)
Automation threat: low	11.14	(31.46)	7.73	(26.70)	10.93	(31.21)	12.76	(33.36)
Automation threat: middle	17.26	(37.79)	25.45	(43.56)	23.41	(42.34)	25.12	(43.37)
Automation threat: high	71.60	(45.09)	66.82	(47.08)	65.66	(47.48)	62.12	(48.51)
No collective agreement	7.75	(26.73)	28.36	(45.07)	31.07	46.28	29.25	(45.49)
Firm level agreement	9.91	(29.88)	13.38	(34.04)	11.80	(32.26)	12.83	(33.43)
Sector level agreement	82.34	(38.13)	58.25	(49.31)	57.13	(49.49)	57.92	(49.36)
Plant size: 1-9 employees	5.30	(22.41)	3.08	(17.27)	3.09	(17.29)	2.19	(14.64)
Plant size: 10-49 employees	14.75	(35.46)	13.71	(34.39)	13.69	(34.37)	10.91	(31.17)
Plant size: 50-199 employees	21.86	(41.33)	23.56	(42.44)	23.02	(42.09)	19.05	(39.27)
Plant size: 200-999 employees	30.79	(46.16)	31.67	(46.52)	32.99	(47.01)	35.08	(47.72)
Plant size: 1000-4999 employees	17.14	(37.68)	18.48	(38.82)	16.68	(37.28)	13.59	(34.27)
Plant size: $\geq$ 5000 employees	10.16	(30.22)	9.50	(29.32)	10.53	(30.71)	19.17	(39.37)
Sector: Food and beverages	6.58	(24.79)	7.05	(25.59)	6.89	(25.33)	9.74	(29.64)
Sector: Textiles	2.93	(16.87)	1.33	(11.44)	1.30	(11.32)	0.76	(8.69)
Sector: Wood, furniture and paper	9.34	(2909)	8.38	(27.71)	7.36	(26.11)	7.01	(25.53)
Sector: Plastic and chemical products	14.20	(34.91)	14.24	(34.95)	13.93	(34.62)	10.46	(30.61)
Sector: Metal products	21.02	(40.75)	22.38	(41.68)	23.77	(42.56)	18.87	(39.13)
Sector: Electrical products	10.49	(30.64)	14.15	(34.86)	12.06	(32.57)	10.76	(30.98)
Sector: Industrial machinery	20.66	(40.48)	16.46	(37.08)	19.41	(39.55)	19.40	(39.54)
Sector: Automotive and other vehicles	14.77	(35.48)	16.01	(36.67)	15.28	(35.97)	23.00	(42.08)
Schleswig-Holstein	2.12	(14.39)	2.46	(15.48)	1.94	(13.78)	1.59	(12.51)
Hamburg	2.04	(14.18)	3.37	(18.04)	3.71	(18.90)	3.69	(18.85)
Lower Saxony	11.86	(32.33)	10.31	(30.40)	10.36	(30.47)	8.81	(28.34)
Bremen	1.18	(10.81)	0.52	(7.19)	1.01	(10.00)	0.74	(8.57)
North Rhine-Westphalia	30.29	(45.95)	27.83	(44.82)	27.93	(44.87)	22.87	(42.00)
Hesse	8.85	(28.39)	6.66	(24.93)	7.80	(26.81)	7.95	27.06
Rhineland-Palatinate	5.13	(22.05)	5.86	(23.49)	5.51	(22.81)	5.98	(23.71)
Baden-Wuerttemberg	18.69	(38.98)	20.88	(40.64)	19.52	(39.63)	17.46	(37.96)
Bavaria	18.04	(38.44)	20.38	(40.28)	21.25	(40.91)	30.07	(45.85)
Saarland	1.80	(13.28)	1.73	(13.05)	0.97	(9.82)	0.83	(9.09)
Observations	576,895		389,624		437,336		320,970	

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Notes*: The table presents the descriptive statistics for four time points, standard deviations are given in parentheses. All variables, except the real wage, are reported in percent. Sampling weights are employed.

Regarding plant characteristics, one striking development is presented when it comes to collective bargaining coverage. Between 1996 and 2017 the group of workers that is not covered by any sort of collective bargaining agreement increased from 8% to 29%, whereas the group with sector level agreements decreased from 82% to 58%. The fraction of workers with firm level agreements slightly increased. Regarding the size of the plants, a tendency away from smaller firms with less than 200 employees becomes apparent. In total, the share of the group with more than 5,000 employees increased by 9 percentage points. Looking at compositional changes of the sectors and changes in employment shares of the different federal states no major differences over the years appear.

When it comes to our proposed automation threat variable, there is an observable trend towards the medium group of automation between 1996 and 2010. At the same time, this observation is accompanied with a reduction by nearly 5 percentage points in the highest automation group and a decrease in the group with the lowest automation threat by more than 3 percentage points. From this one could conclude two movements. On the one hand, it seems that workers are displaced by automation in the groups of high automation threat. On the other hand, it becomes more and more impossible to resist automation in work life, which leads to a decrease in the share of the lowest automation threat group. In the second time period the share of workers which are faced with high automation threat decreased further, although at a smaller amount and the middle automation threat group is still increasing. In contrast to the first period, the share of workers in the lowest automation threat group slightly increased between 2012 and 2017.

To get a first impression about the relation between automation threat and changes in wage inequality, we provide descriptive evidence of differences in within-group wage inequality. In Figure 2.2 the estimated Gini coefficients for the respective groups of automation threat for the whole period of observation are illustrated. In all three groups the significant increase of wage inequality between 1996 and 2008 and the stagnation thereafter becomes apparent. However, there is a substantial difference in the level of wage inequality between the high automation threat group and the groups with middle and low automation threat. The lowest wage inequality is found in the highest group of automation threat. Table 2.B.2 in Appendix 2.B reveals that the average real daily wages of the high automation threat group are predominantly lower than those from the medium or lowest automation threat groups, however the distribution of wages within this group is the most equal.

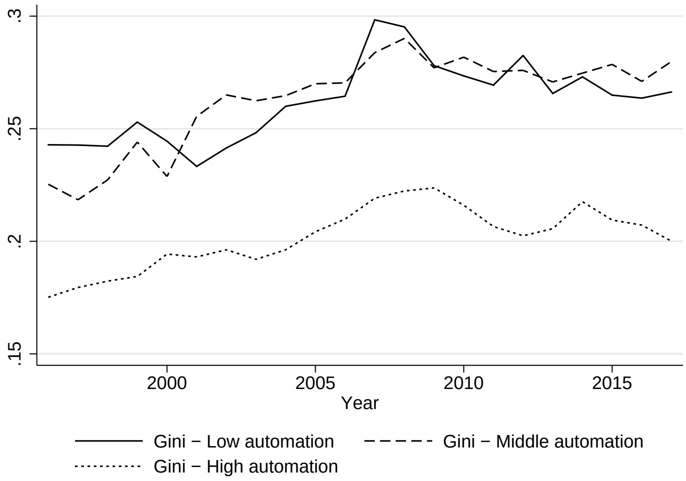


Figure 2.2: Gini coefficients of different automation threat groups, 1996-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: The figure presents the evolution of the group-specific Gini coefficient estimations between 1996 and 2017. We distinguish between low, medium and high automation threat. Sampling weights are employed.

In order to figure out the reasons behind these results, we have a closer look at the educational and occupational structures within these three groups. Table 2.B.2 in Appendix 2.B shows that the highest automation threat group exhibits a mainly similar level of education with more than 80% in the medium group throughout the entire period of observation. Thus, the two remaining educational groups play only a minor role in this case. A different picture emerges when it comes to the medium and lowest groups of automation threat. Although the medium educational level still makes up the largest group in both cases, especially the highest educational level plays a more important role and therefore leads to a more diverse structure. When it comes to the requirement levels a similar picture emerges. A significant clustering of workers in the second requirement level of specialist activities in the highest group of automation threat is revealed. Other levels are much less present. Again the low and medium group of automation threat exhibit a more varied distribution of requirement levels and no extreme outstanding grouping as seen before occurs. As a result of these observations, we conclude that the more equal distribution of wages in the highest group of automation threat stems from the mainly identical levels of education and occupations with similar levels of requirements.

2.5 Decomposition Analysis and Discussion

The goal of this section is to identify the major factors associated with changes in wage inequality and their specific contribution in the two defined time periods (1996-2010 and 2012-2017). Our primary focus lies in quantifying the importance of automation and robotization on changes in the wage distribution using our measure of automation threat.

2.5.1 1996-2010

Counterfactual analysis. Since we are mainly interested in the contribution of automation on changes in wage inequality, we first provide results of a ceteris paribus analysis. Multinomial logit estimations are used in order to derive counterfactual weights by which a counterfactual wage distribution is estimated. This distribution reflects the case where the distribution of all covariates is as in point in time 1 except for the distribution of the automation threat groups, which is shifted to that of point in time 0. This procedure is different to that proposed by DiNardo et al. (1996), where a counterfactual distribution is estimated shifting all available covariates. Thus, the conducted analysis makes it possible to show graphically the effect of a compositional change of one specific covariate. The multinomial logit model that estimates the possibility of belonging to one of the three possible types of automation threat is estimated accounting for all remaining covariates we used in the decomposition (for further information see Appendix 2.A).

Figure 2.3 illustrates the actual wage distributions of 1996 and 2010 using kernel density estimations of the log wage distributions of the respective years. In 2010 a lower peak and fatter tails compared to the one in 1996 are observed. Moreover, the widening of the wage distribution is not symmetric, since more mass is shifted to the upper half of the wage distribution. In addition, the counterfactual wage distribution of 2010 with the composition of the automation threat groups shifted back to 1996 is shown. We observe that the counterfactual distribution approaches the density in 1996. A higher peak and a narrower tail at the upper half of the distribution suggest an impact that contributes to a reduction in wage inequality if the composition of the automation threat groups would have been the same in 2010 as in 1996. The actual observed change in the wage distribution between 1996 and 2010 is compared to the difference between the counterfactual and the actual wage distribution in 2010 in Figure 2.C.2 in Appendix 2.C.

Figure 2.3: Actual and counterfactual wage distributions, 1996-2010
Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: The figure presents the actual wage distributions in 1996 and 2010 as well as the counterfactual wage distribution that would have prevailed if automation and robotization had remained at the level of 1996. Counterfactual weights are estimated using multinomial logit estimations, see Appendix 2.A. Sampling weights are employed.

The analysis shows that the observed trend in automation threat contributes to the shift in the upper half of the wage distribution. However, since the counterfactual difference stays close to zero up to the middle of the distribution, a smaller contribution on lower wages is assumed. In Figure 2.C.3 we re-estimate the 85-15 percentile wage gap and the Gini coefficient using our counterfactual weights. Indeed, we are able to show that compositional changes in the automation threat groups have played an important role in the rise in wage inequality between 1996 and 2010 since the counterfactual estimates are at all times below the actual outcomes. Further, Figure 2.C.4 confirms the different impact along the wage distribution. Whereas the counterfactual line stays close to the actual line at the lower half of the distribution, a substantial gap between the two lines is shown for the upper half revealing a higher impact of automation to increasing wage inequality at this part of the wage distribution.

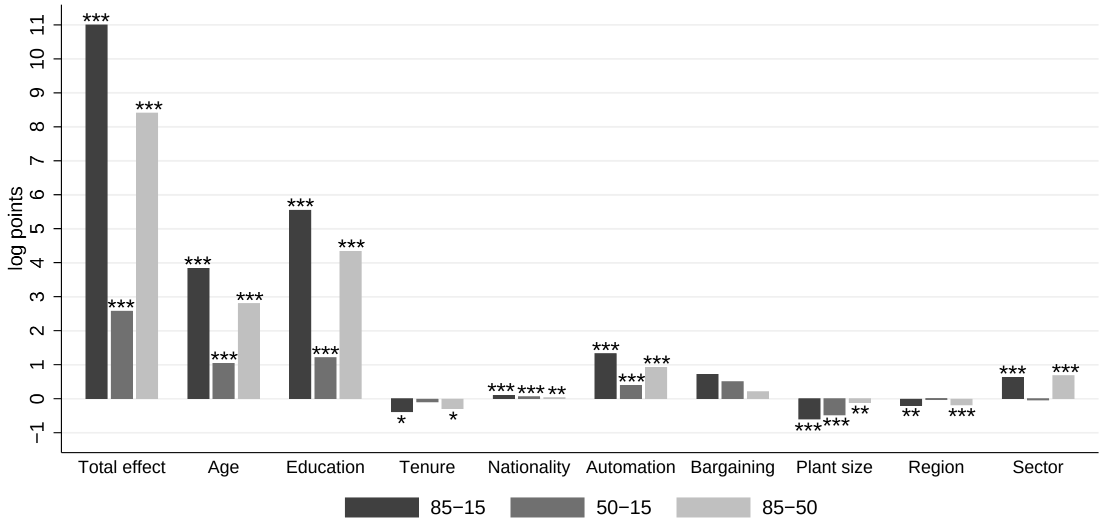
Decomposition results. We now turn to the results of the RIF-regressions based OB decomposition for the period 1996 and 2010 for men working full-time in the manufacturing sector in West Germany. Figure 2.4 presents graphically the estimated results of different percentile wage gaps for the composition effect, see Panel (a), and the wage structure effect, see Panel (b).[25] First of all, we turn to the decomposition results of the wage gap between the 85th and the 15th percentile, which increased by 10.67 log points between 1996 and 2010. The aggregate composition effect mainly contributes to the increase in the wage gap, while the aggregate wage structure effect is not statistically different from zero. The estimated specification error is statistically insignificant and the reweighting error is sufficiently small.[26]

Among the composition effects, depicted in Panel (a) of Figure 2.4, the ones associated with educational levels (5.56 log points) and the age structure of workers (3.85 log points) have played the most important role, which correspond to a relative importance of 41%[27] and 29% of the composition effect, respectively. These findings are supported by the observed shift towards older and higher educated workers in the underlying data. The contribution of the automation-related composition effect has played a slightly smaller, but non-negligible role and amounts to 1.33 log points, which corresponds to a relative importance of roughly 10% of the composition effect. As shown in the descriptive analysis, there is an observable trend towards occupations with medium automation threat, accompanied by decreasing shares of occupations with high and low automation threat between 1996 and 2010. Due to the fact that within-group wage inequality is the lowest in the group with the highest automation threat, those compositional changes contribute to an increase in wage inequality. Less pronounced but still significant effects that contribute to

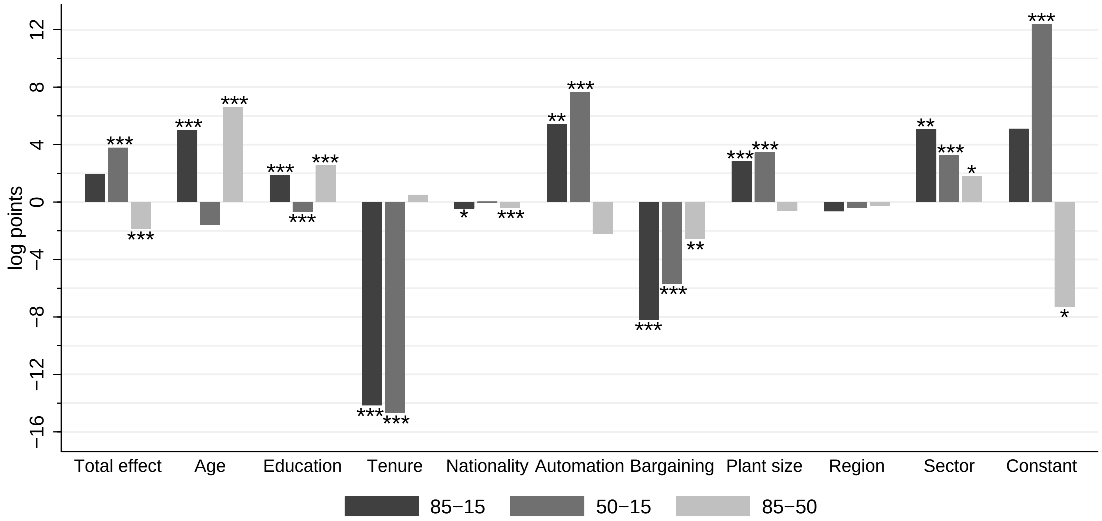
[25] Comprehensive tables of the decomposition results, which also include specification and reweighting errors, can be found in Table 2.B.4 and Table 2.B.5 in Appendix 2.B.

[26] In order to show that the main results are not affected by the definition of the used percentiles, the 90th-10th wage gap is estimated as a robustness check. The relative importance of the different explanatory variables in the detailed decomposition analysis does not shift as well as the signs and statistical significance.

[27] We interpret the specific estimated effect of a covariate as follows: in the observed case we have 5.56/13.42=0.41, where 13.42 is the sum of all detailed composition effects in absolute terms. Thus, we are able to provide percentages that show the respective relative importance in comparison to all other factors and which sum up to 100%.



(a) Composition effect



(b) Wage structure effect

Figure 2.4: Decomposition results of the composition and wage structure effect by percentile wage gaps, 1996-2010

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: The figure presents the results of the RIF-regressions based OB decomposition approach for the composition and wage structure effect based on log daily wages. The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

wage dispersion are changes in the composition of the sector variable and the nationality variable. A factor that has played a small but highly significant role dampening the effect on wage inequality is provided by changes in the composition of the firm size.

When we consider the detailed results of the wage structure effects, presented in Panel (b) of Figure 2.4, very different implications become evident. The interpretation of the wage structure effects of the respective factors depends on the choice of the base category. Due to this, the specific contribution of one covariate to a change in the wage structure has to be interpreted relative to its base category. Moreover, the wage structure effects capture both the between group and the within group inequality component. In other words, on the one hand direct changes in the return for individual factors are considered and on the other hand changes in the residual wage inequality within the observed group relative to the base group are observed. Thus, the constant of the wage structure effect can be interpreted as the change in residual wage inequality of the base category.

The most important factors that are associated with an increase in the 85-15 percentile wage gap are automation threat (5.43 log points), sector differences (5.07 log points) and the age structure (5.03 log points). The positive automation-related wage structure effect could be the result of changes in relative wage returns between workers in occupations with high and low automation threat, as predicted by RBTC. This would suggest an increase in the relative wage of non-routine tasks that are typically at low risk of automation compared to routine tasks that are usually faced with higher risk of automation. In this case, a change in between group wage inequality would be observed. Among the remaining wage structure effects, education profiles of workers and the firm size have played small but non-negligible roles. However, all effects that contribute to wage inequality are compensated by negative effects especially related to tenure and collective bargaining.

In order to show an appropriate comparison with the results of the 85-15 percentile wage gap, the decomposition results of the Gini coefficient are presented in the second column of Table 2.B.4 in Appendix 2.B. In contrast to the previous estimates, the total increase of the Gini coefficient can be divided in equal parts into the composition effect and the wage structure effect.

Among the composition effects, the same covariates like educational levels (1.64) and age (0.7) exhibit the largest statistically significant effects that are associated with an increase in wage inequality. A less pronounced but non-negligible role played collective bargaining (0.37) and automation threat (0.17), which contribute by around 11% and 5%

to the composition effect, respectively. Using the Gini coefficient makes it easier to explain the movements behind the contribution of automation threat on wage inequality in the following. The automation-related positive composition effect stems from the observable trend towards occupations with medium automation threat, accompanied by decreasing shares of occupations with high and low automation threat. Due to the fact that within-group wage inequality is the highest in the lowest automation threat group, the estimated RIF coefficients on the middle and high automation threat groups are mainly negative, see Table 2.B.11.[28] Since the composition effect is defined as the change in the share of employment of the respective groups times the coefficient of the RIF-regression in 1996, it can be shown why compositional changes regarding the automation threat variable are associated with increasing wage inequality. In other words, in this case the composition effect consists of two negative components, which build together a positive effect that contributes to wage dispersion. As a result, we provide evidence that structural shifts in the workforce composition between occupations with different automation threat contributes to increasing wage inequality. Similar to the 85-15 percentile wage gap, changes in the composition of the firm size has played a small but non-negligible role to dampen wage inequality.

Looking at the wage structure effect, the same covariates like automation threat, age, education, sector and the firm size contribute the rise in wage inequality, where automation threat is the major factor, which amounts to 2.55 log points. Again, a closer look at the results of the RIF-regressions explains this result, see Table 2.B.11. As already seen, in 1996 both coefficients of the middle and high automation threat group are negative. This suggests that an increase in the share of the highest automation threat group is associated with a decrease in the estimated Gini coefficient, since this group exhibits a lower within-group wage inequality than the base group of low automation risk. Moreover, regarding the wage structure effect it is important to observe how the coefficients change over time. We see that between 1996 and 2010, the RIF-regressions estimates for the medium and high automation risk group either decrease in absolute terms or even get positive. This means that in 1996 the contribution of the two groups on dampening wage inequality was

[28] All RIF-regressions estimation results of the applied inequality measures and percentiles are presented in Table 2.B.8 - 2.B.12 in Appendix 2.B.

more pronounced than in 2010, keeping everything else equal. Looking at the equation for the wage structure effect it can be seen that the change in the coefficients becomes positive and is multiplied by the positive employment share of 2010. As a result of this condition, a positive automation-related wage structure effect is estimated.

Among the remaining wage structure effects, the same covariates such as tenure and collective bargaining are associated with a reduction in wage inequality. Other inequality decreasing wage structure effects are either weakly or not statistically significant. In summary, the main results of the two presented inequality measures concerning the whole wage distribution are comparable for most parts. Further, we provide decomposition results of the variance in Table 2.B.13 in Appendix 2.B. Again, the automation-related composition effect has played a small but non-negligible role in rising wage inequality, which amounts to 0.17 log points and corresponds to a relative importance of 4% of the composition effect. The wage structure effect associated with automation threat is the major factor that contributes to wage inequality, amounting to 3.82 log points.

We now turn to the decomposition results of the two inequality measures considering either the lower part or the upper part of the wage distribution. The wage gap between the 50th and 15th percentile increased by 7.11 log points, whereas the 85-50 percentile wage gap increased only by 3.56 log points, see Table 2.B.5 in Appendix 2.B. The sum of both increases is again the whole increase of the 85-15 percentile wage gap. Looking at the aggregate composition and wage structure effects we observe different results. Whereas the 50-15 percentile wage gap can be divided roughly into equal positive parts, the 85-50 percentile wage gap exhibits a four times as big positive composition effect compared to the negative wage effect in absolute terms.

In general, the key results of the detailed composition effect are for both measures similar to the overall wage gap, see Panel (a) of Figure 2.4. Comparing the composition effects on the lower and upper half of the wage distribution, we find that the effects on the upper half of the wage distribution are more pronounced than on the lower part. This holds also true for the automation threat variable. Turning to the wage structure effects on the lower and upper half of the wage distribution different outcomes become apparent, see Panel (b) of Figure 2.4. Regarding our measure of automation and robotization, we can state that automation threat has a clear inequality-increasing and highly significant wage structure effect at the lower part of the wage distribution, while it has no statistically significant effect at the upper part of the wage distribution. Thus, the changes in relative wage returns between workers in occupations with high and low automation threat, as predicted by RBTC, are only observable at the lower part of the wage distribution.

2.5.2 2012-2017

Counterfactual analysis. Figure 2.C.5 in Appendix 2.C shows the changes in the wage distribution and the corresponding difference between 2012 and 2017. The shift of the wage distribution to the right is more pronounced. Moreover, no major drop of the peak compared to the development between 1996 and 2010 is observed. In fact, a rather horizontal shift of the distribution where the peak is more located to the right becomes apparent. Furthermore, the counterfactual distribution in 2017, where the composition of the automation threat groups is shifted back to 2012, is illustrated. As seen before, the counterfactual density approaches to the actual distribution in 2012. However, it becomes evident that changes in the composition of automation threat are not responsible for the horizontal shift to the right.

The comparison of the counterfactual difference to the actual difference between 2012 and 2017 is illustrated in Figure 2.C.6 in Appendix 2.C. Again, changes in the lower part of the distribution are not affected by a large extent through compositional changes in the automation threat groups, which is represented by a counterfactual difference close to zero. In Figures 2.C.7 and 2.C.8 we re-estimate the standard inequality measures using counterfactual weights. In this case, we also find supporting results of the above described findings.

Decomposition results. In the more recent time period, the rise in the wage gap between the 85th and the 15th percentile is less pronounced and increased by only 2.17 log points.[29] This is due to the fact that the positive aggregate composition effect is

[29] Comprehensive tables of the decomposition results, which also include specification and reweighting errors, can be found in Table 2.B.6 and Table 2.B.7 in Appendix 2.B.

mitigated by the negative aggregate wage structure effect.

Among the composition effects for the 85-15 percentile wage gap, presented in Table 2.B.6 in Appendix 2.B, the one associated with the age structure of workers is no more statistically significant in comparison to the first time period. A still significant although less pronounced composition effect comes from education (1.15 log points), which corresponds to a relative importance of 27% of the composition effect. The most important inequality-increasing composition effect is associated with automation threat (1.72 log points), which corresponds to a relative importance of 41%. Rather small but still significant effects that contribute to wage inequality are driven by changes in the composition of the firm size, sector and nationality variables. Composition effects that are associated with decreasing wage inequality are related to tenure and the bargaining regime, even if their contribution is relatively small.

When turning to the decomposition results of the wage structure effect for the 85-15 percentile wage gap, there are observable differences compared to the previous period. The wage structure effects related to collective bargaining (2.32 log points) and nationality (0.49 log points) contribute positively to rising wage dispersion in the more recent time period, while the ones associated with tenure, age, regional differences, education and the plant size dampen it. Again, the most important wage structure effect, which is associated with decreasing wage dispersion is related to tenure, which amounts to -9.63 log points. In comparison to the first time period, automation threat has no more a statistically significant wage structure effect. It seems that in the recent past the change in the composition of automation threat is the prominent channel through which automation contributes to rising wage dispersion.

The decomposition results for the Gini coefficient show a slightly decrease in the overall wage inequality by around 0.31 log points during the considered time period. The aggregate composition effect is positive, while the aggregate wage structure effect is negative, both are rather small (0.77 and 0.81, respectively). Among the composition effects, the ones associated with education (0.32), automation threat (0.23) and the plant size (0.22) contribute the most to the increase in wage inequality. The relative importance of automation threat belongs to 26% of the composition effect. The positive automation-related composition effect is supported by the observed shift from 2012 to 2017 towards occupations with low and middle automation threat, which are faced with significantly higher wage dispersion. The estimated RIF coefficients on the middle and high automation risk groups are again negative, see Table 2.B.11. Thus, we see the same dynamics behind the automation-related composition effect as in the first period. Sectoral differences have played a small but non-negligible role in rising wage dispersion with a relative importance of around 8% of the composition effect. Small but still significant effects that contribute to a decrease in wage inequality are associated with changes in the composition of tenure and the bargaining regime, which is in line with the decomposition results of the 85-15 percentile wage gap.

The results of the detailed wage structure effect are more or less equal to the results of the 85-15 percentile wage gap, although the automation-related wage structure effect is now the most important factor associated with decreasing wage dispersion, which amounts to -2.22 log points. A closer look at the results of the RIF-regressions explains this result, see Table 2.B.11. In 2012 as well as in 2017 both coefficients of the middle and high automation threat group are negative. This suggests that an increase in the share of the middle and high automation threat group is associated with a decrease in the estimated Gini coefficient. Moreover, we see that between 2012 and 2017, the RIF-regressions estimates for the middle automation threat group increase in absolute terms, while the estimates for the high automation threat group decreases slightly in absolute terms. This means that the contribution of the middle automation threat group on dampening wage inequality was more pronounced in 2017 than in 2012, while the contribution of the high automation threat group on dampening wage inequality was more pronounced in 2012 than in 2017, keeping everything else equal. Due to the fact that the automation-related wage structure effect is negative, the contribution of the middle automation threat group overweighs the contribution of the high automation threat group, thus, the change in the coefficients becomes negative and is multiplied by the positive employment share of 2019 leading to a negative automation-related wage structure effect.

The decomposition results regarding the automation threat variable are comparable to the decomposition results for the variance, see Table 2.B.13 in Appendix 2.B. The automation-related composition effect has played a major role in rising wage inequality, which amounts to 0.33 log points and corresponds to a relative importance of 24% of the composition effect. The wage structure effect associated with automation threat is an important factor, which contributes to a decrease in wage inequality, amounting to -1.96 log points.

We now turn to the decomposition results of the two inequality measures considering the lower and upper part of the wage distribution, see Table 2.B.7 in Appendix 2.B. It becomes obvious that the less pronounced total increase of the 85-15 percentile wage gap is due to the fact that the lower and upper part of the wage distribution are faced with different inequality trends during the last years. While the wage gap at the lower end of the wage distribution increased by 4.66 log points, the wage gap at the upper end of the wage distribution decreased by 2.48 log points.

The aggregate composition effect is for both inequality measures positive. At the lower part of the wage distribution the composition effects related to sectoral differences, automation threat and plant size contribute the most to rising wage inequality, while tenure, collective bargaining and regional fixed effects played a small but significant role to dampen wage dispersion. Those effects are more or less similar to the detailed composition effects at the upper part of the wage distribution. However, it is evident that the automation-related composition effect is more pronounced at the upper part of the wage distribution then at the lower part. This observed difference in the contribution of automation threat along the wage distribution confirms the results from the counterfactual analysis presented in Figure 2.C.5 in Appendix 2.C.

Among the wage structure effects, differences between the two inequality measures become apparent. The aggregate wage structure effect for the 50-15 percentile wage gap is positive, while it is negative for the 85-50 percentile wage gap. At the lower part of the wage distribution, collective bargaining and nationality are relatively small but highly significant factors associated with increasing wage dispersion, while those effects have played no significant role for the upper part of the wage distribution. Regional differences and the plant size contribute to a decrease in wage inequality at the lower part of the wage distribution. Turning to the upper part of the wage distribution, inequality-increasing wage structure effects are related only to the RIF constant. As explained earlier in this subsection, the constant of the wage structure effect can be interpreted as the change in residual wage inequality of the base category. However, this effect is fully compensated by inequality-decreasing factors associated with automation threat, tenure, age, education and regional fixed effects. Automation threat is the most important factor associated with a dampening effect on wage dispersion at the upper part of the wage distribution, which amounts to -5.98 log points, while it has no significant effect at the lower part of the wage distribution.

2.5.3 Robustness Check

The preceding decomposition analyses show a clear impact of automation threat on the development of wage inequality in the manufacturing sector in Germany. In order to validate our findings, we test the robustness using alternative model specifications. First, we replace the automation probabilities by Dengler and Matthes (2015) with the common used probabilities of computerisation provided by Frey and Osborne (2017). In a second robustness check we test whether the automotive and other vehicles sector has a superior influence on the analysis and thus leads to biased estimates. Similar to this, we exclude the electronics sector and the plastic, chemicals and glass sector as further robustness checks.

Probability of computerisation by Frey and Osborne (2017). Frey and Osborne (2017) estimate the probability of computerisation of different occupations in the US, which is a commonly used measure of automation risk. Using these estimated automation probabilities for German occupations creates several problems, which are described in Appendix 2.A. Those compatibility and conceptual problems have to be taken into account by interpreting the results.

Frey and Osborne (2017) provide three types of „engineering bottlenecks“ to automation, which are (1) perception and manipulation, (2) creative intelligence and (3) social intelligence (Frey and Osborne, 2017, p. 264). The higher the relevance of these bottlenecks for a given occupation, the lower the probability for workers to be substituted by machines. In total, there are estimates for 702 occupations. The data are available at the 6-digit SOC 2010 classification, thus, we have to translate the data into the 3-digit German KldB 2010 classification, see Appendix 2.A. The alternative automation threat variable is estimated in a similar way as before, see equation (2.5), using the computerisation probabilities provided by Frey and Osborne (2017) as θ_j.

The descriptive statistics of this alternative automation threat variable are presented in Table 2.B.3 in Appendix 2.B. Similar to the findings in Section 2.4, the lowest within-group wage inequality is found in the group with the highest automation threat, because workers within the highest automation threat group tend to have similar education and requirement levels. However, the distinct differences in the level of within-group wage inequality are not that much pronounced as in our base variable, which is likely influenced by the different estimation strategies. In the case of Dengler and Matthes (2015), higher automation probabilities are associated with routine tasks, which are often conducted by workers with middle education and similar requirement levels, while lower automation probabilities are associated with non-routine tasks, which could be performed by low and high educated workers with a broader range of requirement levels. This would lead to lower within-group wage inequality in the high automation threat group and higher within-group wage inequality in the middle and low automation threat groups.

In contrast, Frey and Osborne (2017) define some bottlenecks to automation for given occupations. Those bottlenecks are more equally distributed over the whole range of workers. Thus, in all three automation threat groups, the distribution of education and requirement levels tend to be more equal, leading to smaller differences in within-group wage inequality between the automation threat groups. In addition, the employment share of the highest automation threat group decreases within the two time periods, while the employment shares in the low and middle automation threat groups stay rather constant or increase. Those compositional changes could contribute to an increase in wage inequality, although to a smaller amount as compared to our basic automation threat variable.

The decomposition results are presented in Table 2.B.14 and 2.B.15 in Appendix 2.B. Turning to the automation-related composition effect, smaller coefficients are now observable for almost all inequality measures during both periods. This underpins our results from the descriptive analysis. For the first time period, the automation-related wage structure effect at the 85-15 percentile wage gap and the Gini coefficient is positive, but no more significant. This is due to the fact that automation threat is now associated with a significant inequality-decreasing wage structure effect at the 85-50 percentile wage gap. This means that wages at the upper part of the wage distribution become more equally distributed between and within the three automation threat groups over the first time period.

In the second time period, the automation-related wage structure effect at the 85-15 percentile wage gap is now positive and significant. Thus, changes in wage dispersion between or within the automation threat groups lead to an increase in the 85-15 percentile wage gap. This is due to the fact that automation threat is now associated with a large positive and highly significant wage structure effect at the 50-15 percentile wage gap, while the automation-related wage structure effect contributes no more to a decline in the 85-50 percentile wage gap.

Due to the different estimation strategy of Frey and Osborne (2017), the contribution of the automation-related composition effect is smaller. In addition, changes in wage dispersion between or within the automation threat groups lead to an increase in wage inequality during the second time period. However, the compatibility and conceptual problems that occur by using the estimations of Frey and Osborne (2017) for German occupations lead to biased results, which we avoid by using the automation probabilities provided by Dengler and Matthes (2015).

Automotive and other vehicles sector. The automotive and other vehicles sector (in the following automotive sector) is by far the most affected sector by automation threat, as already seen in Figure 2.C.1. In order to check whether our results are mainly driven by the development in this sector, we exclude the automotive sector in Table 2.B.16 and Table 2.B.17 in Appendix 2.B.

For both periods, the automation-related composition effect at the 85-15 percentile wage gap, the Gini coefficient and the variance is still positive and significant, but even larger than our basic decomposition results. This can be explained by the fact that most workers within the automotive sector belong to the high automation threat group, see Table 2.B.1. In addition, the employment share in the automotive sector increased over the whole period, see Table 2.1. Due to the fact that wage inequality is the lowest in the group with the highest automation threat, as it is depicted in Figure 2.2, those structural changes towards the automotive sector lead to a decrease in overall wage inequality. Therefore, this dampening effect on wage inequality is not existent if we exclude the automotive sector, leading to a higher automation-related composition effect. The same pattern becomes apparent if we have a look at the results of the lower and upper part of the wage distribution. As in the basic decomposition, the automation-related composition effect is more pronounced at the upper part of the wage distribution. But again, the contribution to the 50-15 and the 85-50 percentile wage gap is higher than in our basic decomposition analysis.

Turning to the wage structure effect in the first period, the positive contribution of automation to the 85-15 percentile wage gap is no more statistically significant. This is due to the fact that automation threat is now associated with a significant inequality-decreasing wage structure effect at the 85-50 percentile wage gap. This means that without the automotive sector wages at the upper part of the wage distribution become more equally distributed between and within the three automation threat groups over the first time period. This effect at the upper part of the wage distribution vanishes if we include the automotive sector in our basic decomposition analysis, leading to a positive and significant automation-related wage structure effect at the 85-15 percentile wage gap.

In the second time period, the automation-related wage structure effect at the 85-15 percentile wage gap is now positive and significant. Thus, changes in wage dispersion between or within the automation threat groups lead to an increase in the 85-15 percentile wage gap if the automotive sector is excluded. This is due to the fact that automation threat is now associated with a large positive and highly significant wage structure effect at the 50-15 percentile wage gap, while the automation-related wage structure effect contributes no more to a decline in the 85-50 percentile wage gap.

This robustness check shows, that the automotive sector plays an important role for the automation-related wage structure effect. It seems that the automotive sector exhibits a different evolution of the wage structure within and between the automation threat groups than other manufacturing sectors. However, the automation-related composition effect is still positive and significant and differs only in its magnitude.

Further affected sectors. As presented in Figure 2.C.1 in Appendix 2.C there are further sectors that are outstandingly affected by automation and robotization. Therefore, additional robustness checks are conducted in order to exclude possible misinterpretations. At first the observations of the electronics sector are dropped. The overall estimated results reveal slightly smaller sizes of changes in the used inequality measures. Thus, the effects of the automation threat variable are as well smaller in absolute terms. However, the relative size and statistical significance do not change. Further, since the plastic, chemicals and glass sector is also highly affected by our estimated automation threat, we additionally conduct the robustness check excluding observations of this sector. The results reveal slightly higher sizes of changes in the used inequality measures, however as already seen before the relative effects and information regarding significance do not change. Concluding, it can be seen that the development of these two sectors do not bias the overall estimated results.

2.6 Conclusion

Germany is faced with one of the highest industrial robot density in the world. At the same time, wage inequality in Germany underwent substantial changes in the last 25 years. Thus, possible impacts of automation and robotization on wage inequality should be observable in Germany. We conduct a detailed decomposition analysis based on RIF-regressions on several inequality indices considering automation threat. Using rich linked employer-employee data, we are able to account for further different individual-, firm- and industry-specific characteristics.

The analysis contributes to the existing literature in examining the relative importance of automation technologies on wage inequality in the German manufacturing sector. Our newly introduced measure of automation threat combines occupation- and requirement-specific scores of automation risk with yearly sector-specific robot densities to approximately cover the whole dimension of automation and robotization. We provide evidence that automation threat contributes significantly to rising wage inequality in the German manufacturing sector in the last two decades. Moreover, we present general findings on the development of wage inequality and the associated driving forces for the recent years until 2017, in which wage inequality stayed rather constant or even declined.

We distinguish between two channels through which automation threat contributes to rising wage inequality. First, there is an observable trend towards occupations with medium automation threat, accompanied by decreasing shares of occupations with high and low automation threat. Due to the fact that within-group wage inequality is the lowest in the group with the highest automation threat, those compositional changes contribute to an increase in wage inequality. This automation-related composition effect corresponds to a relative importance of roughly 10% of the overall composition effect between 1996 and 2010 and actually 41% in the time period until 2017. Second, we find evidence that there is a growing wage dispersion between occupations with low automation threat (containing especially non-routine tasks) and occupations with high automation threat (containing especially routine tasks). This trend contributes to rising wage inequality as predicted by RBTC, where technology increases the relative demand, and consequently the relative wages, for non-routine tasks compared to routine tasks. This automation-related wage structure effect is prevalent in the 1990s and 2000s, while there is no evidence that this effect has played a significant role in the more recent time period.

Dauth et al. (2021) confirm our findings that automation contributes to rising wage inequality within the manufacturing sector. They provide evidence that this increase stems from the fact that workers who remain by their employer experienced higher wages, whereas those who are forced to leave their original firm are faced with wage losses. Our findings according to the composition effect of automation threat are in line with the decomposition results of Kaltenberg and Foster-McGregor (2020). They find evidence that the composition effect of increasing automation contributes to a large extent to wage inequality across European countries, where the automation related impact occurs mainly at the upper part of the wage distribution.

The decomposition analysis enables us to identify automation threat as an important source that contributes to increasing wage inequality, however, our results cannot be interpreted as causal effects. An analysis of the sources of wage inequality, especially of automation and robotization, in a more causal sense is highly important for future research. Another interesting research area examines the effects of industrial robots by gender and on the gender wage gap. This could be a valuable extension of future research based on the approach presented in this analysis. Moreover, considering only wage inequality could underestimate the effect of automation and robotization on the earning capacity of the society. Due to our data structure we are not able to analyse if workers are forced into unemployment as a result of increasing automation in their occupational field. Future research could examine whether such displacement effects lead to even higher inequality.

Appendix 2.A

Classification of economic activities. The robot data can be matched with the LIAB data without using a crosswalk. The LIAB data are available in the Classification of Economic Activities for the Statistics of the Federal Employment Services, edition 2008 (Klassifikation der Wirtschaftszweige 2008, WZ 2008). WZ 2008 is equivalent to the Statistical Classification of Economic Activities in the European Community (NACE) Rev. 2 and this classification is equal to ISIC Rev. 4 at the 2-digit level. There is one drawback that has to be taken into account when using the industrial classification WZ 2008. The data provides original values between 2008 and 2017. However, before the classifications of the economic activity have been updated, the industry codes rely on prior editions. Thus, the IAB provides a variable for industry classification WZ 2008, where the industry codes have been extrapolated and imputed to obtain time-consistent information for the period prior 2008. The imputation procedure is described in Eberle et al. (2011).

Advantages of the substitution potential provided by Dengler and Matthes (2015). Frey and Osborne (2017) estimate the probability of computerisation of different occupations in the US. Using these estimated automation probabilities for German occupations creates several problems. First, there are compatibility problems by mapping the occupation classification, used by Frey and Osborne (2017), into the German occupation classification, see Appendix 2.A. Second, it is not likely that occupations in the US have the same job profiles and thus the same automation probabilities than the corresponding occupations in Germany. Given the problems by establishing a similar concept for occupations practised in Europe, see Sloane (2008), it is unlikely that the job profiles in the US and Germany are so similar that a direct transformation of the US automation probabilities to Germany is appropriate. Third, Frey and Osborne (2017) estimate the automation probabilities using an occupation-based approach. This underlies the assumption that whole jobs are replaced by automation. As Arntz et al. (2016) argue, it is more realistic to assume that single job-tasks rather than whole occupations are substituted by automation, because high-risk occupations still contain some tasks that are difficult to automate. By applying the occupation-based approach, it is likely that they overestimate the probability of job automatibility, see e.g. Arntz et al. (2016) and Bonin et al. (2015). In order to avoid those problems, it is necessary to investigate the probability of job automatibility directly for occupations in Germany, based on a task-based approach.

Counterfactual wage distributions. In total we consider three different groups of possible automation threat, $r = 1, 2, 3$. Following Hyslop and Maré (2005) and Biewen and Juhasz (2012), a multinomial logit model is estimated accounting for all remaining covariates of our main analysis in order to estimate counterfactual weights, ω_{0r}. With the resulting weights it is possible to establish a counterfactual distribution that accounts for changes in the composition of the automation groups. This counterfactual distribution illustrates the distribution, where the automation groups are shifted back to the level of point in time 0 and everything else is fixed at the level of point in time 1. As a result of this, we obtain counterfactual weights, which are multiplied with the initial sample weights provided by the LIAB data. For further details see DiNardo (2002). The counterfactual wage distribution is then estimated as follows:

$$f_1(w|t_r = 0) = \sum_{r=1}^{3} \omega_{0r} f_{1r}(w), \tag{A.1}$$

where $f_{1r}(w)$ is the initial wage distribution of point in time 1.

Using the weights ω_{0r}, it is also possible to estimate counterfactual values of our described inequality measures.

SOC 2010 - KldB 2010 crosswalk. Mapping the occupations at the 6-digit SOC 2010 classification into the 3-digit KldB 2010 classification creates ambiguous cases, because one KldB 2010 occupation can be allocated to several SOC 2010 occupations. Brzeski and Burk (2015) and Bonin et al. (2015) (in a first step) transfer the occupations at the 6-digit SOC 2010 classification into the KldB 2010 classification by using the average of the automation probability, if the mapping is not unique. In order to improve the crosswalk we apply in those ambiguous cases a weighted average of the automation probability, using employment shares.

First, we use the crosswalk provided by the Bureau of Labor Statistics (BLS)[30] to map the data from the 6-digit SOC 2010 into the international 4-digit ISCO 2008 classification. We assign a weighted average of the job automation probability, using 2014 US employment weights provided by the BLS[31], in case that the mapping is not unique. Next, we map the international 4-digit ISCO 2008 classification into the German 5-digit KldB 2010 classification, where the crosswalk is provided by the German Federal Employment Agency[32], again applying 2014 US employment weights.[33] As a last step, we aggregate the 5-digit KldB 2010 classification into the 3-digit code, using 2014 German employment weights provided by the German Federal Employment Agency.[34]

[30] https://www.bls.gov/soc/soccrosswalks.htm

[31] https://www.bls.gov/oes/tables.htm

[32] https://statistik.arbeitsagentur.de/Navigation/Statistik/Grundlagen/Klassifikationen/Klassifikation-der-Berufe/KldB2010/Arbeitshilfen/Umsteigeschluessel/Umsteigeschluessel-Nav.html

[33] Due to the fact that US employment data are only available for SOC 2010 classification, we apply the crosswalk provided by the BLS to map the US employment data from the 6-digit SOC 2010 into the international 4-digit ISCO 2008 classification, using 2014 US employment weights.

[34] https://statistik.arbeitsagentur.de/Statistikdaten/Detail/201406/iiia6/beschaeftigung-sozbe-bo-heft/bo-heft-d-0-201406-xlsx.xlsx?__blob=publicationFile&v=1

Appendix 2.B

Table 2.B.1: Comparison between the estimated automation threat and the automation probability provided by Dengler and Matthes (2015), by sector

	Automation threat defined by equation (2.5)			Automation probability by Dengler and Matthes (2015)		
Economic Sector	Low automation	Medium automation	High automation	Low automation	Medium automation	High automation
1996						
Food and beverages	52.20	4.43	0	10.73	11.37	0.43
Textiles	5.08	13.73	0	3.40	2.32	3.50
Wood, furniture and paper	6.81	13.95	8.62	7.70	5.10	14.31
Plastic and chemical products	13.12	12.92	14.68	22.61	11.29	15.45
Metal products	5.37	6.85	26.88	18.10	14.08	29.23
Electrical products	5.18	8.44	11.81	10.15	12.94	7.91
Industrial machinery	11.37	38.91	17.71	13.38	25.68	16.87
Automotive and other vehicles	0.87	0.77	20.31	13.93	17.22	12.30
2010						
Food and beverages	14.68	20.30	1.11	12.60	11.37	0.45
Textiles	17.19	0	0	1.79	1.01	1.60
Wood, furniture and paper	22.99	25.94	0	9.28	4.26	13.11
Plastic and chemical products	6.85	5.75	18.33	19.69	9.86	18.17
Metal products	14.19	13.01	26.90	14.80	16.42	31.45
Electrical products	14.00	13.12	14.57	16.33	16.79	10.44
Industrial machinery	9.94	21.68	15.22	10.40	20.10	13.58
Automotive and other vehicles	0.16	0.19	23.87	15.11	20.20	11.19
2012						
Food and beverages	9.19	21.16	1.42	8.96	11.25	1.12
Textiles	11.86	0	0	1.44	1.05	1.54
Wood, furniture and paper	43.93	10.92	0	7.14	4.40	10.90
Plastic and chemical products	3.49	9.92	17.10	18.73	10.59	16.29
Metal products	7.53	10.84	31.09	14.40	17.47	34.18
Electrical products	11.29	17.16	10.37	17.35	14.00	8.07
Industrial machinery	12.36	29.78	16.89	18.26	22.15	16.58
Automotive and other vehicles	0.35	0.23	23.13	13.72	19.08	11.32
2017						
Food and beverages	13.49	30.40	0.61	13.03	14.47	1.12
Textiles	5.98	0	0	0.64	0.48	1.25
Wood, furniture and paper	54.94	0	0	7.45	3.95	11.50
Plastic and chemical products	2.49	7.33	13.37	13.50	7.69	13.41
Metal products	2.15	10.18	25.82	11.79	12.98	30.88
Electrical products	8.47	22.12	6.63	12.86	11.80	8.28
Industrial machinery	12.04	29.72	16.73	18.17	21.39	16.87
Automotive and other vehicles	0.46	0.24	36.83	22.57	27.25	16.69

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Notes*: The table presents the descriptive statistics for four time points separately for each automation threat group. It is a comparison of our proposed variable measuring automation threat and the automation probabilities provided by Dengler and Matthes (2015). All employment shares are reported in percent. Sampling weights are employed.

Table 2.B.2: Descriptive statistics of the automation threat variable, by groups

	1996	Std. Dev.	2010	Std. Dev.	2012	Std. Dev.	2017	Std. Dev.
Automation threat: low								
Real daily wage	127.62	(61.12)	141.74	(77.25)	143.28	(79.92)	140.54	(76.99)
Education: low	12.58	(33.16)	8.67	(28.14)	6.13	(23.99)	4.55	(20.84)
Education: middle	75.48	(43.01)	71.60	(45.09)	72.33	(44.74)	76.98	(42.09)
Education: high	11.94	(32.42)	19.73	(39.79)	21.55	(41.11)	18.47	(38.80)
Requirement level: unskilled activities	0.78	(8.79)	0.79	(8.85)	9.11	(28.77)	10.21	(30.28)
Requirement level: specialist activities	67.82	(46.72)	56.24	(49.61)	44.95	(49.74)	52.64	(49.93)
Requirement level: complex activities	17.25	(37.78)	15.78	(36.45)	25.12	(43.37)	20.51	(40.38)
Requirement level: highly complex activities	14.15	(34.85)	27.19	(44.49)	20.82	(40.60)	16.64	(37.25)
Automation threat: middle								
Real daily wage	147.36	(65.55)	145.86	(82.24)	158.28	(84.46)	160.45	(85.43)
Education: low	9.60	(29.45)	7.56	(26.44)	4.86	(21.51)	4.88	(21.54)
Education: middle	68.56	(46.43)	70.59	(45.56)	65.93	(47.39)	66.37	(47.24)
Education: high	21.84	(41.31)	21.85	(41.32)	29.21	(45.47)	28.74	(45.25)
Requirement level: unskilled activities	1.07	(10.28)	2.77	(16.39)	10.92	(31.19)	12.42	(32.98)
Requirement level: specialist activities	55.65	(49.68)	59.56	(49.07)	36.35	(48.10)	36.24	(48.06)
Requirement level: complex activities	25.86	(43.78)	23.67	(42.50)	26.58	(44.17)	26.83	(44.31)
Requirement level: highly complex activities	17.43	(37.93)	14.01	(34.71)	26.15	(43.94)	24.52	(43.02)
Automation threat: high								
Real daily wage	121.20	(43.90)	133.85	(62.96)	128.65	(56.16)	143.43	(60.81)
Education: low	12.78	(33.38)	9.06	(28.70)	8.25	(27.51)	6.80	(25.17)
Education: middle	81.44	(38.88)	81.03	(39.21)	83.63	(37.00)	83.69	(36.94)
Education: high	5.78	(23.34)	9.92	(29.88)	8.12	(27.32)	9.51	(29.33)
Requirement level: unskilled activities	3.10	(17.32)	1.16	(10.73)	16.34	(36.97)	12.61	(33.19)
Requirement level: specialist activities	83.53	(37.09)	84.88	(35.82)	68.39	(46.49)	68.86	(46.30)
Requirement level: complex activities	9.40	(29.18)	7.76	(26.75)	10.51	(30.67)	11.58	(32.00)
Requirement level: highly complex activities	3.98	(19.55)	6.19	(24.10)	4.75	(21.27)	6.94	(25.41)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Notes: The table presents the descriptive statistics for four time points separately for each automation threat group. All variables, except the wage are reported in percent, standard deviations are given in parentheses. Sampling weights are employed.

Table 2.B.3: Descriptive statistics of the alternative automation threat variable with automation probabilities provided by Frey and Osborne (2017), by groups

	1996	2010	2012	2017
Automation threat: low				
Employment share	18.29	21.38	16.90	16.53
Real daily wage	129.05	140.67	145.29	154.94
Gini coefficient	0.2142	0.2469	0.2644	0.2546
Education: low	9.63	5.31	5.13	3.61
Education: middle	80.13	77.55	71.04	72.04
Education: high	10.24	17.14	23.83	24.35
Requirement level: unskilled activities	0.08	2.67	10.66	7.38
Requirement level: specialist activities	59.77	59.36	45.59	46.68
Requirement level: complex activities	28.73	21.92	21.53	23.54
Requirement level: highly complex activities	11.42	16.04	22.22	22.40
Automation threat: middle				
Employment share	37.77	37.73	35.45	36.06
Real daily wage	127.59	137.09	138.93	141.06
Gini coefficient	0.1950	0.2530	0.2370	0.2378
Education: low	10.01	8.28	5.24	5.34
Education: middle	79.15	77.21	79.04	79.87
Education: high	10.85	14.51	15.72	14.79
Requirement level: unskilled activities	5.36	1.95	10.09	12.05
Requirement level: specialist activities	74.65	75.12	60.27	60.32
Requirement level: complex activities	11.47	12.52	18.69	17.49
Requirement level: highly complex activities	8.52	10.41	10.96	10.15
Automation threat: high				
Employment share	43.95	40.89	47.65	47.41
Real daily wage	124.34	136.28	133.01	149.46
Gini coefficient	0.1924	0.2241	0.2252	0.2218
Education: low	15.17	10.73	9.44	7.40
Education: middle	77.39	78.09	80.22	79.69
Education: high	7.44	11.18	10.34	12.91
Requirement level: unskilled activities	1.02	0.58	18.70	14.12
Requirement level: specialist activities	86.11	86.06	61.40	61.45
Requirement level: complex activities	8.03	7.38	11.76	13.40
Requirement level: highly complex activities	4.84	5.98	8.13	11.03

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Frey and Osborne (2017), own calculations.
Notes: The table presents the descriptive statistics for four time points separately for each automation threat group. All variables, except the wage are reported in percent. Sampling weights are employed.

Table 2.B.4: Decomposition of the 85-15 percentile wage gap and the Gini coefficient, 1996-2010

Inequality measure	85-15		Gini coefficient	
	Coefficient	Standard Error	Coefficient	Standard Error
Total change	10.67***	(0.40)	4.24***	(0.10)
Pure composition effect				
Age	3.85***	(0.23)	0.70***	(0.05)
Education	5.56***	(0.31)	1.64***	(0.09)
Tenure	−0.39*	(0.22)	−0.04	(0.05)
Nationality	0.11***	(0.03)	0.01	(0.01)
Automation threat	1.33***	(0.16)	0.17***	(0.03)
Collective bargaining	0.73	(0.51)	0.37***	(0.11)
Plant size	−0.61***	(0.12)	−0.22***	(0.03)
Region	−0.20**	(0.08)	−0.03	(0.02)
Sector	0.64***	(0.09)	0.11***	(0.02)
Total	11.01***	(0.69)	2.71***	(0.15)
Specification error	−0.85	(0.62)	−0.57***	(0.10)
Pure wage structure effect				
Age	5.03***	(1.59)	1.57***	(0.44)
Education	1.88***	(0.58)	1.10***	(0.12)
Tenure	−14.16***	(5.08)	−2.56**	(1.17)
Nationality	−0.45**	(0.18)	−0.06	(0.04)
Automation threat	5.43**	(2.69)	2.55***	(0.80)
Collective bargaining	−8.18***	(1.25)	−1.46***	(0.26)
Plant size	2.84***	(0.68)	0.58***	(0.16)
Region	−0.65	(0.84)	−0.22	(0.21)
Sector	5.07***	(1.12)	0.70***	(0.26)
Constant	5.11	(6.02)	0.20	(1.47)
Total	1.92	(0.55)	2.38***	(0.15)
Reweighting error	−1.42***	(0.16)	−0.28***	(0.05)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Notes*: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages (85-15) and daily wages (Gini coefficient). The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Table 2.B.5: Decomposition of the 50-15 and the 85-50 percentile wage gap, 1996-2010

Inequality measure	50-15		85-50	
	Coefficient	Standard Error	Coefficient	Standard Error
Total change	7.11***	(0.32)	3.56***	(0.27)
Pure composition effect				
Age	1.05***	(0.15)	2.80***	(0.17)
Education	1.21***	(0.07)	4.35***	(0.27)
Tenure	−0.10	(0.18)	−0.29*	(0.17)
Nationality	0.06***	(0.02)	0.04**	(0.02)
Automation threat	0.40***	(0.06)	0.93***	(0.13)
Collective bargaining	0.51	(0.35)	0.21	(0.37)
Plant size	−0.49***	(0.08)	−0.12**	(0.06)
Region	−0.01	(0.05)	−0.19***	(0.06)
Sector	−0.05	(0.06)	0.69***	(0.08)
Total	2.59***	(0.40)	8.42***	(0.57)
Specification error	1.17***	(0.36)	−2.02***	(0.57)
Pure wage structure effect				
Age	−1.57	(1.25)	6.61***	(1.31)
Education	−0.68***	(0.20)	2.55***	(0.56)
Tenure	−14.67***	(4.01)	0.51	(2.42)
Nationality	−0.03	(0.14)	−0.41***	(0.10)
Automation threat	7.67***	(1.65)	−2.24	(1.91)
Collective bargaining	−5.61***	(0.96)	−2.57**	(1.00)
Plant size	3.45***	(0.61)	−0.61	(0.64)
Region	−0.41	(0.72)	−0.24	(0.69)
Sector	3.26***	(0.99)	1.81*	(1.02)
Constant	12.39***	(4.80)	−7.28*	(3.85)
Total	3.79***	(0.46)	−1.87***	(0.49)
Reweighting error	−0.44***	(0.09)	−0.98***	(0.11)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Notes*: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages. The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Table 2.B.6: Decomposition of the 85-15 percentile wage gap and the Gini coefficient, 2012-2017

Inequality measure	85-15		Gini coefficient	
	Coefficient	Standard Error	Coefficient	Standard Error
Total change	2.17***	(0.49)	−0.31***	(0.09)
Pure composition effect				
Age	−0.03	(0.10)	0.00	(0.02)
Education	1.15***	(0.17)	0.32***	(0.05)
Tenure	−0.19***	(0.04)	−0.04***	(0.01)
Nationality	0.02**	(0.01)	0.00	(0.00)
Automation threat	1.72***	(0.15)	0.23***	(0.02)
Collective bargaining	−0.11***	(0.04)	−0.02**	(0.01)
Plant size	0.68***	(0.14)	0.22***	(0.03)
Region	−0.08	(0.06)	0.00	(0.01)
Sector	0.24***	(0.09)	0.07***	(0.02)
Total	3.40***	(0.28)	0.77***	(0.06)
Specification error	1.24***	(0.13)	−0.16***	(0.01)
Pure wage structure effect				
Age	−6.12***	(1.74)	−1.39***	(0.31)
Education	−2.76***	(0.48)	−0.38***	(0.06)
Tenure	−9.63**	(4.10)	−1.99**	(0.82)
Nationality	0.49***	(0.18)	0.05*	(0.03)
Automation threat	−3.52	(2.78)	−2.22***	(0.45)
Collective bargaining	2.32**	(0.93)	0.39**	(0.18)
Plant size	−1.16*	(0.64)	−0.30**	(0.12)
Region	−4.23***	(0.81)	−0.86***	(0.20)
Sector	1.10	(0.99)	0.19	(0.20)
Constant	21.72***	(5.67)	5.70***	(1.02)
Total	−1.79***	(0.51)	−0.81***	(0.09)
Reweighting error	−0.69***	(0.06)	−0.11***	(0.02)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Notes*: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages (85-15) and daily wages (Gini coefficient). The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Table 2.B.7: Decomposition of the 50-15 and the 85-50 percentile wage gap, 2012-2017

Inequality measure	50-15		85-50	
	Coefficient	Standard Error	Coefficient	Standard Error
Total change	4.66***	(0.39)	−2.48***	(0.24)
Pure composition effect				
Age	−0.03	(0.04)	0.00	(0.08)
Education	0.20***	(0.03)	0.95***	(0.14)
Tenure	−0.14***	(0.03)	−0.05**	(0.02)
Nationality	0.01	(0.01)	0.01***	(0.00)
Automation threat	0.58***	(0.06)	1.14***	(0.10)
Collective bargaining	−0.09***	(0.03)	−0.02**	(0.01)
Plant size	0.49***	(0.10)	0.19**	(0.08)
Region	−0.10**	(0.04)	0.02	(0.04)
Sector	0.61***	(0.05)	−0.37***	(0.08)
Total	1.54***	(0.15)	1.86***	(0.22)
Specification error	0.02	(0.09)	1.22***	(0.10)
Pure wage structure effect				
Age	−1.69	(1.31)	−4.42***	(1.07)
Education	0.13	(0.16)	−2.89***	(0.43)
Tenure	−4.05	(3.08)	−5.58**	(2.31)
Nationality	0.42***	(0.15)	0.07	(0.09)
Automation threat	2.47	(2.10)	−5.98***	(1.90)
Collective bargaining	1.79**	(0.78)	0.53	(0.58)
Plant size	−1.12**	(0.46)	−0.05	(0.42)
Region	−1.69***	(0.64)	−2.54***	(0.66)
Sector	0.07	(0.73)	1.03	(0.71)
Constant	6.86	(4.66)	14.86***	(3.29)
Total	3.19***	(0.39)	−4.98***	(0.33)
Reweighting error	−0.10***	(0.03)	−0.59***	(0.05)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Notes*: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages. The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Table 2.B.8: RIF-regressions 15th quantile, 1996 2010 2012 2017

	1996	2010	2012	2017
Age: 18-25	-0.0406**	-0.0827***	-0.0618***	-0.0347*
	(0.0166)	(0.0171)	(0.0155)	(0.0208)
Age: 36-45	-0.0442***	-0.0442***	-0.0589***	-0.0582***
	(0.0086)	(0.0104)	(0.0104)	(0.0137)
Age: 46-55	-0.0442***	-0.0887***	-0.0962***	-.0692***
	(0.0104)	(0.0114)	(0.0117)	(.0164)
Age: $\geq$ 56	-0.0506***	-0.0946***	-0.0983***	-0.1165***
	(0.0115)	(0.0130)	(0.0126)	(0.0172)
Education: low	-0.1148***	-0.1534***	-0.1568***	-.1383***
	(0.0069)	(0.0084)	(0.0101)	(.0133)
Education: high	0.0779***	0.1227***	0.1197***	0.1277***
	(0.0060)	(0.0051)	(0.0051)	(0.0066)
Tenure: 2-4 years	0.0997***	0.0984***	0.1237***	0.0993***
	(0.0219)	(0.0232)	(0.0179)	(0.0222)
Tenure: 4-8 years	0.2144***	0.1975***	0.1875***	0.2661***
	(0.0189)	(0.0241)	(0.0177)	(0.0231)
Tenure: 8-16 years	0.2721***	0.3239***	0.2938***	0.3606***
	(0.0189)	(0.0267)	(0.0187)	(0.0240)
Tenure: $\geq$ 16 years	0.3412***	0.4645***	0.4519***	0.4806***
	(0.0198)	(0.0286)	(0.0207)	(0.0269)
Nationality	-0.0392***	-0.0311***	-0.0455***	-0.0881***
	(.0084)	(0.0084)	(0.0091)	(0.0127)
Automation threat: middle	0.0021	-0.0563***	-0.0042	-0.0350
	(0.0099)	(0.0117)	(0.0097)	(0.0244)
Automation threat: high	-0.0180*	-0.0673***	-0.0314***	-0.0191
	(0.0108)	(0.0109)	(0.0097)	(0.0221)

Continued on next page

Table 2.B.8 – *Continued from previous page*

	1996	2010	2012	2017
Firm level agreement	-0.0097	0.1666***	0.1377***	0.1274***
	(0.0198)	(0.0072)	(0.0069)	(0.0090)
Sector level agreement	0.0379**	0.1762***	0.1781***	0.1863***
	(0.0172)	(0.0071)	(0.0066)	(0.0074)
Plant size: 1-9 employees	-0.3037***	-0.6222***	-0.6038***	-0.5561***
	(0.0320)	(0.0358)	(0.0365)	(0.0481)
Plant size: 10-49 employees	-0.1651***	-0.2516***	-0.2717***	-0.2482***
	(0.0111)	(0.0111)	(0.0109)	(0.0152)
Plant size: 50-199 employees	-0.0472***	-0.1045***	-0.1064***	-0.1031***
	(0.0037)	(0.0048)	(0.0048)	(0.0072)
Plant size: 1000-4999 employees	0.0219***	0.0404***	0.0438***	0.0528***
	(0.0021)	(0.0025)	(0.0024)	(0.0045)
Plant size: ≥ 5000 employees	0.0313***	0.0386***	0.0326***	0.0796***
	(0.0029)	(0.0035)	(0.0026)	(0.0066)
Sector: Food and beverages	-0.1033***	-0.2407***	-0.2665***	-0.5079***
	(0.0179)	(0.0141)	(0.0135)	(0.0226)
Sector: Textiles	-0.1922***	-0.3958***	-0.3723***	-0.3915***
	(0.0181)	(0.0282)	(0.0330)	(0.0429)
Sector: Wood, furniture and paper	0.0229*	-0.1248***	-0.1117***	-0.1047***
	(0.0132)	(0.0129)	(0.0135)	(0.0270)
Sector: Plastic and chemical products	0.0418***	-0.0183**	0.0056	-0.0516***
	(0.0084)	(0.0076)	(0.0078)	(0.0099)
Sector: Electrical products	0.0307***	0.0217***	0.0198***	0.0188*
	(0.0093)	(0.0072)	(0.0077)	(0.0108)

Continued on next page

Table 2.B.8 – *Continued from previous page*

	1996	2010	2012	2017
Sector: Industrial machinery	0.0438***	0.0846***	0.0949***	0.0696***
	(0.0095)	(0.0065)	(0.0065)	(0.0077)
Sector: Automotive and other vehicles	0.0572***	0.0198***	0.0248***	-0.0373***
	(0.0066)	(0.0061)	(0.0057)	(0.0079)
Schleswig-Holstein	0.0035	-0.0655***	-0.0592***	-0.0093
	(0.0182)	(0.0149)	(0.0126)	(0.0161)
Hamburg	0.0527***	0.0145*	0.0601***	-0.0092
	(0.0117)	(0.0087)	(0.0094)	(0.0157)
Lower Saxony	-0.0676***	-0.0718***	-0.0359***	-0.0071
	(0.0100)	(0.0077)	(0.0076)	(.0091)
Bremen	-0.0119	-0.0056	0.0183**	-0.0805***
	(0.0231)	(0.0132)	(0.0079)	(0.0111)
Hesse	-0.0125	-0.0871***	-0.0636***	-0.0697***
	(0.0096)	(0.0092)	(0.0091)	(0.0096)
Rhineland-Palatinate	-0.0828***	-0.0487***	-0.0473***	0.0249
	(0.0147)	(0.0087)	(0.0095)	(0.0088)
Baden-Wuerttemberg	0.0019	0.0117*	0.0022	0.0264***
	(0.0074)	(0.0066)	(0.0069)	(0.0090)
Bavaria	-0.0565***	-0.0554***	-0.0396***	-0.0325***
	(0.0069)	(0.0074)	(0.0071)	(0.0092)
Saarland	0.0328**	-0.0854***	-0.1410***	-0.0695***
	(0.0132)	(0.0097)	(0.0128)	(0.0152)
Constant	4.2661***	4.1694***	4.1530***	4.1578***
	(0.0295)	(0.0275)	(0.0209)	(0.0334)
Observations	576,895	389,624	437,336	320,970

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Notes: The table presents the RIF-regressions for the 15th quantile. The observed years are 1996, 2010, 2012 and 2017. Standard errors are given in parentheses. Sampling weights are employed.

Table 2.B.9: RIF-regressions 50th quantile, 1996 2010 2012 2017

	1996	2010	2012	2017
Age: 18-25	-0.0720***	-0.1081***	-0.0723***	-0.0496***
	(0.0071)	(0.0076)	(0.0070)	(0.0065)
Age: 36-45	0.0049	0.0033	-0.0019	-0.0043
	(0.0052)	(0.0051)	(0.0054)	(0.0053)
Age: 46-55	0.0198***	-0.0141**	-0.0251***	-0.0077
	(0.0064)	(0.0055)	(0.0061)	(0.0066)
Age: $\geq$ 56	0.0179**	-0.0187***	-0.0357***	-0.0348***
	(0.0082)	(0.0065)	(0.0068)	(0.0072)
Education: low	-0.1721***	-0.1666***	-0.1567***	-0.1059***
	(0.0038)	(0.0037)	(0.0042)	(0.0047)
Education: high	0.2435***	0.2769***	0.2668***	0.2792***
	(0.0050)	(0.0035)	(0.0038)	(0.0043)
Tenure: 2-4 years	0.0313***	0.0289***	0.0426***	0.0394***
	(0.0097)	(0.0105)	(0.0079)	(0.0080)
Tenure: 4-8 years	0.0608***	0.0529***	0.0763***	0.0870***
	(0.0092)	(0.0125)	(0.0077)	(0.0084)
Tenure: 8-16 years	0.1447***	0.1239***	0.1571***	0.1676***
	(0.0100)	(0.0144)	(0.0087)	(0.0089)
Tenure: $\geq$ 16 years	0.2259***	0.2172***	0.2607***	0.2489***
	(0.0107)	(0.0154)	(0.0100)	(0.0101)
Nationality	-0.0621***	-0.0660***	-0.0660***	-0.0602***
	(0.0046)	(0.0043)	(0.0045)	(0.0045)
Automation threat: middle	-0.0074	-0.0428***	-0.0613***	-0.0245***
	(0.0075)	(0.0070)	(0.0055)	(0.0090)
Automation threat: high	-0.1009***	-0.1390***	-0.2038***	-0.1649***
	(0.0074)	(0.0068)	(0.0058)	(0.0087)

Continued on next page

Table 2.B.9 – *Continued from previous page*

	1996	2010	2012	2017
Firm level agreement	0.0026	0.0477***	0.0397***	0.0475***
	(0.0119)	(0.0042)	(0.0049)	(0.0047)
Sector level agreement	0.0169*	0.0666***	0.0799***	0.1020***
	(0.0102)	(0.0037)	(0.0036)	(0.0038)
Plant size: 1-9 employees	-0.1746***	-0.2226***	-0.2331***	-0.2131***
	(0.0180)	(0.0154)	(0.0143)	(0.0196)
Plant size: 10-49 employees	-0.1350***	-0.1495***	-0.1387***	-0.1271***
	(0.0081)	(0.0058)	(0.0060)	(0.0074)
Plant size: 50-199 employees	-0.0319***	-0.0719***	-0.0801***	-0.0819***
	(0.0034)	(0.0032)	(0.0036)	(0.0041)
Plant size: 1000-4999 employees	0.0313***	0.1098***	0.1319***	0.1317***
	(0.0018)	(0.0021)	(0.0022)	(0.0028)
Plant size: $\geq$ 5000 employees	0.1607***	0.2317***	0.2211***	0.2282***
	(0.0024)	(0.0026)	(0.0024)	(0.0038)
Sector: Food and beverages	-0.0946***	-0.1487***	-0.1886***	-0.3234***
	(0.0106)	(0.0071)	(0.0074)	(0.0086)
Sector: Textiles	-0.1808***	-0.1958***	-0.2469***	-0.2124***
	(0.0113)	(0.0147)	(0.0161)	(0.0182)
Sector: Wood, furniture and paper	0.0129	-0.1461***	-0.2175***	-0.2177***
	(0.0087)	(0.0065)	(0.0075)	(0.0111)
Sector: Plastic and chemical products	0.0375***	0.0168***	0.0117**	-0.0274***
	(0.0059)	(0.0042)	(0.0048)	(0.0052)
Sector: Electrical products	0.0365***	0.0858***	0.0419***	0.0250***
	(0.0072)	(0.0043)	(0.0045)	(0.0065)

Continued on next page

Table 2.B.9 – *Continued from previous page*

	1996	2010	2012	2017
Sector: Industrial machinery	0.0557***	0.0929***	0.0876***	0.0811***
	(0.0058)	(0.0040)	(0.0041)	(0.0047)
Sector: Automotive and other vehicles	0.0955***	0.0841***	0.1013***	0.0733***
	(0.0046)	(0.0037)	(0.0038)	(0.0045)
Schleswig-Holstein	-0.0019***	-0.0350***	-0.0286***	-0.0302***
	(0.0139)	(0.0067)	(0.0067)	(0.0074)
Hamburg	0.0688***	0.0616***	0.0828***	0.0400***
	(0.0116)	(0.0052)	(0.0081)	(0.0078)
Lower Saxony	-0.0608***	-0.0271***	-0.0255***	0.0026
	(0.0057)	(0.0040)	(0.0046)	(0.0048)
Bremen	0.0375**	0.0749***	0.0577***	0.0575***
	(0.0189)	(0.0075)	(0.0049)	(0.0055)
Hesse	-0.0076	-0.0470***	-0.0477***	-0.0355***
	(0.0072)	(0.0045)	(0.0049)	(0.0049)
Rhineland-Palatinate	-0.0722***	-0.0548***	-0.0474***	0.0297***
	(0.0078)	(0.0043)	(0.0050)	(0.0052)
Baden-Wuerttemberg	0.0317***	0.0422***	0.0557***	0.0646***
	(0.0051)	(0.0037)	(0.0039)	(0.0049)
Bavaria	-0.0573***	-0.0538***	-0.0399***	-0.0240***
	(0.0045)	(0.0039)	(0.0039)	(0.0046)
Saarland	-0.0582***	-0.0721***	-0.0643***	-0.0019
	(0.0087)	(0.0061)	(0.0074)	(0.0090)
Constant	4.6348***	4.6585***	4.6683***	4.6855***
	(0.0150)	(0.0146)	(0.0102)	(0.0129)
Observations	576,895	389,624	437,336	320,970

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Notes: The table presents the RIF-regressions for the 50th quantile. The observed years are 1996, 2010, 2012 and 2017. Standard errors are given in parentheses. Sampling weights are employed.

Table 2.B.10: RIF-regressions 85th quantile, 1996 2010 2012 2017

	1996	2010	2012	2017
Age: 18-25	0.1309	0.1533***	0.1564***	0.1391***
	(0.0106)	(0.0089)	(0.0107)	(0.0099)
Age: 36-45	0.1239	0.1355***	0.1406***	0.0914***
	(0.0085)	(0.0075)	(0.0083)	(0.0105)
Age: 46-55	0.2275	0.1785***	0.1940***	0.1518***
	(0.0101)	(0.0081)	(0.0095)	(0.0121)
Age: $\geq$ 56	0.2649	0.1902***	0.1939***	0.1332***
	(0.0127)	(0.0095)	(0.0107)	(0.0130)
Education: low	-0.1830***	-0.1191	-0.1187***	-0.0882***
	(0.0046)	(0.0038)	(0.0049)	(0.0055)
Education: high	0.9562***	1.0164	1.0184***	0.9216***
	(0.0146)	(0.0095)	(0.0109)	(0.0115)
Tenure: 3-4 years	0.0530***	-0.0044***	-0.0022	-0.0059
	(0.0155)	(0.0106)	(0.0118)	(0.0138)
Tenure: 5-8 years	0.1376***	0.0658***	0.0755***	0.0684***
	(0.0139)	(0.0111)	(0.0130)	(0.0133)
Tenure: 9-16 years	0.2469***	0.1902***	0.1943***	0.1734***
	(0.0148)	(0.0126)	(0.0145)	(0.0150)
Tenure: $\geq$ 17 years	0.2671***	0.2219***	0.2505***	0.2529***
	(0.0155)	(0.0139)	(0.0158)	(0.0174)
Nationality	-0.0759***	-0.0885***	-0.0863***	-0.0679***
	(0.0058)	(0.0049)	(0.0066)	(0.0065)
Automation threat: middle	-0.0706***	-0.0209	-0.1377***	-0.1402***
	(0.0166)	(0.0124)	(0.0112)	(0.0188)
Automation threat: high	-0.3492***	-0.2708***	-0.5368***	-0.4575***
	(0.0160)	(0.0126)	(0.0120)	(0.0179)

Continued on next page

Table 2.B.10 – *Continued from previous page*

	1996	2010	2012	2017
Firm level agreement	0.0060***	0.0045***	0.0194	0.0902***
	(0.0179)	(0.0066)	(0.0087)	(0.0077)
Sector level agreement	0.0079***	0.0454***	0.0673***	0.0912***
	(0.0161)	(0.0057)	(0.0061)	(0.0065)
Plant size: 1-9 employees	-0.1042***	-0.1108***	-0.1295***	-0.1155***
	(0.0264)	(0.0220)	(0.0210)	(0.0360)
Plant size: 10-49 employees	-0.1133***	-0.0923***	-0.1138***	-0.0643***
	(0.0130)	(0.0086)	(0.0097)	(0.0131)
Plant size: 50-199 employees	-0.0168***	-0.0526***	-0.0793***	-0.0725***
	(0.0062)	(0.0051)	(0.0067)	(0.0063)
Plant size: 1000-4999 employees	0.0261***	0.0771***	0.1119***	0.1179***
	(0.0032)	(0.0039)	(0.0046)	(0.0053)
Plant size: $\geq$ 5000 employees	0.1221***	0.2125***	0.2626***	0.1862***
	(0.0043)	(0.0047)	(0.0047)	(0.0064)
Sector: Food and beverages	-0.2853***	-0.1827***	-0.3242***	-0.3437***
	(0.0194)	(0.0108)	(0.0123)	(0.0138)
Sector: Textiles	-0.3253***	-0.2836***	-0.4845***	-0.3932***
	(0.0189)	(0.0237)	(0.0264)	(0.0307)
Sector: Wood, furniture and paper	-0.0649***	-0.2411***	-0.4705***	-0.4698***
	(0.0124)	(0.0106)	(0.0125)	(0.0204)
Sector: Plastic and chemical products	0.0176*	0.0308***	0.0500***	0.0056
	(0.0098)	(0.0064)	(0.0086)	(0.0081)
Sector: Electrical products	0.0355***	0.1485***	0.0398***	0.0017
	(0.0097)	(0.0075)	(0.0089)	(0.0129)

Continued on next page

Table 2.B.10 – *Continued from previous page*

	1996	2010	2012	2017
Sector: Industrial machinery	-0.0219**	0.0212***	-0.0178***	-0.0197***
	(0.0091)	(0.0062)	(0.0068)	(0.0072)
Sector: Automotive and other vehicles	0.0775***	0.0294***	0.0719***	0.0233***
	(0.0070)	(0.0053)	(0.0061)	(0.0075)
Schleswig-Holstein	-0.0851***	-0.0165	-0.0283**	-0.0234
	(0.0169)	(0.0113)	(0.0123)	(0.0145)
Hamburg	-0.0086	0.0186*	0.0525***	-0.0801***
	(0.0134)	(0.0098)	(0.0141)	(0.0176)
Lower Saxony	-0.0631***	-0.0124*	0.0008	-0.0334***
	(0.0089)	(0.0065)	(0.0081)	(0.0082)
Bremen	0.0214	0.0519***	-0.0440***	-0.0044
	(0.0180)	(0.0139)	(0.0097)	(0.0112)
Hesse	0.0045	-0.0313***	-0.0214**	0.0129
	(0.0137)	(0.0072)	(0.0085)	(0.0083)
Rhineland-Palatinate	-0.1184***	-0.0664***	-0.0317***	-0.0189**
	(0.0123)	(0.0066)	(0.0082)	(0.0090)
Baden-Wuerttemberg	-0.0088	0.0319***	0.0879***	0.0679***
	(0.0080)	(0.0063)	(0.0070)	(0.0093)
Bavaria	-0.0533***	-0.0383***	-0.0369***	-0.0815***
	(0.0064)	(0.0058)	(0.0065)	(0.0081)
Saarland	-0.0932***	-0.0862***	-0.0415***	0.0089
	(0.0136)	(0.0083)	(0.0122)	(0.0162)
Constant	5.0507***	4.9485***	5.1143***	5.1670***
	(0.0244)	(0.0177)	(0.0192)	(0.0235)
Observations	576,895	389,624	437,336	320,970

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Notes: The table presents the RIF-regressions for the 85th quantile. The observed years are 1996, 2010, 2012 and 2017. Standard errors are given in parentheses. Sampling weights are employed.

Table 2.B.11: RIF-regressions Gini coefficient, 1996 2010 2012 2017

	1996	2010	2012	2017
Age: 18-25	0.0591***	0.0779***	0.0664***	0.0502***
	(0.0010)	(0.0021)	(0.0018)	(0.0020)
Age: 36-45	0.0306***	0.0368***	0.0371***	0.0227***
	(0.0007)	(0.0013)	(0.0012)	(0.0013)
Age: 46-55	0.0544***	0.0589***	0.0599***	0.0424***
	(0.0008)	(0.0015)	(0.0014)	(0.0015)
Age: $\geq$ 56	0.0635***	0.0628***	0.0613***	0.0489***
	(0.0010)	(0.0017)	(0.0015)	(0.0016)
Education: low	0.0059***	0.0248***	0.0278***	0.0231***
	(0.0007)	(0.0012)	(0.0012)	(0.0014)
Education: high	0.2834***	0.2996***	0.2582***	0.2298***
	(0.0008)	(0.0011)	(0.0009)	(0.0010)
Tenure: 3-4 years	-0.0139***	-0.0326***	-0.0332***	-0.0325***
	(0.0014)	(0.0028)	(0.0023)	(0.0027)
Tenure: 5-8 years	-0.0134***	-0.0292***	-0.0331***	-0.0538***
	(0.0012)	(0.0027)	(0.0022)	(0.0026)
Tenure: 9-16 years	0.0023	-0.0236***	-0.0251***	-0.0535***
	(0.0012)	(0.0028)	(0.0023)	(0.0027)
Tenure: $\geq$ 17 years	-0.0099***	-0.0409***	-0.0442***	-0.0520***
	(0.0013)	(0.0029)	(0.0025)	(0.0029)
Nationality	-0.0051***	-0.0095***	0.0004	0.0074***
	(0.0007)	(0.0012)	(0.0011)	(0.0012)
Automation threat: middle	-0.0145***	0.0153***	-0.0158***	-0.0238***
	(0.0010)	(0.0015)	(0.0012)	(0.0016)
Automation threat: high	-0.0509***	-0.0195***	-0.0648***	-0.0631***
	(0.0009)	(0.0015)	(0.0014)	(0.0017)

Continued on next page

Table 2.B.11 – *Continued from previous page*

	1996	2010	2012	2017
Firm level agreement	-0.0056***	-0.0322***	-0.0225***	-0.0092***
	(0.0011)	(0.0012)	(0.0011)	(0.0014)
Sector level agreement	-0.0162***	-0.0211***	-0.0228***	-0.0224***
	(0.0009)	(0.0009)	(0.0007)	(0.0009)
Plant size: 1-9 employees	0.0616***	0.1097***	0.1128***	0.0950***
	(0.0011)	(0.0020)	(0.0018)	(0.0024)
Plant size: 10-49 employees	0.0208***	0.0348***	0.0369***	0.0334***
	(0.0007)	(0.0011)	(0.0010)	(0.0012)
Plant size: 50-199 employees	0.0101***	0.0109***	0.0087***	0.0083***
	(0.0006)	(0.0009)	(0.0008)	(0.0010)
Plant size: 1000-4999 employees	0.0011	0.0163***	0.0205***	0.0187***
	(0.0007)	(0.0010)	(0.0009)	(0.0011)
Plant size: $\geq$ 5000 employees	0.0417***	0.0668***	.0639***	0.0306***
	(0.0009)	(0.0014)	(.0011)	(0.0014)
Sector: Food and beverages	-0.0066***	0.0269***	0.0125***	0.0622***
	(0.0013)	(0.0016)	(0.0014)	(0.0016)
Sector: Textiles	-0.0119***	0.0303***	-0.0023	0.0436***
	(0.0015)	(0.0032)	(0.0030)	(0.0043)
Sector: Wood, furniture and paper	-0.0153***	-0.0111***	-0.0395***	-0.0464***
	(0.0009)	(0.0015)	(0.0016)	(0.0022)
Sector: Plastic and chemical products	0.0007	0.0049***	0.0102***	0.0121***
	(0.0008)	(0.0011)	(0.0010)	(0.0013)
Sector: Electrical products	-0.0020**	0.0311***	-0.0021*	-0.0031**
	(0.0009)	(0.0011)	(0.0011)	(0.0014)

Continued on next page

Table 2.B.11 – *Continued from previous page*

	1996	2010	2012	2017
Sector: Industrial machinery	-0.0191***	-0.0228***	-0.0266***	-0.0289***
	(0.0007)	(0.0011)	(0.0009)	(0.0012)
Sector: Automotive and other vehicles	0.0039***	-0.0094***	0.0093***	0.0056***
	(0.0009)	(0.0012)	(0.0011)	(0.0014)
Schleswig-Holstein	0.0169***	0.0128***	0.0071***	-0.0062**
	(0.0016)	(0.0022)	(0.0022)	(0.0028)
Hamburg	-0.0026***	-0.0124***	-0.0002	-0.0394***
	(0.0016)	(0.0020)	(0.0017)	(0.0022)
Lower Saxony	0.0049***	0.0142***	0.0184***	-0.0051***
	(0.0008)	(0.0012)	(0.0011)	(0.0013)
Bremen	0.0081***	-0.0002	-0.0231***	-0.0029
	(0.0021)	(0.0046)	(0.0030)	(0.0040)
Hesse	0.0045***	0.0149***	0.0122***	0.0253***
	(0.0009)	(0.0014)	(0.0012)	(0.0014)
Rhineland-Palatinate	-0.0069***	-0.0057***	0.0052***	-0.0125***
	(0.0011)	(0.0015)	(0.0014)	(0.0015)
Baden-Wuerttemberg	0.0019***	0.0043***	0.0106***	0.0122***
	(0.0007)	(0.0009)	(0.0009)	(0.0011)
Bavaria	0.0017**	0.0094***	0.0032***	-0.0168***
	(0.0007)	(0.0009)	(0.0009)	(0.0010)
Saarland	-0.0241***	-0.0004	0.0215***	0.0187***
	(0.0017)	(0.0025)	(0.0031)	(0.0037)
Constant	0.1918***	0.1895***	0.2317***	0.2634
	(0.0018)	(0.0033)	(0.0028)	(0.0034)
Observations	576,895	389,624	437,336	320,970

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Notes: The table presents the RIF-regressions for the Gini coefficients. The observed years are 1996, 2010, 2012 and 2017. Standard errors are given in parentheses. Sampling weights are employed.

Table 2.B.12: RIF-regressions variance, 1996 2010 2012 2017

	1996	2010	2012	2017
Age: 18-25	0.0567***	0.0818***	0.0709***	0.0488***
	(0.0013)	(0.0029)	(0.0025)	(0.0029)
Age: 36-45	0.0306***	0.0566***	0.0517***	0.0349***
	(0.0008)	(0.0018)	(0.0017)	(0.0019)
Age: 46-55	0.0573***	0.0854***	0.0829***	.0617***
	(0.0010)	(0.0020)	(0.0019)	(.0022)
Age: $\geq$ 56	0.0684***	0.0923***	0.0851***	0.0699***
	(0.0012)	(0.0023)	(0.0021)	(0.0024)
Education: low	0.0134***	0.0360***	0.0440***	0.0354***
	(0.0009)	(0.0017)	(0.0017)	(0.0020)
Education: high	0.2951***	0.3686***	0.3163***	0.2890***
	(0.0010)	(0.0014)	(0.0013)	(0.0014)
Tenure: 3-4 years	-0.0394***	-0.0883***	-0.0877***	-0.0861***
	(0.0017)	(0.0039)	(0.0032)	(0.0038)
Tenure: 5-8 years	-0.0422***	0.0901***	-0.0976***	-0.1346***
	(0.0015)	(0.0039)	(0.0031)	(0.0037)
Tenure: 9-16 years	-0.0222***	-0.1051***	-0.1015***	-0.1393***
	(0.0015)	(0.0040)	(0.0033)	(0.0038)
Tenure: $\geq$ 17 years	-0.0326***	-0.1319***	-0.1295***	-0.1415***
	(0.0016)	(0.0042)	(0.0035)	(0.0041)
Nationality	-0.0109***	-0.0159***	0.0001	0.0133***
	(0.0009)	(0.0017)	(0.0015)	(0.0017)
Automation threat: middle	-0.0254***	0.0191***	-0.0201***	-0.0254***
	(0.0012)	(0.0020)	(0.0018)	(0.0023)
Automation threat: high	-0.0654***	-0.0360***	-0.0929***	-0.0868***
	(0.0012)	(0.0021)	(0.0019)	(0.0025)

Continued on next page

Table 2.B.12 – *Continued from previous page*

	1996	2010	2012	2017
Firm level agreement	-0.0297***	-0.0432***	-0.0346***	-0.0144***
	(0.0013)	(0.0017)	(0.0016)	(0.0019)
Sector level agreement	-0.0428***	-0.0295***	-0.0347***	-0.0318***
	(0.0011)	(0.0012)	(0.0011)	(0.0013)
Plant size: 1-9 employees	0.0716***	0.2133***	0.1967***	0.1528***
	(0.0013)	(0.0028)	(0.0026)	(0.0034)
Plant size: 10-49 employees	0.0183***	0.0431***	0.0477***	0.0430***
	(0.0009)	(0.0016)	(0.0014)	(0.0017)
Plant size: 50-199 employees	0.0037***	0.0144***	0.0124***	0.0098***
	(0.0007)	(0.0013)	(0.0012)	(0.0014)
Plant size: 1000-4999 employees	-0.0008	0.0281***	0.0339***	0.0339***
	(0.0008)	(0.0014)	(0.0013)	(0.0016)
Plant size: $\geq$ 5000 employees	0.0469***	0.0936***	0.0977***	0.0617***
	(0.0011)	(0.0020)	(0.0017)	(0.0020)
Sector: Food and beverages	0.0090***	0.0504***	0.0292***	0.0797***
	(0.0016)	(0.0022)	(0.0020)	(0.0023)
Sector: Textiles	-0.0170***	0.0503***	0.0140***	0.0764***
	(0.0018)	(0.0046)	(0.0042)	(0.0061)
Sector: Wood, furniture and paper	-0.0181***	-0.0154***	-0.0573***	-0.0639***
	(0.0011)	(0.0022)	(0.0022)	(0.0032)
Sector: Plastic and chemical products	-0.0034***	0.0134***	0.0145***	0.0167***
	(0.0009)	(0.0016)	(0.0015)	(0.0019)
Sector: Electrical products	-0.0028***	0.0439***	0.0045***	-0.0045**
	(0.0010)	(0.0016)	(0.0016)	(0.0020)

Continued on next page

Table 2.B.12 – *Continued from previous page*

	1996	2010	2012	2017
Sector: Industrial machinery	-0.0146***	-0.0236***	-0.0300***	-0.0318***
	(0.0009)	(0.0015)	(0.0013)	(0.0016)
Sector: Automotive and other vehicles	0.0067***	0.0006	0.0198***	0.0141***
	(0.0010)	(0.0017)	(0.0016)	(0.0020)
Schleswig-Holstein	0.0118***	0.0262***	0.0203***	-0.0113***
	(0.0019)	(0.0031)	(0.0032)	(0.0039)
Hamburg	-0.0037*	-0.0044	0.0139***	-0.0328***
	(0.0019)	(0.0028)	(0.0024)	(0.0031)
Lower Saxony	0.0048***	0.0187***	0.0182***	-0.0112***
	(0.0009)	(0.0017)	(0.0016)	(0.0019)
Bremen	0.0138***	0.0102***	-0.0286***	0.0037
	(0.0026)	(0.0065)	(0.0043)	(0.0057)
Hesse	0.0228***	0.0171***	0.0119***	0.0265***
	(0.0010)	(0.0020)	(0.0017)	(0.0020)
Rhineland-Palatinate	-0.0121***	-0.0103***	0.0015	-0.0192***
	(0.0013)	(0.0021)	(0.0020)	(0.0022)
Baden-Wuerttemberg	0.0067***	0.0113***	0.0151***	0.0196***
	(0.0008)	(0.0013)	(0.0013)	(0.0015)
Bavaria	0.0005	0.0108***	0.0021	0.0256***
	(0.0008)	(0.0013)	(0.0012)	(0.0014)
Saarland	-0.0299***	-0.0059	0.0218***	0.0208***
	(0.0021)	(0.0036)	(0.0044)	(0.0053)
Constant	0.1681***	0.1757***	0.2318***	0.2696***
	(0.0022)	(0.0046)	(0.0039)	(0.0047)
Observations	576,895	389,624	437,336	320,970

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Notes: The table presents the RIF-regressions for the log variance. The observed years are 1996, 2010, 2012 and 2017. Standard errors are given in parentheses. Sampling weights are employed.

Table 2.B.13: Decomposition of the variance, 1996-2010 and 2012-2017

	1996-2010		2012-2017	
	Coefficient	Standard Deviation	Coefficient	Standard Deviation
Total change	5.58***	(0.18)	−0.19	(0.17)
Pure composition effect				
Age	0.75***	(0.06)	−0.01	(0.03)
Education	1.67***	(0.09)	0.38***	(0.06)
Tenure	−0.04	(0.07)	−0.09***	(0.02)
Nationality	0.03	(0.02)	0.00	(0.00)
Automation threat	0.17***	(0.04)	0.33***	(0.03)
Collective bargaining	0.94***	(0.22)	−0.03***	(0.01)
Plant size	−0.24***	(0.05)	0.34***	(0.05)
Region	−0.07**	(0.03)	−0.03	(0.02)
Sector	0.08***	(0.03)	0.16***	(0.03)
Total	3.27***	(0.23)	1.06***	(0.08)
Specification error	−0.47***	(0.14)	−0.17***	(0.02)
Pure wage structure effect				
Age	2.55***	(0.70)	−2.12***	(0.52)
Education	1.52***	(0.18)	−0.55***	(0.11)
Tenure	−8.56***	(2.78)	−1.26	(1.59)
Nationality	−0.05	(0.06)	0.10*	(0.06)
Automation threat	3.82**	(1.81)	−1.96***	(0.68)
Collective bargaining	−0.39	(0.47)	0.97***	(0.33)
Plant size	1.99***	(0.24)	−0.48***	(0.18)
Region	−0.70*	(0.38)	−1.36***	(0.39)
Sector	1.22**	(0.59)	0.06	(0.39)
Constant	1.78	(3.55)	5.64***	(1.93)
Total	3.17***	(0.23)	−0.96***	(0.15)
Reweighting error	−0.39***	(0.06)	−0.12***	(0.02)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Notes*: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages. The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Table 2.B.14: Decomposition results using the probability of computerisation by Frey and Osborne (2017), 1996-2010

Inequality measure	85-15		Gini coefficient		50-15		85-50		variance	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Total change	10.67***	(0.37)	4.24***	(0.10)	7.11***	(0.28)	3.56***	(0.26)	5.58***	(0.19)
Pure composition effect										
Age	4.03***	(0.23)	0.72***	(0.05)	1.10***	(0.15)	2.93***	(0.17)	0.78***	(0.07)
Education	5.59***	(0.35)	1.56***	(0.09)	1.23***	(0.07)	4.36***	(0.31)	1.60***	(0.10)
Tenure	−0.37*	(0.22)	−0.03	(0.05)	−0.11	(0.17)	−0.26**	(0.18)	−0.04	(0.07)
Nationality	0.13***	(0.03)	0.02	(0.00)	0.07***	(0.02)	0.07***	(0.02)	0.04***	(0.01)
Automation threat	0.13**	(0.06)	0.01	(0.01)	0.22***	(0.04)	−0.09*	(0.05)	0.03	(0.05)
Collective bargaining	1.28**	(0.54)	0.45***	(0.11)	0.68*	(0.37)	0.60	(0.38)	1.05***	(0.21)
Plant size	−0.57***	(0.09)	−0.21***	(0.02)	−0.49***	(0.07)	−0.08	(0.05)	−0.24***	(0.04)
Region	−0.19***	(0.07)	−0.02	(0.02)	0.00	(0.06)	−0.19***	(0.05)	−0.06**	(0.03)
Sector	0.05	(0.10)	0.08***	(0.02)	−0.11*	(0.06)	0.17**	(0.08)	0.09**	(0.04)
Total	10.09***	(0.80)	2.58***	(0.14)	2.59***	(0.40)	7.50***	(0.60)	3.23***	(0.29)
Specification error	−0.58	(0.60)	−0.50***	(0.08)	1.10***	(0.42)	−1.68***	(0.56)	−0.44***	(0.13)
Pure wage structure effect										
Age	4.66***	(1.69)	1.66***	(0.38)	−1.22	(1.34)	5.88***	(1.33)	2.75***	(0.66)
Education	1.87***	(0.59)	1.03***	(0.12)	−0.91***	(0.19)	2.79***	(0.59)	1.52***	(0.17)
Tenure	−13.83***	(5.01)	−2.67**	(1.10)	−13.31***	(4.33)	−0.52	(2.39)	−8.39***	(2.70)
Nationality	−0.43***	(0.15)	−0.05*	(0.03)	−0.05	(0.13)	−0.39***	(0.12)	−0.04	(0.06)
Automation threat	1.31	(1.63)	0.22	(0.29)	4.93***	(1.36)	−3.63**	(1.54)	0.54	(0.43)
Collective bargaining	−6.55***	(1.11)	−1.12***	(0.25)	−4.66***	(0.93)	−1.89*	(1.02)	0.06	(0.52)
Plant size	2.61***	(0.70)	0.40**	(0.18)	3.08***	(0.62)	−0.47	(0.64)	1.77***	(0.28)
Region	−1.01	(0.86)	−0.26	(0.22)	−0.90	(0.81)	-0.12	(0.59)	−0.77**	(0.37)
Sector	3.48***	(1.26)	0.17	(0.24)	3.58***	(1.06)	−0.10	(0.88)	0.71	(0.49)
Constant	10.09*	(5.92)	3.00**	(1.40)	13.11***	(4.60)	-3.03	(3.53)	4.93	(3.10)
Total	2.19***	(0.64)	2.37***	(0.18)	3.65***	(0.47)	−1.45***	(0.55)	3.09***	(0.29)
Reweighting error	−1.04***	(0.17)	−0.21***	(0.05)	−0.23**	(0.11)	−0.81***	(0.11)	−0.30***	(0.06)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Frey and Osborne (2017), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach using the probability of computerisation by Frey and Osborne (2017) based on log daily wages (85-15, 50-15, 85-50, variance) and daily wages (Gini coefficient). The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Table 2.B.15: Decomposition results using the probability of computerisation by Frey and Osborne (2017), 2012-2017

Inequality measure	85-15		Gini coefficient		50-15		85-50		variance	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Total change	2.17***	(0.57)	−0.31***	(0.10)	4.65***	(0.48)	−2.48***	(0.36)	−0.19***	(0.15)
Pure composition effect										
Age	−0.01	(0.09)	0.00	(0.02)	−0.02	(0.04)	0.01	(0.06)	0.02	(0.03)
Education	1.29***	(0.22)	0.33***	(0.06)	0.24***	(0.04)	1.05***	(0.18)	0.40***	(0.10)
Tenure	−0.18***	(0.04)	−0.04***	(0.01)	−0.13***	(0.03)	−0.05**	(0.02)	−0.09***	(0.02)
Nationality	0.02**	(0.01)	0.00	(0.00)	0.01**	(0.00)	0.01	(0.01)	0.00	(0.00)
Automation threat	0.06	(0.20)	0.00***	(0.00)	0.05	(0.03)	0.01	(0.01)	0.01	(0.01)
Collective bargaining	−0.11*	(0.04)	−0.02**	(0.01)	−0.09***	(0.03)	−0.02**	(0.01)	−0.03***	(0.01)
Plant size	0.71***	(0.13)	0.23***	(0.03)	0.48***	(0.09)	0.23**	(0.07)	0.34***	(0.05)
Region	−0.07	(0.06)	−0.00	(0.01)	−0.09**	(0.04)	0.02	(0.04)	−0.02***	(0.03)
Sector	0.05	(0.07)	0.04***	(0.02)	0.62	(0.06)	−0.57***	(0.05)	0.11***	(0.03)
Total	1.75***	(0.29)	0.54***	(0.07)	1.05***	(0.16)	0.70***	(0.20)	0.73***	(0.10)
Specification error	1.47	(0.16)	−0.07***	(0.01)	0.00	(0.10)	1.47***	(0.13)	−0.08***	(0.02)
Pure wage structure effect										
Age	−6.88***	(1.65)	−1.40***	(0.32)	−1.08	(1.37)	−5.80***	(1.04)	−2.06***	(0.62)
Education	−3.90***	(0.59)	−0.42***	(0.06)	0.33*	(0.18)	−4.24***	(0.57)	−0.56***	(0.19)
Tenure	−11.53***	(4.24)	−2.13*	(0.90)	−4.72	(3.44)	−6.82***	(2.14)	−1.62	(1.97)
Nationality	0.54***	(0.16)	0.06*	(0.03)	0.38	(0.14)	0.16***	(0.10)	0.11	(0.16)
Automation threat	3.87	(2.09)	−0.13	(0.38)	4.33***	(1.13)	−0.46	(1.64)	−0.22	(0.57)
Collective bargaining	1.83*	(0.94)	0.42**	(0.18)	1.88***	(0.77)	−0.05	(0.66)	0.96	(0.29)
Plant size	−1.58***	(0.57)	−0.35***	(0.12)	−1.22***	(0.48)	−0.36	(0.36)	−0.52***	(0.20)
Region	−3.31	(0.92)	−0.78	(0.19)	−1.16	(0.57)	−2.16***	(0.72)	−1.23***	(0.36)
Sector	4.33***	(1.08)	0.84***	(0.22)	2.15***	(0.77)	2.18***	(0.79)	0.82**	(0.40)
Constant	16.08***	(4.97)	3.21***	(1.04)	2.75	(3.58)	13.33	(3.04)	3.58*	(2.12)
Total	−0.57	(0.51)	−0.69	(0.09)	3.64***	(0.40)	−4.21*	(0.28)	−0.76***	(0.14)
Reweighting error	−0.48***	(0.06)	−0.09***	(0.01)	−0.04**	(0.02)	−0.44***	(0.05)	−0.09***	(0.02)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Frey and Osborne (2017), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach using the probability of computerisation by Frey and Osborne (2017) based on log daily wages (85-15, 50-15, 85-50, variance) and daily wages (Gini coefficient). The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Table 2.B.16: Decomposition results without the automotive and other vehicles sector, 1996-2010

Inequality measure	85-15		Gini coefficient		50-15		85-50		variance	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Total change	12.04***	(0.50)	4.56***	(0.13)	7.35***	(0.33)	4.69***	(0.36)	5.83***	(0.24)
Pure composition effect										
Age	3.56***	(0.25)	0.69***	(0.06)	0.91***	(0.18)	2.64***	(0.17)	0.72***	(0.07)
Education	4.96***	(0.32)	1.55***	(0.10)	1.15***	(0.09)	3.81***	(0.27)	1.57***	(0.10)
Tenure	−0.41	(0.26)	−0.02	(0.06)	−0.05	(0.21)	−0.37**	(0.17)	−0.02	(0.08)
Nationality	0.04	(0.03)	0.00	(0.01)	0.05**	(0.02)	-0.01	(0.02)	0.02	(0.02)
Automation threat	1.74***	(0.20)	0.33***	(0.04)	0.39***	(0.06)	1.34***	(0.16)	0.32***	(0.05)
Collective bargaining	0.96*	(0.55)	0.34***	(0.13)	0.69*	(0.40)	0.27	(0.38)	0.94***	(0.21)
Plant size	−0.42***	(0.11)	−0.15***	(0.04)	−0.24***	(0.08)	−0.18**	(0.08)	−0.16***	(0.05)
Region	−0.10	(0.08)	−0.02	(0.02)	0.00	(0.06)	−0.10	(0.07)	−0.08***	(0.03)
Sector	0.80***	(0.11)	0.19***	(0.02)	−0.09	(0.07)	0.89***	(0.10)	0.16***	(0.03)
Total	11.12***	(0.83)	2.90***	(0.18)	2.81***	(0.54)	8.30***	(0.63)	3.48***	(0.24)
Specification error	−0.77	(0.66)	−0.57***	(0.11)	0.91**	(0.46)	−1.68***	(0.59)	−0.44***	(0.14)
Pure wage structure effect										
Age	5.07**	(2.45)	1.42***	(0.54)	0.03	(1.75)	5.04***	(1.64)	2.36***	(0.83)
Education	1.93***	(0.59)	1.16***	(0.13)	−0.62***	(0.20)	2.55***	(0.57)	1.59***	(0.19)
Tenure	−16.37***	(5.67)	−2.46*	(1.28)	−17.57***	(4.72)	1.20	(2.49)	−7.75**	(3.13)
Nationality	−0.67***	(0.20)	−0.11***	(0.04)	−0.04	(0.16)	−0.63***	(0.13)	−0.10	(0.08)
Automation threat	3.68	(2.28)	1.84**	(0.81)	7.46***	(1.68)	−3.78**	(1.82)	3.00	(1.85)
Collective bargaining	−6.44***	(1.11)	−1.00***	(0.26)	−3.84***	(0.80)	−2.61**	(1.04)	0.25	(0.44)
Plant size	2.70***	(0.84)	0.58***	(0.21)	3.31***	(0.62)	−0.61	(0.70)	1.93***	(0.33)
Region	−0.65	(1.05)	0.05	(0.23)	−1.11	(0.88)	0.46	(0.72)	−0.45	(0.38)
Sector	4.90***	(1.28)	0.91***	(0.34)	2.63***	(1.00)	2.27**	(1.05)	1.34*	(0.70)
Constant	9.14	(6.19)	0.18	(1.51)	14.10***	(4.78)	-4.96	(3.44)	1.11	(3.60)
Total	3.27***	(0.70)	2.57***	(0.19)	4.34***	(0.48)	−1.07*	(0.56)	3.28***	(0.29)
Reweighting error	−1.57***	(0.20)	−0.35***	(0.05)	−0.71***	(0.13)	−0.86***	(0.13)	−0.49***	(0.06)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach without the automotive and other vehicles sector based on log daily wages (85-15, 50-15, 85-50, variance) and daily wages (Gini coefficient). The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Table 2.B.17: Decomposition results without the automotive and other vehicles sector, 2012-2017

Inequality measure	85-15		Gini coefficient		50-15		85-50		variance	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Total change	3.41***	(0.60)	0.03	(0.12)	2.96***	(0.50)	0.44	(0.40)	−0.05	(0.20)
Pure composition effect										
Age	−0.07	(0.09)	0.00	(0.02)	−0.04	(0.04)	−0.03	(0.07)	0.01	(0.03)
Education	0.67***	(0.18)	0.20***	(0.06)	0.09***	(0.03)	0.59***	(0.15)	0.23***	(0.07)
Tenure	−0.12***	(0.04)	−0.03***	(0.01)	−0.08**	(0.04)	−0.04**	(0.02)	−0.06***	(0.02)
Nationality	0.00	(0.01)	0.00	(0.00)	0.00	(0.01)	0.00	(0.00)	0.00	(0.00)
Automation threat	3.98***	(0.22)	0.70***	(0.03)	1.07***	(0.08)	2.91***	(0.17)	0.93***	(0.05)
Collective bargaining	0.24***	(0.04)	0.05***	(0.01)	0.22***	(0.04)	0.02	(0.02)	0.07***	(0.01)
Plant size	−0.97***	(0.12)	−0.26***	(0.03)	−0.75***	(0.09)	−0.22***	(0.04)	−0.37***	(0.05)
Region	−0.05	(0.08)	−0.03	(0.02)	-0.05	(0.06)	0.00	(0.06)	−0.05*	(0.03)
Sector	−0.64***	(0.11)	−0.12***	(0.02)	0.19***	(0.07)	−0.84***	(0.10)	−0.11***	(0.03)
Total	3.04***	(0.32)	0.50***	(0.07)	0.65***	(0.17)	2.40***	(0.23)	0.64***	(0.10)
Specification error	1.16**	(0.50)	−0.04***	(0.01)	0.11	(0.07)	1.05**	(0.49)	−0.03	(0.02)
Pure wage structure effect										
Age	−6.36***	(2.20)	−1.06***	(0.34)	−0.57	(1.65)	−5.79***	(1.34)	−1.38**	(0.65)
Tenure	−8.16*	(4.97)	−1.23	(1.02)	0.45	(3.67)	−8.61***	(2.69)	0.55	(2.17)
Nationality	0.37	(0.23)	0.00	(0.04)	0.43**	(0.18)	−0.06	(0.12)	0.02	(0.07)
Education	−3.79***	(0.56)	−0.37***	(0.07)	0.29	(0.20)	−4.08***	(0.53)	−0.41***	(0.13)
Collective bargaining	1.53*	(0.90)	0.42***	(0.14)	2.45***	(0.74)	−0.91	(0.57)	0.85***	(0.27)
Automation threat	5.48**	(2.67)	−1.99***	(0.50)	4.92***	(1.89)	0.56	(2.15)	−1.78***	(0.68)
Plant size	1.13*	(0.68)	−0.05	(0.13)	−1.11**	(0.50)	2.24***	(0.48)	−0.16	(0.21)
Region	−2.92***	(1.01)	−0.45**	(0.19)	−0.42	(0.69)	−2.50***	(0.84)	−0.75**	(0.36)
Sector	2.39**	(1.05)	−0.35*	(0.19)	0.58	(0.79)	1.81**	(0.91)	−0.48	(0.32)
Constant	10.19*	(6.14)	4.76***	(1.24)	−4.63	(4.41)	14.82***	(3.76)	3.01	(2.44)
Total	−0.14	(0.82)	−0.33***	(0.11)	2.38***	(0.46)	−2.52***	(0.70)	−0.53***	(0.17)
Reweighting error	−0.65***	(0.08)	−0.10***	(0.02)	−0.17***	(0.03)	−0.48***	(0.06)	−0.13***	(0.02)

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach without the automotive and other vehicles sector based on log daily wages (85-15, 50-15, 85-50, variance) and daily wages (Gini coefficient). The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrapped standard errors with 100 replications are presented in parentheses. Sampling weights are employed.

Appendix 2.C

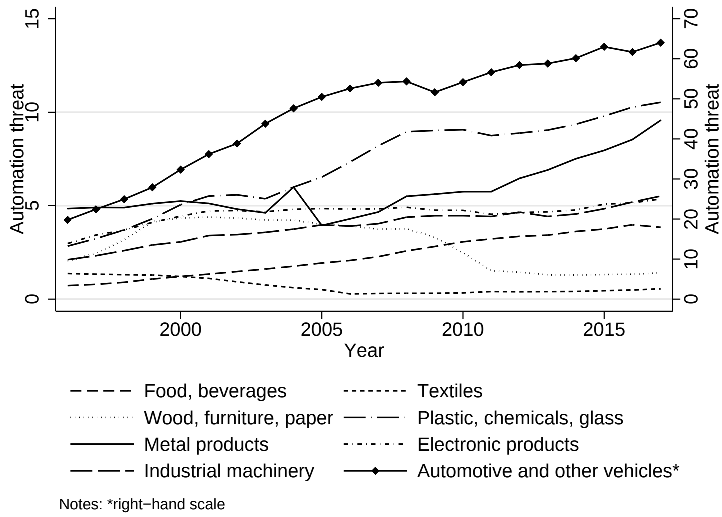
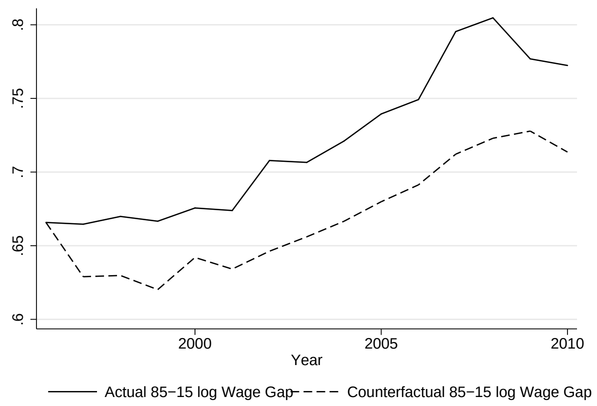


Figure 2.C.1: Automation threat in Germany across sectors in the manufacturing industry from 1996 to 2017

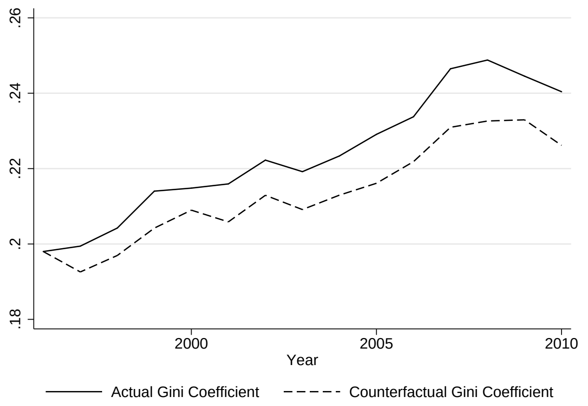
Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: The figure presents the evolution of the automation threat variable across sectors in the German manufacturing industry. In the case of the automotive and other vehicles sector the development is right-hand scaled. Sampling weights are employed.

Figure 2.C.2: Actual and counterfactual differences, 1996-2010

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: The figure presents the comparison between the actual and counterfactual differences between 1996 and 2010. Counterfactual weights are estimated using multinomial logit estimations, see Appendix 2.A. Sampling weights are employed.



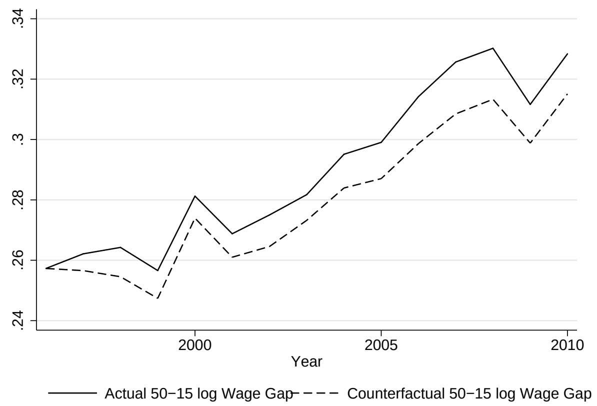
(a) 85-15 percentile wage gap



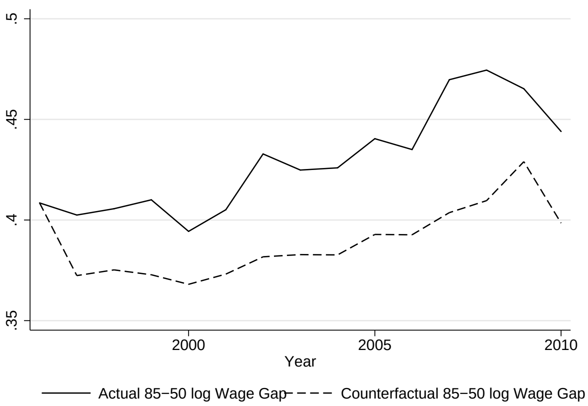
(b) Gini coefficient

Figure 2.C.3: Actual and counterfactual 85-15 percentile wage gap and Gini coefficient from 1996 to 2010

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: Panel (a) (Panel (b)) of the figure presents the evolution of the actual 85-15 percentile wage gap (Gini coefficient estimations) as well as the counterfactual 85-15 percentile wage gap (Gini coefficient estimations) that would have prevailed if automation and robotization had remained at the level of 1996. Counterfactual weights are estimated using multinomial logit estimations, see Appendix 2.A. Sampling weights are employed.



(a) 50-15 percentile wage gap



(b) 85-50 percentile wage gap

Figure 2.C.4: Actual and counterfactual 50-15 and 85-50 percentile wage gap from 1996 to 2010

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: Panel (a) (Panel (b)) of the figure presents the evolution of the actual 50-15 (85-50) percentile wage gap as well as the counterfactual 50-15 (85-50) percentile wage gap that would have prevailed if automation and robotization had remained at the level of 1996. Counterfactual weights are estimated using multinomial logit estimations, see Appendix 2.A. Sampling weights are employed.

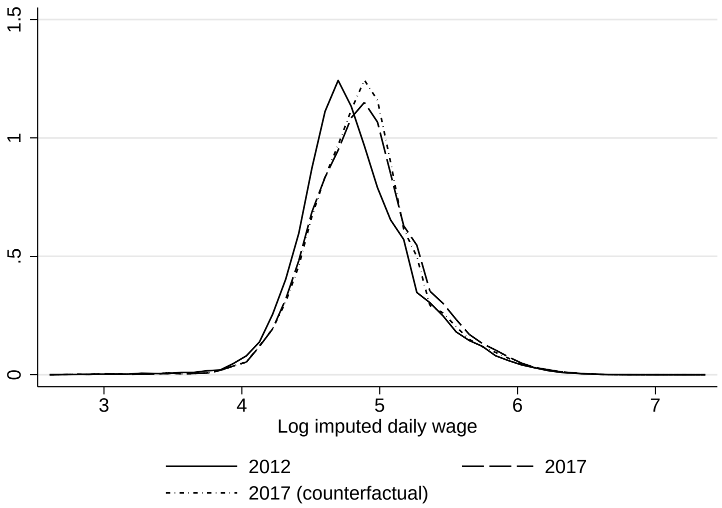


Figure 2.C.5: Actual and counterfactual wage distributions, 2012-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: The figure presents the actual wage distributions in 2012 and 2017 as well as the counterfactual wage distribution that would have prevailed if automation and robotization had remained at the level of 2012. Counterfactual weights are estimated using multinomial logit estimations, see Appendix 2.A. Sampling weights are employed.

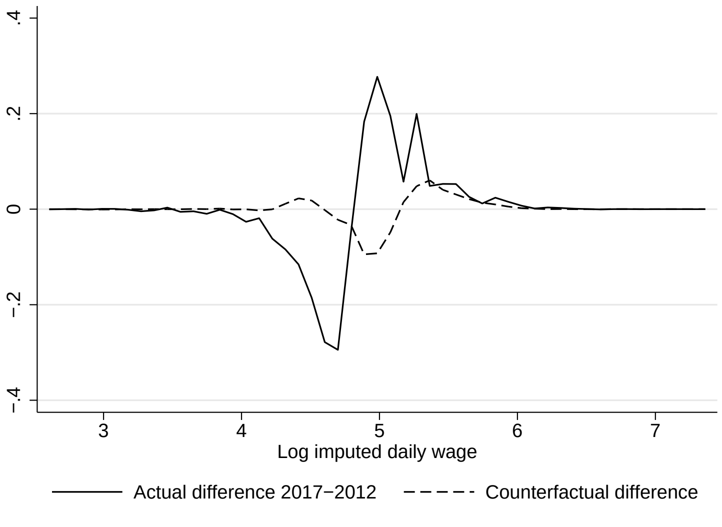
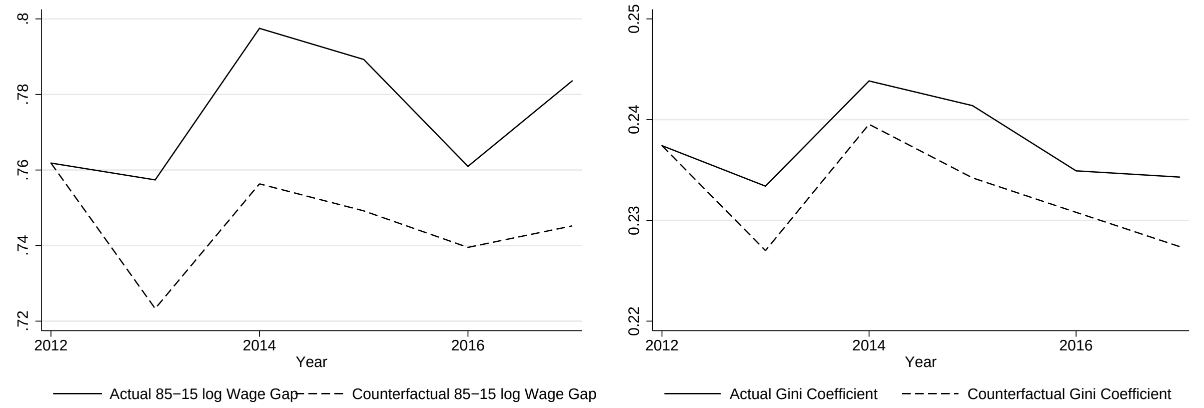


Figure 2.C.6: Actual and counterfactual differences, 2012-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations. *Note*: The figure presents the comparison between the actual and counterfactual differences between 2012 and 2017. Counterfactual weights are estimated using multinomial logit estimations, see Appendix 2.A. Sampling weights are employed.

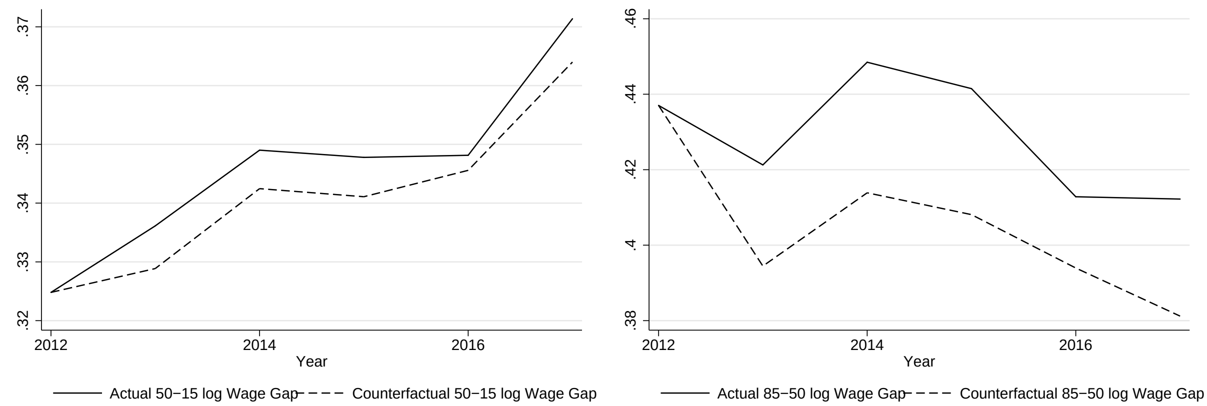


(a) 85-15 percentile wage gap

(b) Gini coefficient

Figure 2.C.7: Actual and counterfactual 85-15 percentile wage gap and Gini coefficient from 2012 to 2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Note: Panel (a) (Panel (b)) of the figure presents the evolution of the actual 85-15 percentile wage gap (Gini coefficient estimations) as well as the counterfactual 85-15 percentile wage gap (Gini coefficient estimations) that would have prevailed if automation and robotization had remained at the level of 2012. Counterfactual weights are estimated using multinomial logit estimations, see Appendix 2.A. Sampling weights are employed.



(a) 50-15 percentile wage gap

(b) 85-50 percentile wage gap

Figure 2.C.8: Actual and counterfactual 50-15 and 85-50 percentile wage gap from 2012 to 2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.
Note: Panel (a) (Panel (b)) of the figure presents the evolution of the actual 50-15 (85-50) percentile wage gap as well as the counterfactual 50-15 (85-50) percentile wage gap that would have prevailed if automation and robotization had remained at the level of 2012. Counterfactual weights are estimated using multinomial logit estimations, see Appendix 2.A. Sampling weights are employed.

References

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, volume 4, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2018). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6):2188–2244.

Aksoy, C. G., Özcan, B., and Philipp, J. (2021). Robots and the gender pay gap in Europe. *European Economic Review*, 134:103693.

Anelli, M., Colantone, I., and Stanig, P. (2019). We Were the Robots: Automation and Voting Behavior in Western Europe. *BAFFI CAREFIN Centre Research Paper*, 2019-115.

Anelli, M., Giuntella, O., and Stella, L. (2021). Robots, Marriageable Men, Family, and Fertility. *Journal of Human Resources*, pages 1020–11223R1.

Antonczyk, D., DeLeire, T., and Fitzenberger, B. (2018). Polarization and Rising Wage Inequality: Comparing the U.S. and Germany. *Econometrics*, 6(2):1–33.

Antonczyk, D., Fitzenberger, B., and Sommerfeld, K. (2010). Rising Wage Inequality, the Decline of Collective Bargaining, and the Gender Wage Gap. *Labour Economics*, 17(5):835 – 847.

Arntz, M., Gregory, T., and Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. *OECD Social, Employment and Migration Working Papers*, (No. 189).

Atkinson, A. B. (1970). On the measurement of inequality. *Journal of Economic Theory*, 2(3):244–263.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118(4):1279–1333.

Barsky, R., Bound, J., Charles, K. K., and Lupton, J. P. (2002). Accounting for the Black-White Wealth Gap. *Journal of the American Statistical Association*, 97(459):663–673.

Baumgarten, D., Felbermayr, G., and Lehwald, S. (2020). Dissecting Between-Plant and Within-Plant Wage Dispersion: Evidence from Germany. *Industrial Relations: A Journal of Economy and Society*, 59(1):85–122.

Biewen, M. and Juhasz, A. (2012). Understanding Rising Income Inequality in Germany, 1999/2000–2005/2006. *Review of Income and Wealth*, 58(4):622–647.

Biewen, M. and Seckler, M. (2019). Unions, Internationalization, Tasks, Firms, and Worker Characteristics: A Detailed Decomposition Analysis of Rising Wage Inequality in Germany. *The Journal of Economic Inequality*, 17:461–498.

Bonin, H., Gregory, T., and Zierahn, U. (2015). Übertragung der Studie von Frey/Osborne (2013) auf Deutschland. ZEW Kurzexpertise 57, Mannheim.

Brzeski, C. and Burk, I. (2015). Die Roboter kommen: Folgen der Automatisierung für den deutschen Arbeitsmarkt. *ING DiBa Economic Research, Frankfurt am Main u.a.O.*

Card, D., Heining, J., and Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics*, 128(3):967–1015.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 00(0):1–50.

De Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, 66:101885.

Dengler, K. and Matthes, B. (2015). Folgen der Digitalisierung für die Arbeitswelt: Substituierbarkeitspotenziale von Berufen in Deutschland. IAB-Forschungsbericht 11/2015, Nürnberg.

Dengler, K. and Matthes, B. (2018). Substituierbarkeitspotenziale von Berufen: Wenige Berufsbilder halten mit der Digitalisierung Schritt. IAB-Kurzbericht 4/2018, Nürnberg.

Dengler, K. and Matthes, B. (2021). Auch komplexere Tätigkeiten könnten zunehmend automatisiert werden. IAB-Kurzbericht 13/2021, Nürnberg.

Dengler, K., Matthes, B., and Paulus, W. (2014). Occupational Tasks in the German Labour Market. IAB-Forschungsbericht 12/2014, Nürnberg.

DiNardo, J. (2002). Propensity Score Reweighting and Changes in Wage Distributions. *University of Michigan, mimeograph.*

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64(5):1001–1044.

Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the German Wage Structure. *The Quarterly Journal of Economics*, 124(2):843–881.

Eberle, J., Jacobebbinghaus, P., Ludsteck, J., and Witter, J. (2011). Generation of Time-Consistent Industry Codes in the Face of Classification Changes: Simple heuristic based on the Establishment History Panel (BHP). FDZ Methodenreport 201105_en, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.

Felbermayr, G., Baumgarten, D., and Lehwald, S. (2014). Increasing Wage Inequality in Germany: What Role Does Global Trade Play? *Docbase - Publication Database of the CESifo Group, Bertelsmann Stiftung, Gütersloh.*

Firpo, S., Fortin, N. M., and Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica*, 77(3):953–973.

Firpo, S. P., Fortin, N. M., and Lemieux, T. (2018). Decomposing Wage Distributions Using Recentered Influence Function Regressions. *Econometrics*, 6(2):1–40.

Fortin, N., Lemieux, T., and Firpo, S. (2011). Decomposition Methods in Economics. In *Handbook of Labor Economics*, volume 4, pages 1–102. Elsevier.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254–280.

Gartner, H. (2005). The Imputation of Wages Above the Contribution Limit with the German IAB Employment Sample. *FDZ Methodenreport 02/2005, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.*

Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in britain. *The Review of Economics and Statistics*, 89(1):118–133.

Graetz, G. and Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics*, 100(5):753–768.

Hémous, D. and Olsen, M. (2022). The rise of the machines: Automation, horizontal innovation, and income inequality. *American Economic Journal: Macroeconomics*, 14(1):179–223.

Hyslop, D. R. and Maré, D. C. (2005). Understanding New Zealand's Changing Income Distribution, 1983–1998: A Semi-parametric Analysis. *Economica*, 72(287):469–495.

International Federation of Robotics (2018). World Robotics Industrial Robots 2018. *IFR Statistical Department, Frankfurt am Main.*

Kaltenberg, M. and Foster-McGregor, N. (2020). The Impact of Automation on Inequality across Europe. *UNU-MERIT Working Paper.*

Kariel, J. (2021). Job Creators or Job Killers? Heterogeneous Effects of Industrial Robots on UK Employment. *LABOUR*, 35(1):52–78.

Lankisch, C., Prettner, K., and Prskawetz, A. (2019). How can robots affect wage inequality? *Economic Modelling*, 81:161–169.

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

Prettner, K. and Strulik, H. (2019). Innovation, Automation, and Inequality: Policy Challenges in the Race Against the Machine. *Journal of Monetary Economics*, 116:249–265.

Schmidtlein, L., Seth, S., and Umkehrer, M. (2019). Linked EmployerEmployee Data from the IAB: LIAB Cross-Sectional Model 2 (LIAB QM2) 1993 – 2017. FDZ-Datenreport, 06/2019 (en), Nuremberg.

Sloane, P. F. (2008). Zu den Grundlagen eines Deutschen Qualifikationsrahmens (DQR): Konzeptionen, Kategorien, Konstruktionsprinzipien. *W. Bertelsmann Verlag, Bielefeld.*

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, 70(1):65–94.

Stehrer, R., Bykova, A., Jäger, K., Reiter, O., and Schwarzhappel, M. (2019). Industry Level Growth and Poductivity Data with Special Focus on Intangible Assets. *wiiw Statistical Report No. 8.*

Migration and Wage Inequality: A Detailed Analysis for German Metropolitan and Non-Metropolitan Regions

Author: Ramona Schmid

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 labour 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, the economic sector affiliation and the extent of labour market experience. 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.

Status: Accepted for publication in Review of Regional Research and published in an earlier version in Hohenheim Discussion Papers in Business, Economics and Social Sciences.

JEL classification: J15, J31, J61, R23, R58

Keywords: Immigrant-Native Wage Gap, Oaxaca-Blinder Decomposition, Unconditional Quantile Regressions, Ethnic Clustering, Germany

Acknowledgments: I would like to thank Thomas Beißinger for his guidance throughout this project and his helpful suggestions. I wish to thank Klaus Prettner for helping with valuable comments. Further, I am grateful for valuable remarks from participants of the 14th Workshop on Labour Economics of the IAAEU at Trier University (April, 2022) and the Brown Bag Seminar of the University of Hohenheim (July, 2022).

Chapter 3

Migration and Wage Inequality: A Detailed Analysis for German Metropolitan and Non-Metropolitan Regions

3.1 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 labour market conditions. In the presence of urban-rural wage gaps (Brixy et al., 2022) and higher shares of foreign population in German metropolitan areas (Glitz, 2014; Schaffner and Treude, 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 labour market and society. Thus, analysing 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 over time as well as in different regions are thus of high relevance for decisions in immigration and labour market policies (Brunow and Jost, 2022; Ingwersen and Thomsen, 2021).

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 Centre 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 at 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: Section 3.2 provides an overview on related literature. In Section 3.3, the used data set is described and corresponding to that, general trends in migration and regional differences in Germany as well as descriptive statistics are presented in Section 3.4. Further, in Section 3.5 the empirical approaches are specified and finally, the empirical results are presented in Section 3.6. Discussion and conclusion of the estimated findings are provided in Section 3.7.

3.2 Related Literature

General literature on immigrant-native wage differentials. Due to recent migration developments, studies analysing 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 analyse 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, labour 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 labour 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 labour 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 (Destatis), 2021b). The literature provides evidence that ethnic clustering plays a non-negligible role in the decision of residence for foreign born workers in Germany (Glitz, 2014; Schaffner and Treude, 2014). The resulting consequences with respect to labour 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 labour market participation (Beaman, 2011; Bertrand et al., 2000). 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 labour market of the host country could be reduced and labour 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

[1]The metropolitan areas are based on the definition of the Initiative Circle European Metropolitan Regions in Germany (IKM) (2022). For more details, see Section 3.4.

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.

3.3 Data

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

The main variable identifying German or Non-German workers is defined on the basis of citizenship. As a result, the study covers mainly first-generation migrants, since second-generation migrants more likely accept the German citizenship. Due to this data design, workers that are identified as Non-Germans more likely obtained their school-leaving qualification abroad and exhibit differences regarding their human capital endowments

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

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 labour market and should represent less marginalised 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 the West of Germany. The decision of excluding East Germany stems from the still present significantly different labour market and 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; Ohlert et al., 2016). For the same reasons, it is

[3]When it comes to analysing 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.

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

unfortunately not possible to consider female workers in the underlying analyses due to the not sufficient extent of observations on German and especially Non-German women on the district level.

Furthermore, the decomposition analyses consider possible effects due to the presence of foreign population on a regional level. The required data set is provided by the German Federal Office of Statistics at the district level (Federal Bureau of Statistics (Destatis), 2021b).[7] Thus, it is possible to match this data set with the administrative labour 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 summarises 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 labour market outcomes can be conducted (BBSR Bonn, 2020).[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.

[7]Between 2000 and 2019 there are several changes in the composition of districts. The major changes are listed in Table in 3.A.1 in Appendix 3.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 (2020).

[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 3.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).

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 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.

3.4 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-

[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.

[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.

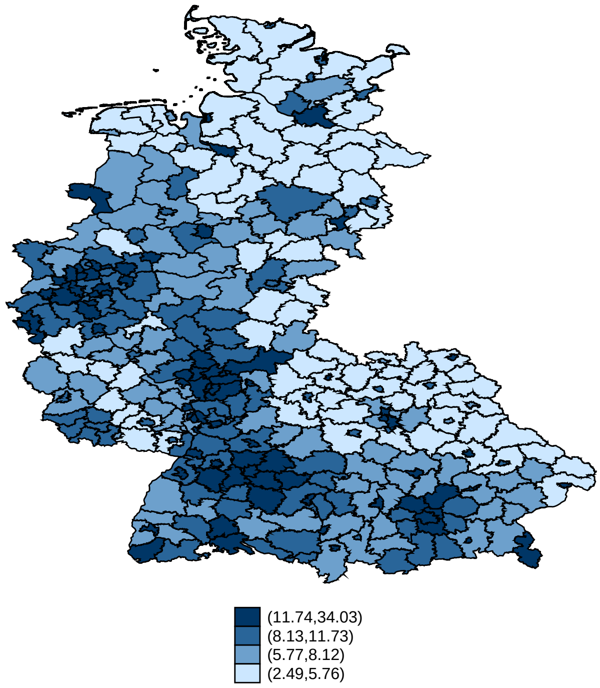
called guest-workers in the 1950s, workers from Turkey and southern Europe dominated immigration in West Germany. The subsequent developments regarding family reunifications and the downfall of the Iron Curtain, which increased migration of Eastern European countries, led to further changes in the foreign 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 (Destatis), 2021b). 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 of the Middle East and Asia, such as Syria, Afghanistan and Iraq (Federal Bureau of Statistics (Destatis), 2021a).

Having a closer look at the regional settlement of the foreign population in West Germany, Figure 3.1 (a) provides evidence of a specific pattern. The figure presents the share of Non-Germans on the level of administrative districts, where a darker colour reflects a higher value. Thus, regions with concentrated higher numbers of foreign population are revealed.

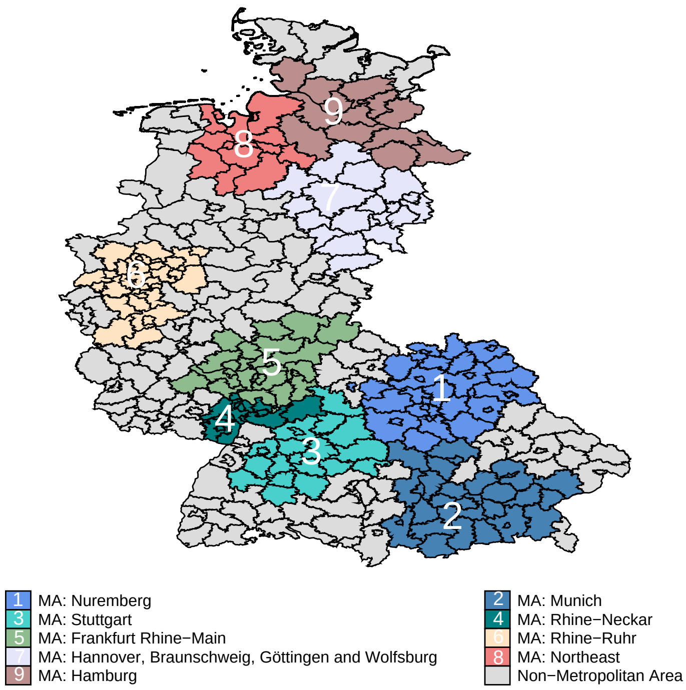
Figure 3.1 (b) presents metropolitan regions of West Germany defined by the Initiative Circle European Metropolitan Regions in Germany (IKM) in 2008 (Kawka, 2016).[17] The concept of European Metropolitan Regions was introduced in the mid-1990s as a program of social, economical and cultural advancement aiming to support the international performance and competitiveness of Germany.[18]

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

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



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



(b) Metropolitan areas in the West of Germany

Figure 3.1: Regional differences

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

Comparing these areas with the observed ethnic clusters of Figure 3.1 (a), 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, Figure 3.2 presents kernel density estimations considering the whole period of observation from 2000 to 2019. For the first half of the distributions, the density of German workers is at any point lower than that of Non-German workers implying substantial differences. The two densities cross at the log wage level of 4.6 and show that more German workers are present in the upper half of the wage distribution. In total, a shift to the left for Non-German workers compared to German workers and thus a substantial wage gap at any point to the detriment of the former is revealed.

Since this study seeks in providing evidence on changes in wage differentials over time, Figure 3.3 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.

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

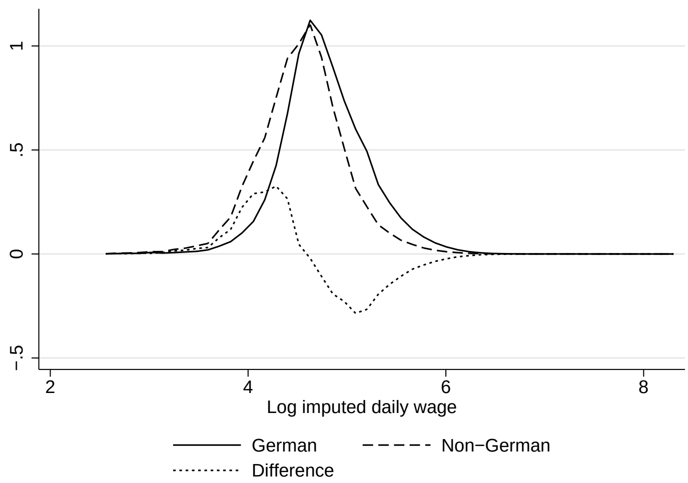
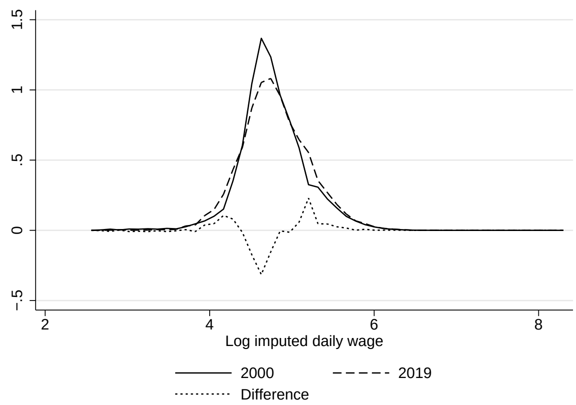
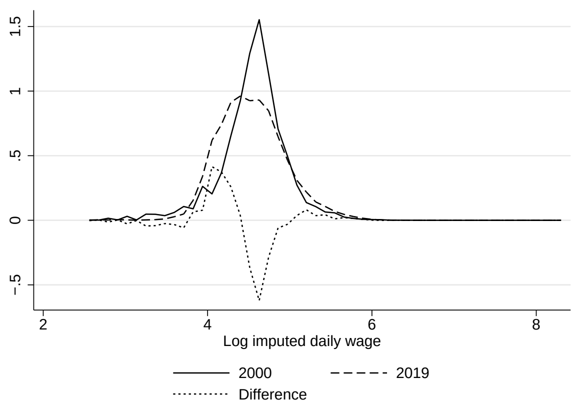


Figure 3.2: Wage densities, 2000-2019

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.



(a) German workers



(b) Non-German workers

Figure 3.3: Change in wage densities over time

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.

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

Going into more detail how wage differentials evolve over time at different points of the wage distribution, Figure 3.4 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.

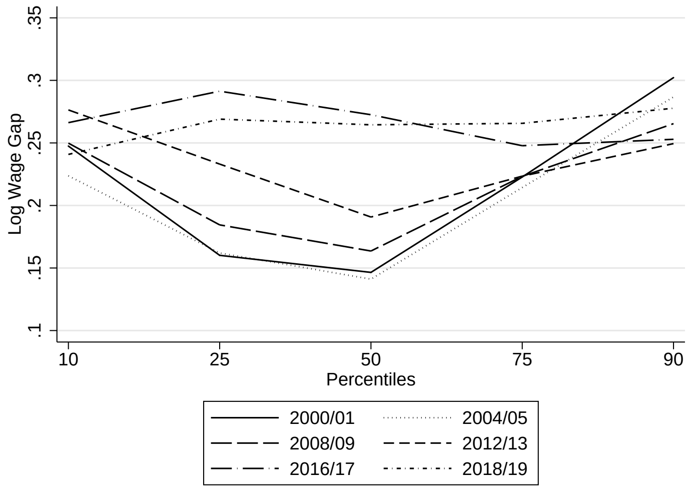


Figure 3.4: Log wage gaps by percentiles, 2000-2019

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

Since this study seeks in providing evidence on differences between metropolitan and non-metropolitan areas, Figure 3.5 presents mean wage differentials at the level of ROR-regions in West Germany. Once again, regional accumulations of certain value ranges are identified. Areas with the highest observed wage gaps between German and Non-German workers noticeably correspond to the defined metropolitan areas of Figure 3.1 (b). 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 Figures 3.B.1-

3.B.3 in Appendix 3.B, where a higher wage dispersion and a larger shift between German and Non-German workers are presented in metropolitan regions.[20]

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

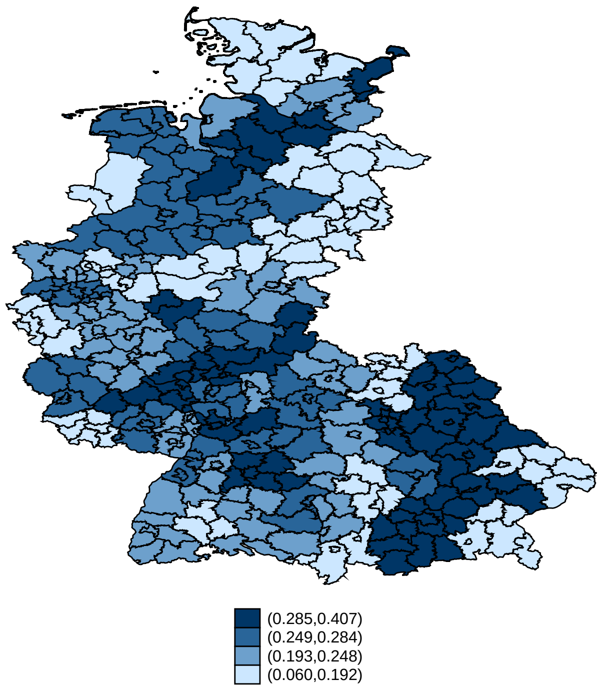


Figure 3.5: Wage differentials between German and Non-German workers, by regions

Source: LIAB QM2 9319, own calculations.

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

Who are the observed workers? A closer look at explanatory factors provides first information of possible differences in the composition of workforce. The descriptive statistics for selected variables are presented in Table 3.1.[21] The first group of characteristics summarises individual endowments of workers such as age, education, days in employment

[20]Table 3.A.2 in Appendix 3.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 analysed by Brixy et al. (2022). In general, the existing literature provides results on wage advantages for workers in large urban areas (see e.g. Gould, 2007; Heuermann et al., 2010; Yankow, 2006).

[21]In order to present clear descriptive statistics, Table 3.1 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.

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 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 sur-

Table 3.1: 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 (Destatis) (2021b), 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.

rounded 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 3.1 also the overall numbers of observations for selected time points are given.[22]

[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 Centre of the IAB.

3.5 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, $IF(w;v)$, 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 $RIF(w;v)$ can be estimated:

$$E[RIF(w;v)|X] = X\gamma, \tag{3.1}$$

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 estimation strategy is related to the case of quantiles. Here, the estimated coefficients are interpreted as unconditional (quantile) partial effects (UQPE) of small location shifts in the covariates (Firpo et al., 2009). In contrast to the commonly known conditional quantile regressions, it is possible to identify the effect of a changing explanatory variable on the τth quantile of the unconditional distribution of w.

Decomposition method. In order to identify the explanatory factors that drive differentials between Germans, N, and non-Germans, F, at different parts of the wage distribution, the standard decomposition method introduced by Oaxaca (1973) and Blinder (1973) (OB decomposition) on the basis of RIF-regressions is applied. Assuming linear wage equations of the two groups, g, where w denotes the log wage and X is a vector of covariates, the following equation presents the standard (aggregate) decomposition of the log wage gap at the mean[23], μ:

$$\begin{aligned}\hat{\Delta}_O^\mu &= \bar{w}_N - \bar{w}_F \\ &= (\bar{X}_N - \bar{X}_F)'\hat{\beta}_F + \bar{X}_N'(\hat{\beta}_N - \hat{\beta}_F).\end{aligned} \tag{3.2}$$

The first half of equation (3.2) 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, $\hat{\gamma}_{g,\tau}$[25], for each group, where $g = N, F$, the OB decomposition of equation (3.2) at quantile τ is defined as:

$$\hat{\Delta}_O^\tau = (\bar{X}_N - \bar{X}_F)'\hat{\gamma}_{F,\tau} + \bar{X}_N'(\hat{\gamma}_{N,\tau} - \hat{\gamma}_{F,\tau}) \tag{3.3}$$

where $\hat{\Delta}_O^\tau$ presents the wage gap at the τth unconditional quantile. Using this extended method, it is possible to decompose log wage gaps between German and Non-German workers at the level of quantiles. Further, as proposed by Firpo et al. (2018) the two-step procedure is applied decomposing wage gaps in order to fulfill the linearity assumption of

[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:
$\hat{\gamma}_{g,\tau} = (\sum X_i X_i')^{-1} \sum \widehat{RIF}(w_{gi}; Q_{g,\tau})X_i$, where $g = N, F$.

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]

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

$$\hat{\Delta}^{\tau}_{X,R} = (\bar{X}_C - \bar{X}_F)'\hat{\gamma}_{F,\tau} + \bar{X}'_C(\hat{\gamma}_{C,\tau} - \hat{\gamma}_{F,\tau}). \tag{3.4}$$

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:

$$\hat{\Delta}^{\tau}_{S,R} = \bar{X}'_N(\hat{\gamma}_{N,\tau} - \hat{\gamma}_{C,\tau}) + (\bar{X}_N - \bar{X}_C)'\hat{\gamma}_{C,\tau}. \tag{3.5}$$

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

In order to show the regional-specific aggregate and detailed decomposition results

[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 $\bar{X}_N\hat{\beta}_F$.

[27]The reweighting function is estimated as follows:

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

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

equations (3.4) and (3.5) 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 Figure 3.1 (b) 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 labour market.

3.6 Decomposition Results

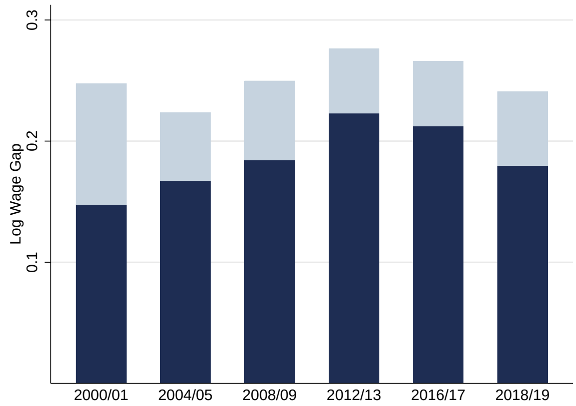
3.6.1 Aggregate Decomposition

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.

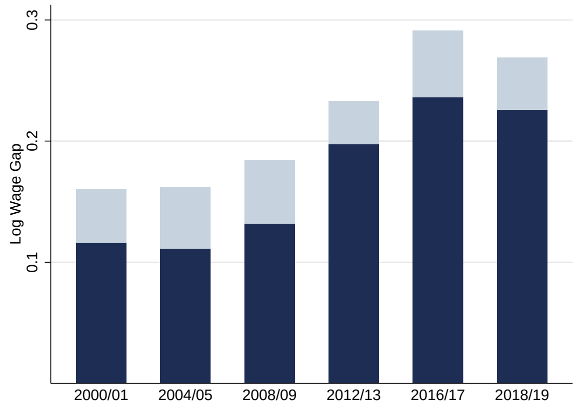
Overall wage gaps. In advance to the analyses on regional differences between metropolitan and non-metropolitan areas, it is evident to have at first a look on the general developments in West Germany as a whole. On this basis, it is subsequently possible to compare the regional results to the baseline model and put them into relation. Figure 3.6 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

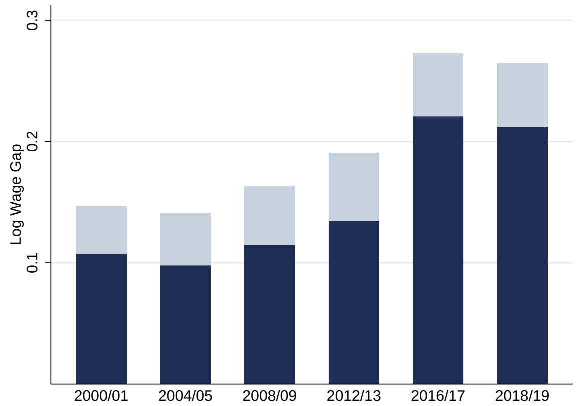
[28] Due to the availability of data only until 2019, there is no distance between the two last time points. However, due to the special relevance of this time period, regarding migration developments, both time points are considered.



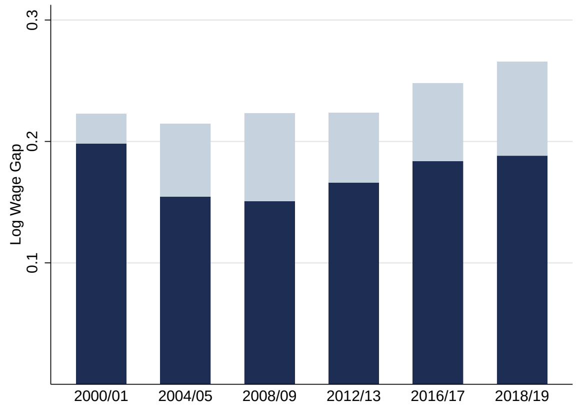
(a) 10th percentile



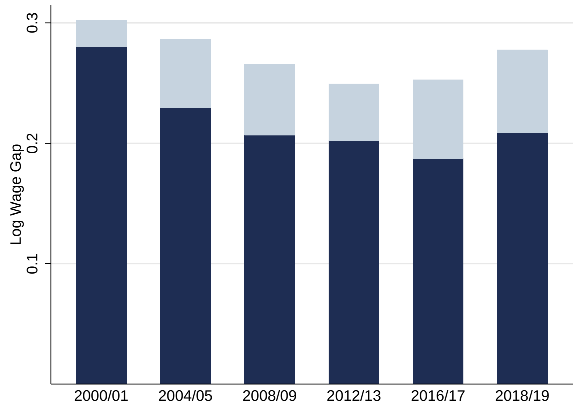
(b) 25th percentile



(c) 50th percentile



(d) 75th percentile



(e) 90th percentile

Figure 3.6: Aggregate decomposition of immigrant-native wage gaps along the wage distribution, 2000-2019

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

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 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%.

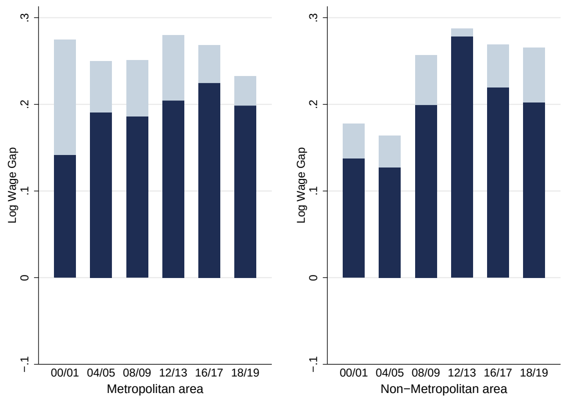
As presented above, the group of foreign workers in Germany consists out of various nationalities with different motives of settlement and time points of immigration. In order to account for possible heterogeneity among Non-German workers, the aggregate analysis is estimated separately on the one side 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. Table 3.A.3 and Table 3.A.4 in Appendix 3.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 labour 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

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

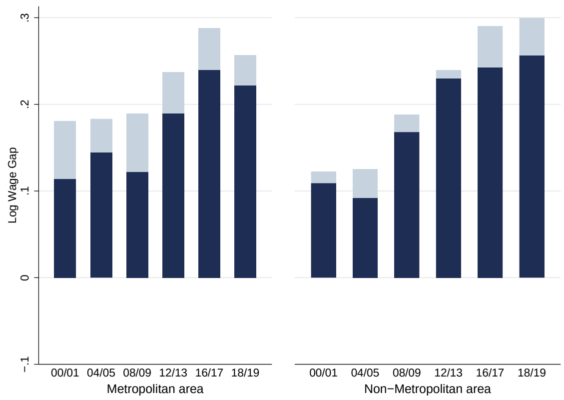
access to the German labour market as domestic individuals. In contrast to this, Non-EU workers are confronted by specific regulations and required permissions (see Brunow and Jost, 2019; Dorn and Zweimueller, 2021). Thus, regarding the extent of unexplained effects and resulting measures by policy makers, 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 Figure 3.7).[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 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.

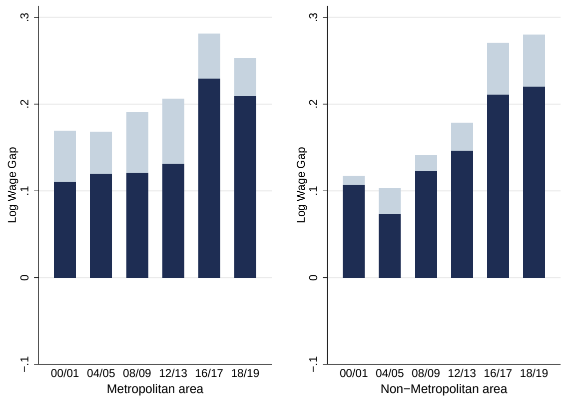
[30]In Tables 3.A.11 and 3.A.12 in Appendix A the aggregate decomposition results are presented.



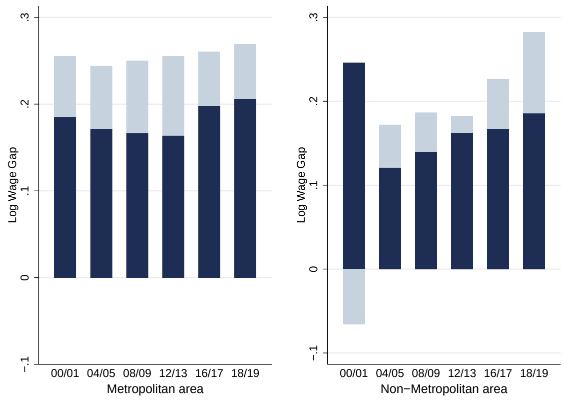
(a) 10th percentile



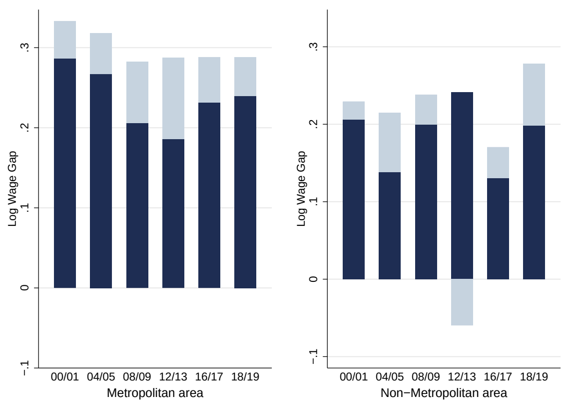
(b) 25th percentile



(c) 50th percentile



(d) 75th percentile



(e) 90th percentile

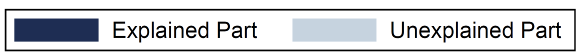


Figure 3.7: Aggregate decomposition of immigrant-native wage gaps along the wage distribution by region, 2000-2019

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021b), 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.

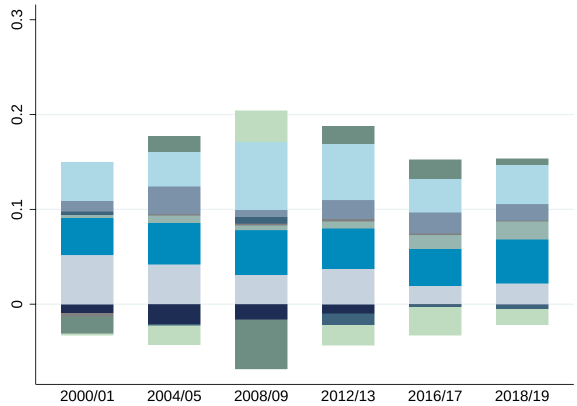
3.6.2 Detailed Decomposition

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.

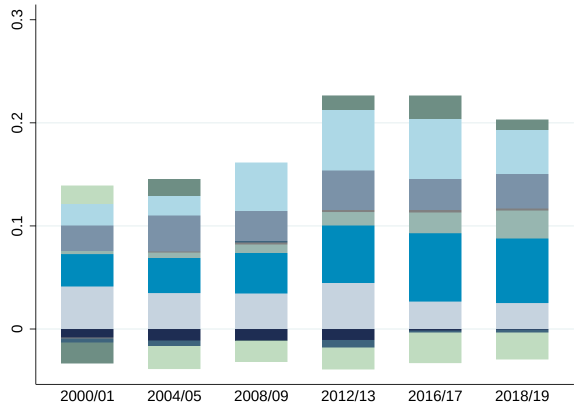
Overall wage gaps. Again, at first the general detailed decomposition estimates of endowment effects at different points of the wage distribution (10th, 25th, 50th, 75th and 90th percentile) over the time span of 20 years (2000-2019) are presented in Figure 3.8.[31] Overall, it is obvious that the relative 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.

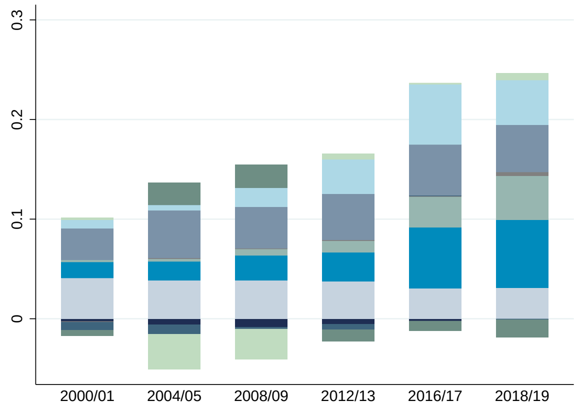
[31] The detailed decomposition is conducted applying the proposed procedure by DiNardo et al. (1996), where at first a counterfactual distribution is estimated. Thus, in Figure 3.8 only the pure composition effects are illustrated. The predominantly statistically insignificant specification errors are omitted. Further, all underlying detailed results to the Figures are presented in Tables 3.A.5-3.A.10 in Appendix 3.A.



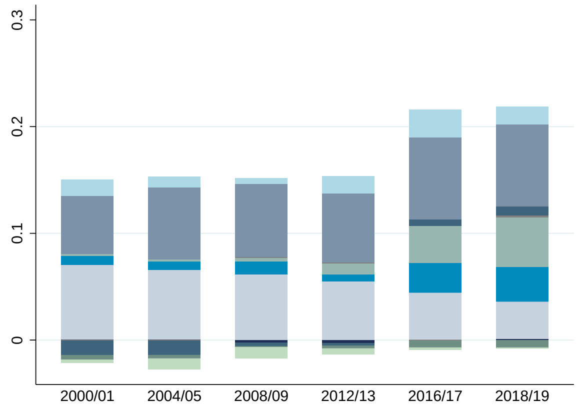
(a) 10th percentile



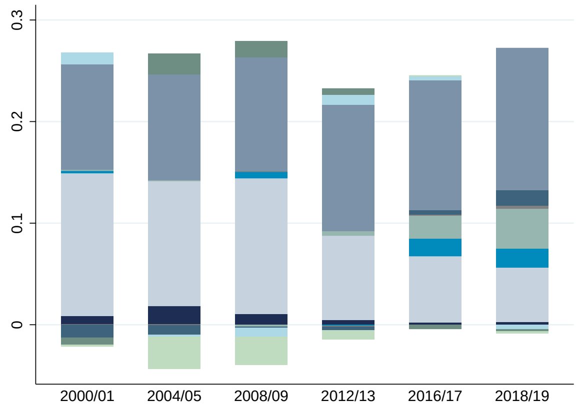
(b) 25th percentile



(c) 50th percentile



(d) 75th percentile



(e) 90th percentile

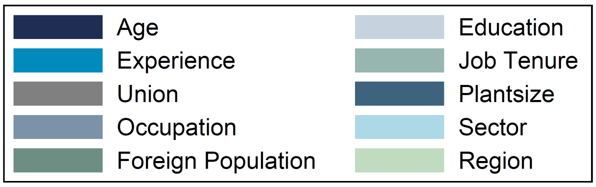


Figure 3.8: Detailed decomposition of the explained part, 2000-2019

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

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.

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 selection 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 effects 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. Figures 3.B.4 and 3.B.5 in Appendix 3.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

[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 3.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 3.C.

results provide evidence for regional-specific higher discrepancies between German and foreign workers in metropolitan areas in seeking for higher levels higher levels of education. Table 3.A.2 in Appendix 3.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.

3.7 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 labour 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

[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 3.C.

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 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 labour 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 labour 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 labour 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 labour markets of metropolitan regions. Future research could therefore attempt to identify further differences between metropolitan and non-metropolitan labour 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 labour 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 labour force of around several hundred thousands each year immigration is essential for the German labour market (Fuchs and Weber, 2018; Kaltwasser and Schludi, 2022; 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 e.g. Buch et al., 2014; Facchini and Lodigiani, 2014; Kühn, 2018). 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 labour 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 labour market and are integrated into society.

Appendix 3.A

Table 3.A.1: Overview of changes in the composition of districts between 2000 and 2019

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

Source: (Federal Bureau of Statistics (Destatis), 2021b).

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.A.2: 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 (Destatis) (2021b), 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 3.A.3: 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)
2016/17										
Log wage gap	27.51***	(0.89)	32.70***	(0.75)	32.68***	(0.81)	27.97***	(1.01)	21.43***	(1.21)
Composition effect	26.05***	(3.41)	32.80***	(2.22)	33.58***	(2.02)	31.63***	(2.19)	23.75***	(2.07)
Wage structure effect	1.46	(21.07)	−0.10	(12.98)	−0.89	(11.65)	−3.67	(13.02)	−2.32	(12.26)
2018/19										
Log wage gap	25.16***	(1.02)	29.16***	(0.84)	30.50***	(0.74)	30.64***	(0.93)	25.31***	(1.29)
Composition effect	23.04***	(5.96)	28.77***	(2.05)	31.04***	(2.00)	33.04***	(2.57)	28.58***	(2.37)
Wage structure effect	2.12	(31.59)	0.39	(10.86)	−0.54	(10.95)	−2.40	(14.70)	−3.27	(13.49)

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021b), 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 3.A.4: 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)
2016/17										
Log wage gap	25.46***	(1.08)	22.92***	(0.86)	20.92***	(0.77)	22.59***	(0.60)	29.11***	(0.86)
Composition effect	17.30***	(2.23)	13.93***	(1.48)	10.99***	(1.44)	9.67***	(1.45)	12.59***	(3.25)
Wage structure effect	8.16	(10.17)	8.98	(6.33)	9.93	(6.19)	12.92	(6.24)	16.52	(14.61)
2018/19										
Log wage gap	23.30***	(0.93)	24.15***	(0.84)	21.00***	(0.80)	23.71***	(0.58)	30.02***	(0.79)
Composition effect	15.88***	(2.65)	17.01***	(1.35)	12.02***	(1.38)	9.45***	(1.51)	10.98***	(2.18)
Wage structure effect	7.42	(12.02)	7.14	(5.89)	9.00	(5.97)	14.26	(6.46)	19.04	(8.47)

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021b), 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 3.A.5: 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 (Destatis) (2021b), 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 3.A.6: 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 (Destatis) (2021b), 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 3.A.7: 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 (Destatis) (2021b), 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 3.A.8: 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 (Destatis) (2021b), 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 3.A.9: 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 (Destatis) (2021b), 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 3.A.10: 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 (Destatis) (2021b), 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 3.A.11: 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 (Destatis) (2021b), 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 3.A.12: 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 (Destatis) (2021b), 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 3.A.13: 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 (Destatis) (2021b), 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 3.A.14: 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 (Destatis) (2021b), 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 3.A.15: 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 (Destatis) (2021b), 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.

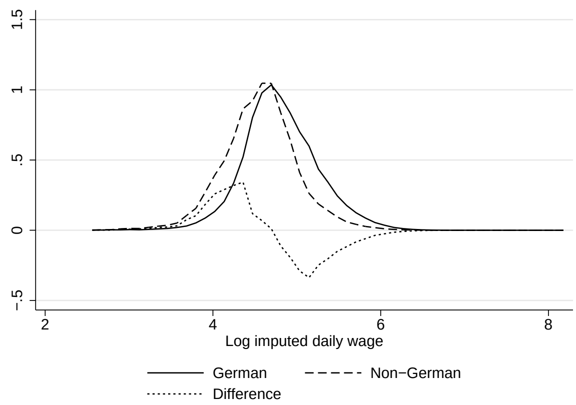
Table 3.A.16: Fixed effects estimation, 2012-2019

	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

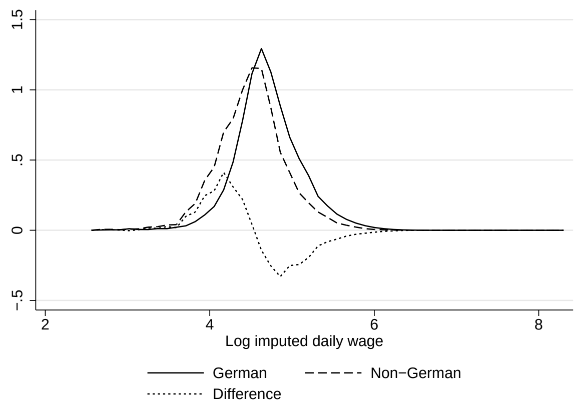
Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021b), own calculations.

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.

Appendix 3.B



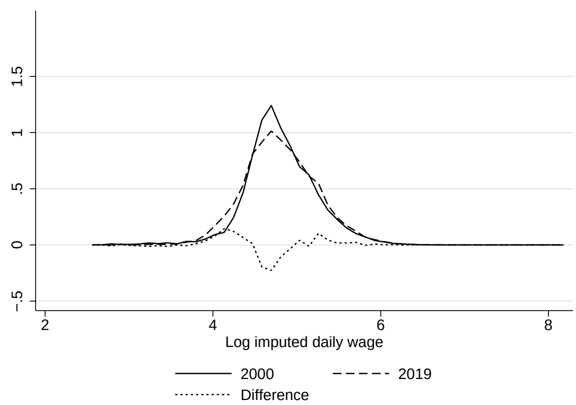
(a) Metropolitan regions



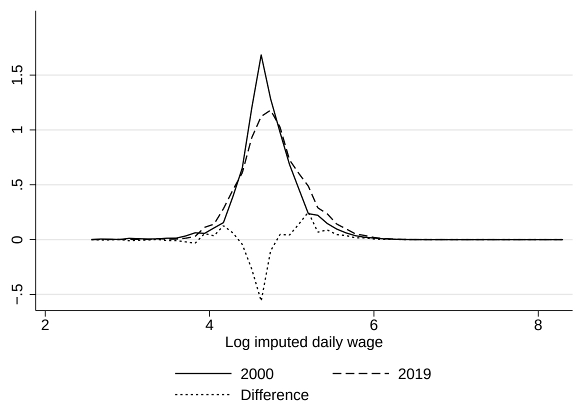
(b) Non-Metropolitan regions

Figure 3.B.1: Wage densities, by region

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



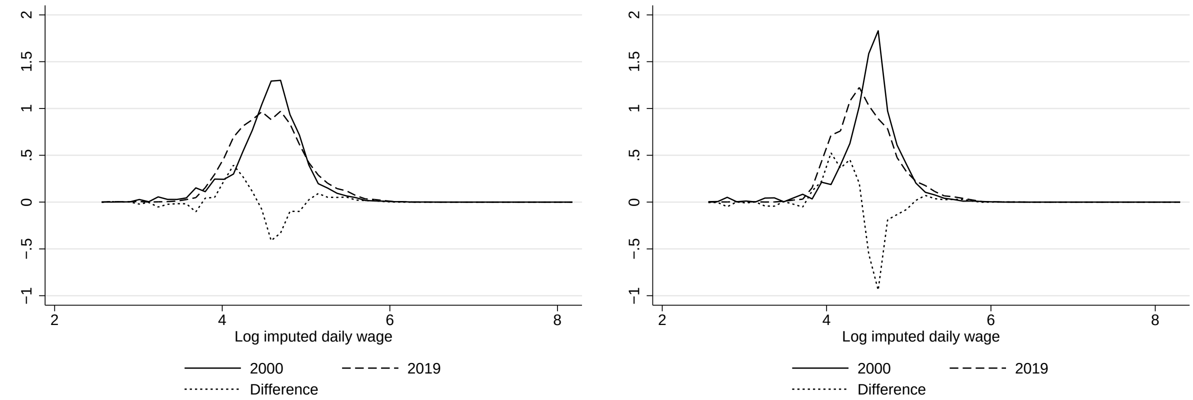
(a) Metropolitan regions



(b) Non-Metropolitan regions

Figure 3.B.2: Wage densities over time of German workers, by region

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

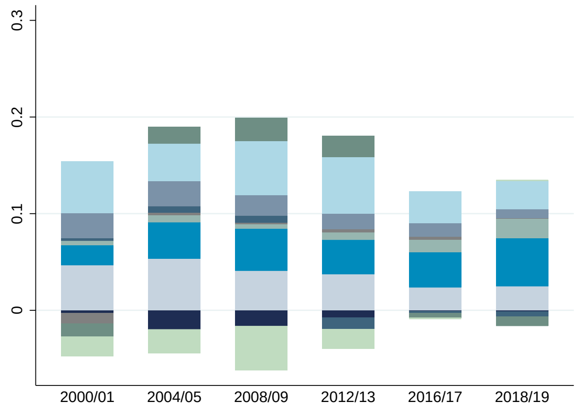


(a) Metropolitan regions

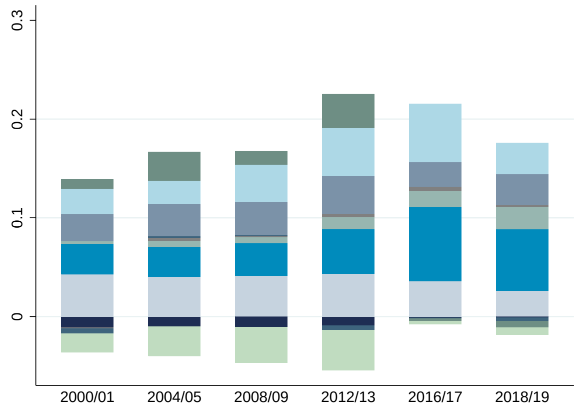
(b) Non-Metropolitan regions

Figure 3.B.3: Wage densities over time of Non-German workers, by region

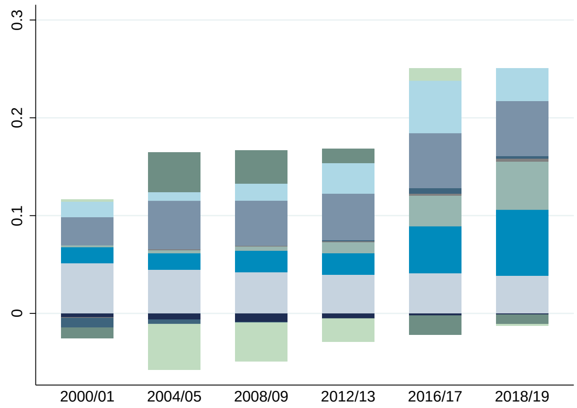
Source: LIAB QM2 9319, own calculations.
Note: The figure presents the kernel density estimations of the wage densities for Non-German workers in Metropolitan and Non-Metropolitan regions for 2000 and 2019. Sampling weights are employed.



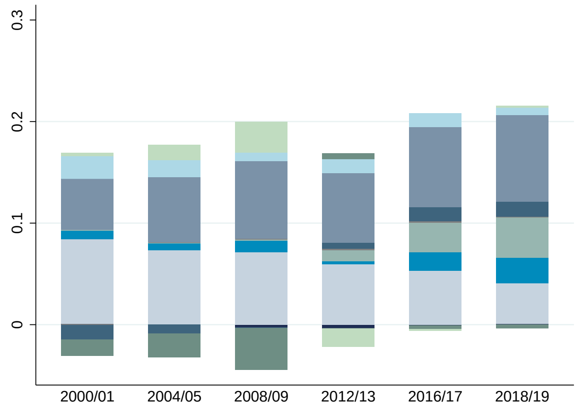
(a) 10th percentile



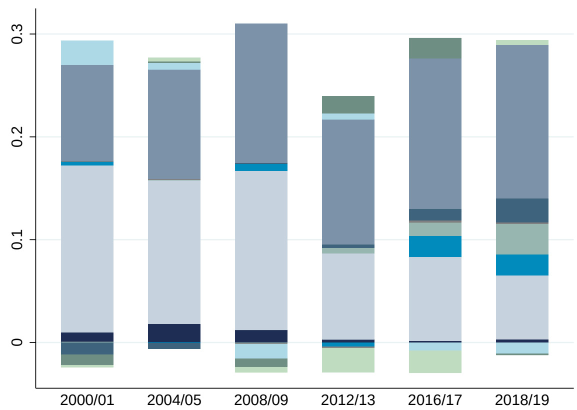
(b) 25th percentile



(c) 50th percentile



(d) 75th percentile



(e) 90th percentile

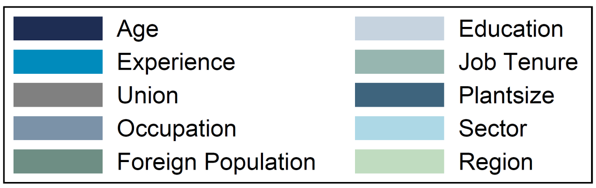
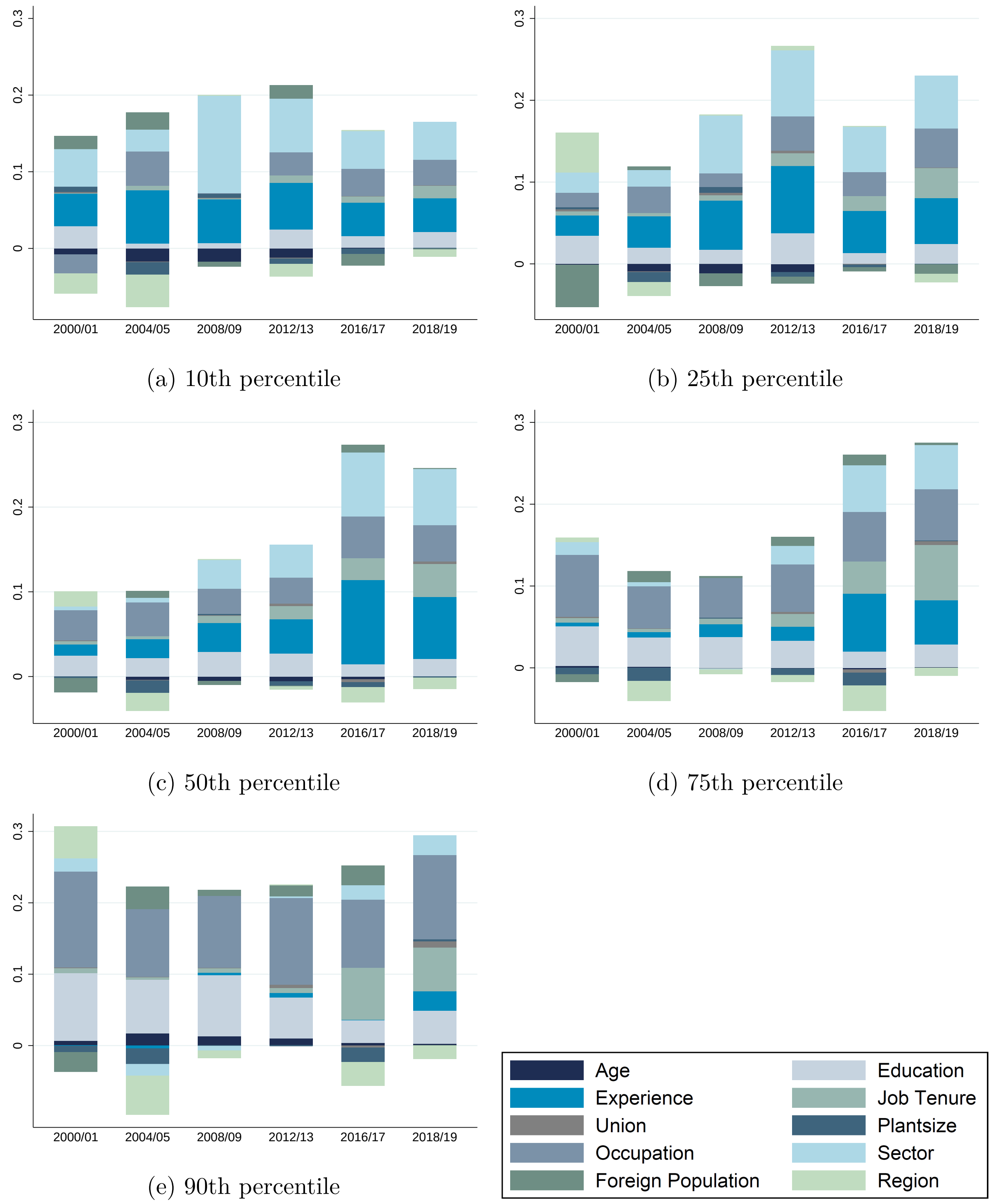


Figure 3.B.4: Detailed decomposition of the explained part in metropolitan areas, 2000-2019

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



(a) 10th percentile

(b) 25th percentile

(c) 50th percentile

(d) 75th percentile

(e) 90th percentile

Figure 3.B.5: Detailed decomposition of the explained part in non-metropolitan areas, 2000-2019

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021b), 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.

Appendix 3.C

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 (IKM) (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 (IKM) (2022) in 2015. The estimated results show no differences regarding the size and decomposition of the wage gaps (see Tables 3.A.11 and 3.A.12 in Appendix 3.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 3.A.13 and 3.A.14 in Appendix 3.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 3.A.15 and 3.A.16 in Appendix 3.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, 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.

References

Aldashev, A., Gernandt, J., and Thomsen, S. L. (2012). The Immigrant-Native Wage Gap in Germany. *Jahrbücher für Nationalökonomie und Statistik*, 232(5):490–517.

Barsky, R., Bound, J., Charles, K. K., and Lupton, J. P. (2002). Accounting for the Black-White Wealth Gap. *Journal of the American Statistical Association*, 97(459):663–673.

Bartolucci, C. (2014). Understanding the Native–Immigrant Wage Gap Using Matched Employer-Employee Data: Evidence from Germany. *ILR Review*, 67(4):1166–1202.

Baumgarten, D., Felbermayr, G., and Lehwald, S. (2020). Dissecting Between-Plant and Within-Plant Wage Dispersion: Evidence from Germany. *Industrial Relations: A Journal of Economy and Society*, 59(1):85–122.

BBSR Bonn (2020). Laufende Raumbeobachtung des BBSR https://www.bbsr.bund.de/BBSR/DE/forschung.html (access on 01-12-2020).

Beaman, L. A. (2011). Social Networks and the Dynamics of Labour Market Outcomes: Evidence from Refugees Resettled in the U.S. *The Review of Economic Studies*, 79(1):128–161.

Bertrand, M., Luttmer, E. F. P., and Mullainathan, S. (2000). Network Effects and Welfare Cultures. *The Quarterly Journal of Economics*, 115(3):1019–1055.

Beyer, R. C. M. (2019). Wage Performance of Immigrants in Germany. *German Economic Review*, 20(4):e141–e169.

Biewen, M. and Juhasz, A. (2012). Understanding Rising Income Inequality in Germany, 1999/2000–2005/2006. *Review of Income and Wealth*, 58(4):622–647.

Biewen, M. and Seckler, M. (2019). Unions, Internationalization, Tasks, Firms, and Worker Characteristics: A Detailed Decomposition Analysis of Rising Wage Inequality in Germany. *The Journal of Economic Inequality*, 17:461–498.

Biewen, M., Ungerer, M., and Löffler, M. (2019). Why did income inequality in Germany not increase further after 2005? *German Economic Review*, 20(4):471–504.

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

Borjas, G. J. (2000). Ethnic enclaves and assimilation. *Swedish Economic Policy Review*, 7(2):89–122.

Borjas, G. J. (2014). *Immigration economics*. Harvard University Press.

Brixy, U., Brunow, S., and Ochsen, C. (2022). On the peripheral-urban wage gap in Germany. *Applied Geography*, 139:102647.

Brunow, S. and Jost, O. (2019). Wages of migrant and native employees in Germany: New light on an old issue. IAB-Discussion Paper 10/2019, Nürnberg.

Brunow, S. and Jost, O. (2021). Foreign Vs. German Wage Differentials in Germany: Does the Home Country Matter? In *Labor Markets, Migration, and Mobility*, pages 55–76. Springer.

Brunow, S. and Jost, O. (2022). Wages of Skilled Migrant and Native Employees in Germany: New Light on an Old Issue. *International Migration Review*, 56(2):410–432.

Buch, T., Hamann, S., Niebuhr, A., and Rossen, A. (2014). What makes cities attractive? The determinants of urban labour migration in Germany. *Urban Studies*, 51(9):1960–1978.

Card, D. (2009). Immigration and inequality. *American Economic Review*, 99(2):1–21.

Diller, C. and Eichhorn, S. (2022). 25 Jahre Metropolregionen in Deutschland im Spagat zwischen Raumordnung und Raumentwicklung. Ein Klassifizierungsvorschlag. *Standort*, 46(1):16–23.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64(5):1001–1044.

Dorn, D. and Zweimueller, J. (2021). Migration and Labor Market Integration in Europe. *Journal of Economic Perspectives*, 35(2):49–76.

Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the German Wage Structure. *The Quarterly Journal of Economics*, 124(2):843–881.

Facchini, G. and Lodigiani, E. (2014). Attracting skilled immigrants: An overview of recent policy developments in advanced countries. *National Institute Economic Review*, 229:R3–R21.

Federal Bureau of Statistics (Destatis) (2021a). Bevölkerung und Erwerbstätigkeit - Ausländische Bevölkerung/Ergebnisse des Ausländerzentralregisters.

Federal Bureau of Statistics (Destatis) (2021b). https://www-genesis.destatis.de/genesis/online. *Genesis-Online*.

Felbermayr, G., Baumgarten, D., and Lehwald, S. (2014). Increasing Wage Inequality in Germany: What Role Does Global Trade Play? *Docbase - Publication Database of the CESifo Group*.

Firpo, S., Fortin, N. M., and Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica*, 77(3):953–973.

Firpo, S. P., Fortin, N. M., and Lemieux, T. (2018). Decomposing Wage Distributions Using Recentered Influence Function Regressions. *Econometrics*, 6(2):1–40.

Fortin, N., Lemieux, T., and Firpo, S. (2011). Decomposition Methods in Economics. In *Handbook of Labor Economics*, volume 4, pages 1–102. Elsevier.

Fuchs, J. and 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 02/2005, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.*

Glitz, A. (2014). Ethnic segregation in Germany. *Labour Economics*, 29:28–40.

Gould, E. D. (2007). Cities, workers, and wages: A structural analysis of the urban wage premium. *The Review of Economic Studies*, 74(2):477–506.

Heuermann, D., Halfdanarson, B., and Suedekum, J. (2010). Human capital externalities and the urban wage premium: Two literatures and their interrelations. *Urban Studies*, 47(4):749–767.

Ingwersen, K. and Thomsen, S. L. (2021). The immigrant-native wage gap in Germany revisited. *The Journal of Economic Inequality*, 19(4):825–854.

Initiative Circle European Metropolitan Regions in Germany (IKM) (2022). https://deutsche-metropolregionen.org (access on 02-02-2022).

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

Kaltwasser, L. and Schludi, M. (2022). Deutschland im demografischen Dilemma: Woher sollen die Arbeitskräfte kommen? *IAB-Forum 9. August 2022*.

Kanas, A., Chiswick, B. R., van der Lippe, T., and van Tubergen, F. (2012). Social Contacts and the Economic Performance of Immigrants: A Panel Study of Immigrants in Germany. *International Migration Review*, 46(3):680–709.

Kawka, R. (2016). Metropolregionen–Kooperation und Wettbewerb in Deutschland und Europa. *Informationen zur Raumentwicklung*, (5).

Kühn, M. (2018). Immigration strategies of cities: local growth policies and urban planning in Germany. *European Planning Studies*, 26(9):1747–1762.

Lehmer, F. and Ludsteck, J. (2011). The Immigrant Wage Gap in Germany: Are East Europeans Worse Off? *International Migration Review*, 45(4):872–906.

Michel, D. (1998). Das Netz der europäischen Metropolregionen in Deutschland. *Raumforschung und Raumordnung*, 56(5):362–368.

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

OECD (2018). Germany Policy Brief - Migration: using migraton to meet skill shortages. *OECD Publishing, Paris*.

OECD (2019). *International Migration Outlook 2019*. OECD Publishing, Paris.

Ohlert, C., Beblo, M., and Wolf, E. (2016). Competition, collective bargaining, and immigrant wage gaps within German establishments. *WiSo-HH Working Paper Series*, (35).

Ottaviano, G. I. P. and Peri, G. (2012a). Rethinking the Effect of Immigration on Wages. *Journal of the European Economic Association*, 10(1):152–197.

Ottaviano, G. I. P. and Peri, G. (2012b). The effects of immigration on US wages and rents: A general equilibrium approach. In *Migration Impact Assessment*. Edward Elgar Publishing.

Ruf, K., Schmidtlein, L., Seth, S., Stüber, H., and 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, K. M. and Oberst, C. A. (2010). Europäische Metropolregionen in Deutschland–eine regionalökonomische Evaluation. *Raumforschung und Raumordnung*, 68(4):243–254.

Sauer, S. and Wollmershäuser, T. (2021). Fachkräftemangel wird zunehmend zur Belastung für die deutsche Wirtschaft. *ifo Schnelldienst digital*, 2(17):1–4.

Schaffner, S. and Treude, B. (2014). The effect of ethnic clustering on migrant integration in Germany. *Ruhr Economic Papers*.

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

Warman, C. (2007). Ethnic enclaves and immigrant earnings growth. *Canadian Journal of Economics/Revue canadienne d'économique*, 40(2):401–422.

Winke, T. (2018). Being close to ethnic peers: the formation of ethnic residential clustering from a household perspective. *Journal of Ethnic and Migration Studies*, 44(11):1932–1953.

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

Mind the Gap: Effects of the National Minimum Wage on the Gender Wage Gap in Germany

Author: Ramona Schmid

Abstract. With its introduction in 2015, the statutory minimum wage in Germany intends to benefit primarily low-wage workers. Thus, this paper aims at estimating the effectiveness of the implemented wage floor on gender wage gaps in the lower half of the wage distribution. Using administrative data, distinct regional differences regarding magnitudes of wage differentials and responses to the minimum wage are identified. Overall, wage gaps between men and women at the 10th percentile decrease by 2.46 and 6.34 percentage points respectively in the West and East of Germany after 2015. Applying difference-in-differences analyses that consider counterfactual wage distributions, the study provides new evidence that around 60% and even 95% of the decline result from the introduction of the minimum wage in each region. Further, group-specific analyses identify concrete responses on the basis of age, educational level and occupational activity. Having yearly data, the study additionally reveals new results on the impact of the successive minimum wage raises in 2017 and 2019. Counterfactual aggregate decompositions of gender wage gaps finally indicate a decrease in discriminatory remuneration structures in the West of Germany due to the introduced wage floor.

Status: Published in an earlier version in Hohenheim Discussion Papers in Business, Economics and Social Sciences and submitted to peer-review Journal.

JEL classification: J16, J31, J38, J71, J78

Keywords: Gender Wage Gap, Minimum Wage, Germany, Policy Evaluation

Acknowledgments: I would like to thank Thomas Beißinger for his guidance throughout this project and his helpful suggestions. I am also grateful to Angelo Martelli, Vassilis Monastiriotis and Klaus Prettner as well as all participants of the LSE Research Workshop in European Studies of the European Institute (London; November, 2022), the members of the IAB working group "Minimum wage" (February, 2023) and all participants of the 15th Workshop on Labour Economics of the IAAEU at Trier University (March, 2023) for helpful discussions and valuable comments.

Chapter 4

Mind the Gap: Effects of the National Minimum Wage on the Gender Wage Gap in Germany

4.1 Introduction

With one of the highest observed unadjusted gender wage gaps in the European Union and significant constant values over time, research on wage differentials between men and women in Germany and possible ways to fight against it is still of high importance (Eurostat, 2022). Existing literature has extensively investigated factors and causes that drive gender wage gaps in Germany (see e.g. Antonczyk et al., 2010; Grandner and Gstach, 2015). In this context, higher shares of women in the low-paid sector and thus resulting persistent gaps between men and women at lower wage levels are observed (see e.g. Boll and Lagemann, 2019; Grabka and Schröder, 2019). The introduction of the national minimum wage in 2015 in Germany should therefore show an impact on observable wage differences between men and women. Thus, to which extent and in which parts of the workforce this policy measure is effective in reducing wage gaps needs to be identified.

The paper contributes to the existing literature in several ways. The study provides first evidence on the effects of the introduced national binding minimum wage in 2015 on the observed gender wage gap in Germany. Further, the effects of subsequent increases in the wage floor in 2017 and 2019 can be observed separately and thus specific results on the effectiveness of the minimum wage at different time points can be provided. Differentiating between the East and the West of Germany allows not only to identify regional-specific conditions before the introduction of the minimum wage but also reveals varied responses in regional gender wage gaps. Most important, the applied method makes it possible to provide new evidence on how decreases in the gender wage gap can be separated into an effect due to changes in the observed characteristics and into an impact resulting from the wage floor. Lastly, decomposition analyses identify implications of changes in the components that drive the adjusted gender wage gap after 2015.

Using administrative data provided by the German Institute for Employment Research, enables to provide detailed regional-specific estimates on the eligibility of male and female workers for the introduced wage floor and to conduct counterfactual analyses on the observed change in the gender wage gap after 2015. The applied type of difference-in-differences analysis allows a specific separation of the impact on the gender wage gap resulting from the minimum wage. Here, additionally to the actual observed wage distributions, counterfactual wage distributions introduced by DiNardo et al. (1996) with constant characteristics of workers over time are estimated.

The presented descriptive statistics reveal on the one hand significantly higher gender wage gaps in the lower half of the wage distribution for the West of Germany compared to the East of Germany. On average, wage differentials between men and women up to the median are 13 percentage points higher in regions of the West. At the same time, descriptive analyses show significantly higher values of minimum wage bites for the East of Germany, in particular for female workers. On the other hand, varied responses in observed gender wage gaps after 2015 for the two different regions in Germany are identified. Overall, gender differentials at the lowest wages decrease by 2.46 and 6.34 percentage points respectively in the West and East of Germany after the introduction of the minimum wage. Using counterfactual wage distributions with constant characteristics from point in time before the introduction of the binding wage floor, it is possible to identify specific separate effects. While for the West of Germany around 60% in the decrease can be traced back to the minimum wage, even 95% of the change are explained by the wage floor in the East of Germany. Distinguishing further between several groups of workers on the basis of educational levels, age and occupational activities it is possible to identify further regional- and group-specific responses. In addition, the study provides evidence on the effects of the two minimum wage increases in the years 2017 and 2019. Lastly, additional to the analyses of the overall observable unadjusted wage gaps, applying aggregate decomposition estimations, this paper reveals indications for a decrease in discriminatory remuneration between men and women in the West of Germany.

The remainder of this paper is structured as follows: Section 4.2 describes the minimum wage legislation in Germany and provides an overview on related literature. In Section 4.3, information on the used data set is provided. General facts on the minimum wage bite and the extent of wage differentials between men and women in Germany as well as descriptive statistics are presented in Section 4.4. Further, in Section 4.5 the empirical approaches are specified and finally, the empirical results are presented in Section 4.6. Discussion and conclusion of the estimated findings are provided in Section 4.7.

4.2 Minimum Wage and Related Literature

4.2.1 Germany's Minimum Wage Legislation

The German government introduced a gross national minimum wage of €8.50 per hour with the primary aim of raising hourly wages in the low-wage sector in January 2015. The introduced Minimum Wage Commission regularly evaluates the value of the wage floor, which should guarantee on the one hand an adequate remuneration of workers and on the other hand functioning market competition without enforcing losses of jobs (see MiLoG §9). Therefore, the minimum wage was steadily increased in the years 2017 (€8.84), 2019 (€9.19) (Mindestlohnkommission, 2016, 2018) and every year thereafter with a current minimum wage of €12.00 since October 2022.[1] Before 2015, there were several sector-specific minimum wage arrangements, such as in the mainstream construction industry since 1997, in the property cleaning sector since 2007, the care sector since 2010 and in the meat industry since 2014.[2] With its introduction, the national minimum wage has

[1]For more information see `https://www.mindestlohn-kommission.de/DE/Home/home_node.html`.

[2]For more details see Wirtschafts- und Sozialwissenschaftliche Institut (WSI) Tarifarchiv, `https://www.wsi.de/de/mindestloehne-in-deutschland-15302.htm`.

a legal force across all regions and almost all sectors as well as affected directly around 11% of all jobs in Germany in 2015 (Destatis, 2016). Specific groups that are exempted from the statutory minimum wage are trainees, most interns, volunteers, and long-term unemployed within the first 6 months of employment (see MiLoG §22).[3] For the very few cases of sectoral-specific minimum wage agreements that lie below the initial value of €8.50 in 2015, a special transition period was allowed until 2017.

4.2.2 Related Literature

After many years of debate about possible threats on the German labour market, the national minimum wage was introduced in 2015. The main argument of several critics aimed at predicted decreases in employment with estimated job losses between 200,000 to over one million in the long run, with circa one fourth of job losses in the East of Germany. These predicted job losses were especially seen among marginal as well as low- and semi-skilled full-time workers (Bauer et al., 2009; Knabe and Schöb, 2009; Müller and Steiner, 2011). Further, assumed increases in consumer prices due to the introduction of the minimum wage and a consequential rise of employers' labour costs would have counteracted any positive direct effect on households' net incomes. Thus, opponents of a general wage floor questioned the general effectiveness regarding the aimed fight against poverty and decrease of income inequality (Knabe et al., 2014; Müller and Steiner, 2008, 2013). In contrast to these arguments, supporters of the general minimum wage emphasised the rapid expansion of the low-wage sector in Germany and the resulting social distortions that should be compensated (see e.g. Bosch, 2007; Kalina and Weinkopf, 2014). Studies on labour market responses to the minimum wage after its introduction provide evidence that the general wage floor increases wages with at the same time hardly any or no employment losses (Bossler and Gerner, 2020; Dustmann et al., 2022). Observed job losses are mainly assignable to establishments in the East of Germany and those that are exposed to strong competitive pressure (Börschlein and Bossler, 2019; Friedrich, 2020). Regarding the main target of achieving higher wages at the lower end of the wage distribution, Bossler and Gerner (2020) reveal average wage increases of around 10% for

[3]For detailed information on the defined groups see MiLoG §22.

affected wage earners and a rise in average overall wages between 3.8% and 6.3% using administrative data. Ahlfeldt et al. (2018) support these findings and present evidence on spatial wage convergence. Wages in low-wage regions increase faster than in high-wage areas with at the same time no significant relative job loss in these regions.

Regarding the overall aim of reducing observed wage disparities among the German workforce, initial studies show that in the short run inequality reduction is not achieved (see e.g. Caliendo et al., 2019; Grabka and Schröder, 2018). Expanding the period of observation until 2017, Bossler and Schank (2020) identify impact of the minimum wage on the recent decrease of inequality using difference-in-differences estimations. They show that overall inequality measured by the variance decreased by 15% after the minimum wage introduction and the reduction would have been only by around 8.5% with no introduced wage floor. However, by not distinguishing between women and men, there is no evidence on the development of between-group wage inequality. Ohlert (2018) provides descriptive evidence on wage developments in the low-wage sector after 2015 by gender and region. Whereas in the East of Germany wages of women increased more rapidly than those of men, gender-specific differences in wage growth were not identified in the West of Germany. Overall, it is shown that from 2014 to 2015 the observed gender wage gap decreases from 22% to 19.3%. However, no causal impact due to the introduction of the minimum wage is provided.

Caliendo and Wittbrodt (2022) identify first effects on the gender wage gap by the minimum wage applying a regional difference-in-differences approach with data from the Structure of Earnings Survey for the years 2014 and 2018. Thus, only joint estimations for the effects resulting from the introduction of the wage floor and its first increase are identified. In this context, the following study presents new evidence in several ways. Having yearly data, it is possible to present estimates separately for the introduction of the wage floor and its subsequent increases. Further, due to the applied counterfactual difference-in-differences estimation strategy, it is possible to present regional-specific results for the West and East of Germany. Therefore, not only estimations for high-bite regions are revealed. In addition, several group-specific results of the workforce can be considered. As a result of the proposed estimation procedure, it is further possible to decompose the whole change in gender wage gaps in the effect that results from changes in the composition of the workforce and in the effect due to the introduced minimum wage. The study of Caliendo and Wittbrodt (2022) shows a significant reduction of 4.6 percentage points in the gender wage gap at the 10th percentile in high-bite regions, where female workers are highly impacted by the minimum wage. These results are strongly in line with international empirical literature on the impact of minimum wages on gender wage gaps. Among others, DiNardo et al. (1996), Dex et al. (2000) and Majchrowska and Strawiński (2018) reveal wage gap decreasing effects resulting from introduced or rising minimum wages in the US, in the UK and Poland.

4.3 Data

The study is based on the weakly anonymous version of the Sample of Integrated Labour Market Biographies (SIAB) with an overall period of observation from 1975 to 2019 (Berge et al., 2021).[4] This administrative data set, provided by the Institute for Employment Research (IAB), is a two percent random sample drawn from the social security records of the Integrated Employment Biographies (IEB) in Germany. The data set consists of mandatory notifications made by employers to social security agencies and thus provides information about all individuals that are covered by the statutory retirement insurance. Therefore, self-employed individuals, civil servants, and family workers are not considered. Overall, the data represent approximately 80 percent of the German workforce.

The data set provides a rich set of information on several individual- and occupation-specific characteristics. In particular, it contains information on gender, the year of birth, the educational attainment, the type of contract (full-time or part-time employment) and the region of work (federal state and district levels). Further, relevant information on the employment related characteristics such as the type of occupation, the occupational

[4] Berge, Philipp vom; Frodermann, Corinna; Graf, Tobias; Grießemer, Stephan; Kaimer, Steffen; Köhler, Markus; Lehnert, Claudia; Oertel, Martina; Schmucker, Alexandra; Schneider, Andreas; Seth, Stefan (2021): "Weakly anonymous Version of the Sample of Integrated Labour Market Biographies (SIAB) – Version 7519 v1". Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). DOI: 10.5164/IAB.SIAB7519.de.en.v1. The data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access.

activity, as well as the number of days in employment and job are presented. Details on the classification of economic activities, total number of employees and region of activity of establishments are included as well.

The SIAB data set is structured by employment spells, which means that there are two identifier-variables indicating the start date and the end date of the observation. Using only the respective job spells referring to 30th June a yearly panel is created. If a worker has more than one job at the point of observation, the following analyses only keep the main job of the individual, which is defined as the job with the highest daily wage. Observations with a wage of zero are not considered in the analysis as well. The sample is restricted to women and men that are between 25 and 55 years old.[5] Using the Consumer Price Index provided by the German Federal Statistical Office, wage information are converted into constant 2015 Euros.

Several advantages of administrative data, such as a high number of observations, no interviewer effects or survey bias as well as yearly data information, qualify the SIAB data set particularly for the underlying study. Nevertheless, the data set has two shortcomings that have to be kept in mind. First, 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) can be applied.[6] However, since the analysis focuses only on wage information of the lower half of the wage distribution, no impact resulting of this characteristic is expected. Second, there is no precise information on the number of hours worked per month or week. Thus, the study is restricted to full-time working individuals, which follows common procedure in existing literature on minimum wage and gender wage gap research in Germany (see e.g. Blömer et al., 2018; Caliendo and Wittbrodt, 2022; Weyh et al., 2022).[7]

The study considers the following individual explanatory factors. Workers are clas-

[5]Following existing literature the age is restricted in order to circumvent possible gender-specific differences in period of education and retirement (see e.g. Schrenker and Zucco, 2020; Selezneva and Van Kerm, 2016).

[6]Using this method in order to impute wages, yearly tobit estimations by gender above the social security threshold are estimated controlling for standard factors such as age, education, tenure and occupational field.

[7]Workers in part-time employment, which is defined as working less than 30 hours per week, are excluded in order to increase comparability.

sified in age groups[8], groups in accordance with their educational level (three dummy variables[9]) and by nationality. Regarding the individual work experience, groups for days in employment and days of job tenure are considered[10]. Further, 14 different occupational segments based on the 2-digit Classification of Occupations 2010 (Klassifizierung der Berufe 2010, KldB 2010) as well as four different groups of occupational activities[11] 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[12]) augment the explanatory factors. Regional-specific effects are controlled by dummy variables indicating the federal state. For descriptive statistics information on the district of employment is used.[13] In order to increase the regional number of observations on a yearly and district-level basis, the regional-specific data is aggregated at the level of German spatial planning regions, „Raumordnungsregionen“ (ROR).[14] This aggregation summarises districts defined by the NUTS (Nomenclature of Territorial Units for Statistics) classifications that belong to a specific economic center and its surrounding areas (BBSR Bonn, 2019).[15]

4.4 Descriptive Evidence

The following section presents descriptive evidence on regional and gender-specific minimum wage bites as well as gender wage gaps in Germany. Further, descriptive statistics are presented and characteristics of minimum wage workers are identified.

Minimum wage bite. With the introduction of the national minimum wage in Ger-

[8](1) 25-34 years, (2) 35-44 years and 45-55 years.

[9](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.

[10](1) $<$ 2 years, (2) 2-4 years, (3) 4-8 years (4) 8-16 years (5) $>$ 16 years.

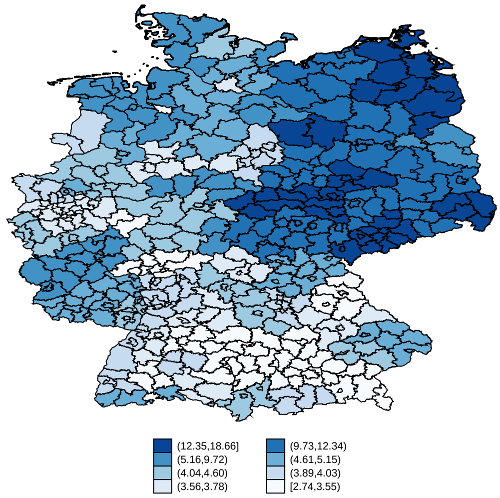
[11](1) unskilled activities, (2) specialist activities, (3) complex activities, (4) highly complex activities.

[12](1) 1-9 employees; (2) 10-49 employees; (3) 50-199 employees; (4) 200-999 employees; (5) 1000-4999 employees; (6) $\geq$5000 employees.

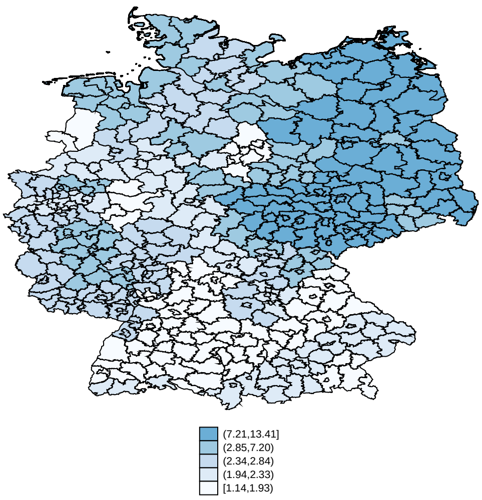
[13]Due to its particular sensitivity with regard to data protection legislation, this variable is only available on application, see Berge et al. (2021).

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

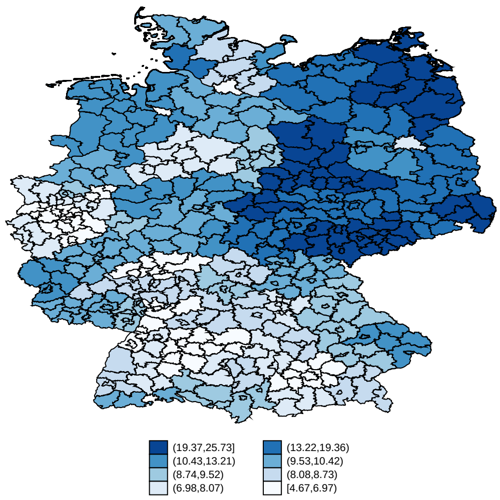
[15]A detailed graphical depiction of the defined ROR-regions with their respective districts is provided by the BBSR Bonn (2019).



(a) Minimum wage bite, overall sample



(b) Minimum wage bite, men



(c) Minimum wage bite, women

Figure 4.1: Estimated minimum wage bite for different groups, 2013/14

Source: SIAB7519, own calculations.
Notes: The different subfigures present the estimated results of the overall minimum wage bite (in percent) as well as for men and women separately at the level of ROR-regions.

many, it is necessary to show who and which regions are especially affected by the defined wage floor. Therefore, in Figure 4.1 the minimum wage bite at the level of German spatial planning regions is presented.[16,17] In detail, the shares of male and female workers that earn less than the specified minimum wage in the pooled time point 2013/14 are

[16]The minimum wage bite is estimated on the basis of hourly wages. Considering only full-time employed individuals, the information on hours worked for administrative data by gender provided by Dustmann et al. (2022) are used to transform daily wages.

[17]German spatial planning regions summarise districts defined by the NUTS (Nomenclature of Territorial Units for Statistics) classifications that belong to a specific economic centre and its surrounding areas (BBSR Bonn, 2019).

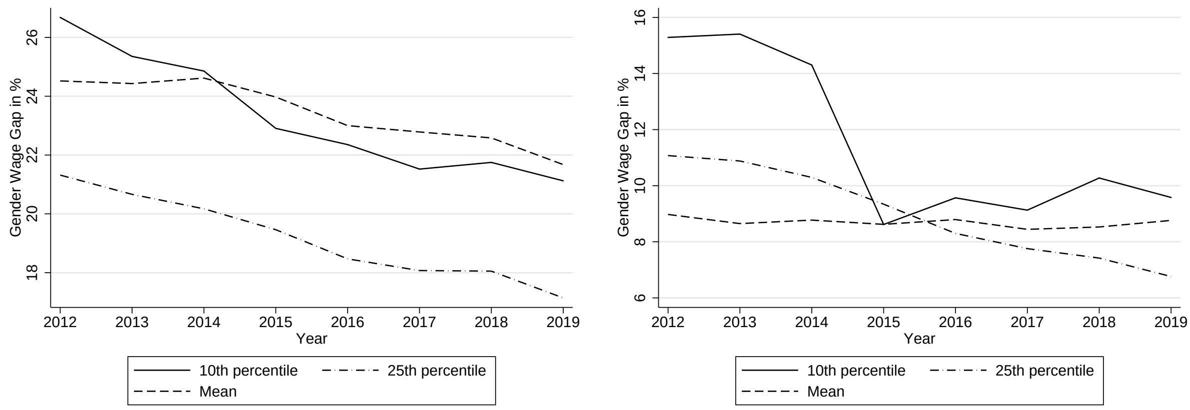
presented.[18] In Figure 4.1 (a) the average minimum wage bite for both men and women, ranging between 2.74% and 18.66%, is revealed. Overall, it can be seen that there is a significant trend towards higher wage bites in the East of Germany. Further, distinguishing between men and women in Figures 4.1 (b) and (c) a more varied picture emerges. While still higher fractions of wage bites for men are observable in the East and also the North of Germany, overall higher values are revealed for women. Female workers are highly affected by the implemented national minimum wage especially in the East of Germany with minimum wage bites being on average three times higher than their male counterparts. In addition, in the West of Germany there are specific regions, where women as well are stronger influenced by the wage floor. These regions are in the North and centre of Germany as well as near to the border. Additional to the usual procedure in existing literature to separate between the East and the West of Germany, due to different characteristics of the regional labour markets, the identified differences regarding the observed minimum wage bite result in subsequent analyses that are conducted separately.

Gender wage gap. The second factor that is observed in this study is the gender wage gap and its development in Germany during recent years. First of all, the developments of differences in pay between men and women from 2012 until 2019 at different parts of the wage distribution are presented in Figures 4.2 (a) and (b) for the West and East of Germany.[19] Overall, a general trend of decreasing wage gaps between men and women in the West of Germany is observable, ranging between 26.68% and 17.14%. Wage differentials at the 10th percentile visibly decrease further after 2014 with the introduction of the minimum wage in 2015. In addition, with the subsequent increases of the minimum wage in 2017 and 2019, there are visible kinks in the development of the gender wage gap at the lowest wages. Regarding wage differences at the 25th percentile and the mean similar trends are revealed, albeit to a smaller extent. For the East of Germany, a significant drop of the wage gap at the 10th percentile is identified in 2015. Further, visible kinks

[18] Pooled time point are used, since in 2014 already an increase in wages in anticipation to the introduced wage floor in 2015 is observable (see e.g. Kubis et al., 2015). Thus, this strategy results in higher sampling precision in order to draw valid conclusions on the overall effect.

[19] The gender pay gap is estimated as the difference between gross daily wages of men and women expressed as a percentage of gross daily earnings of men.

that are more pronounced compared to the West of Germany are observable in the years of minimum wage increases. Looking at wage differences at the 25th percentile, an overall downward sloping trend is revealed. In contrast to this, the mean wage gap remains more or less constant over time. Comparing both figures, overall smaller differences in wages in the East of Germany are identified. On average, gender wage gaps in the lower half of the wage distribution are 12.3 percentage points smaller in the East compared to the West of Germany.



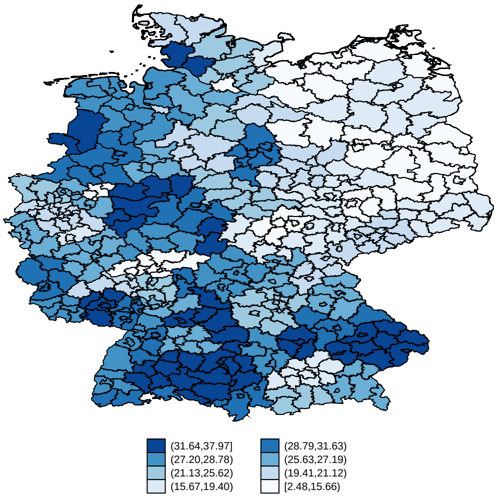
(a) West of Germany

(b) East of Germany

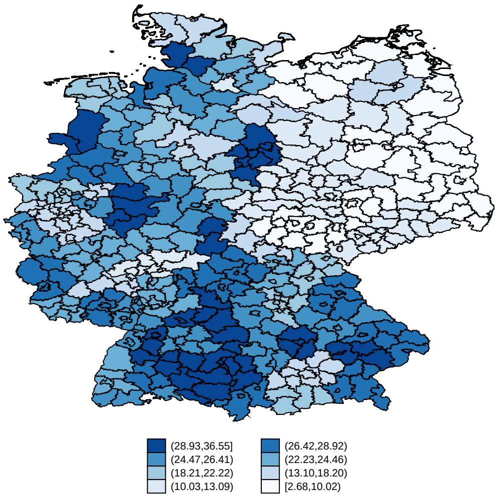
Figure 4.2: Gender wage gap at the 10th, 25th percentile and mean, 2012-2019

Source: SIAB7519, own calculations.
Notes: The figure presents the overall estimated gender wage gap at 10th, 25th percentile and mean between 2012 and 2019.

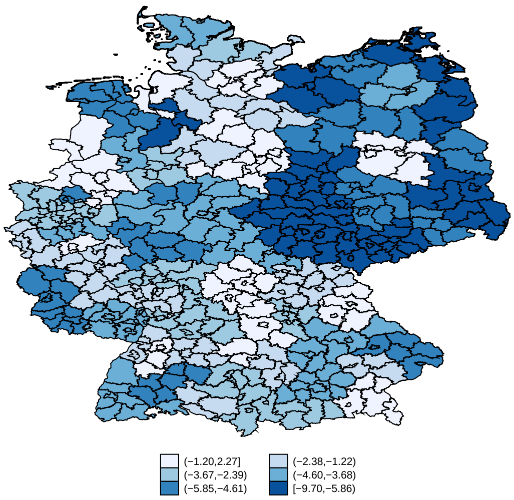
Since the introduced wage floor most likely primarily affects lowest wages, regional gender pay gaps at the 10th percentile are presented in Figures 4.3 (a) and (b) before and after the introduction. On average, significant higher wage gaps between men and women are present in the West of Germany, especially in the middle and south, in both time points. Looking at the change of observed wage differentials between 2013/14 and 2015/16 in Figure 4.3 (c) the highest decreases are observed in the East of Germany. The overall values in this area are very similar across all regions with the exception of Berlin and its surroundings. In contrast to this, the results for the West of Germany show a more diverse picture. There is a mix between regions, where gender wage gaps on the one hand stay rather constant or even increase between 2013/14 and 2015/16. On the other hand, there are also regions, where observed differences in wages between men and



(a) Gender wage gap at the 10th percentile, 2013/14



(b) Gender wage gap at the 10th percentile, 2015/16



(c) Change in the gender wage gap after the introduction of the minimum wage

Figure 4.3: Regional differences, gender wage gap

Source: SIAB7519, own calculations.
Notes: The different subfigures present the estimated gender wage gaps on the level of ROR-regions for the pooled time points 2013/14 and 2015/16. Further, the corresponding change in the gender wage gap over time is presented.

women decrease over time.

Descriptive statistics. Table 4.1 presents the descriptive statistics for the selected pooled time points 2013/14 and 2015/16 by gender and region. On average, there are significant lower wage levels in the East of Germany compared to the West of Germany. Further, wage differentials between men and women are identified as well, with higher values in the West of Germany. Regarding the age of the workforce no major differences are presented, except slightly younger women in the West of Germany compared to their male counterparts. In the East of Germany, there are on average fewer workers in the lowest educational level with at the same time higher fractions in the medium educational level. Overall, no distinct differences in educational attainment between men and women are identified. Except, in the East of Germany an observable higher fraction of women exhibits the highest level of education. Regarding the share of workers with a foreign nationality higher values in the West and among men are presented. This group of workers also shows an on average higher number of days in employment and job. Women in the West of Germany and workers in the East have similar days of tenure and no changes over time are revealed. In general, there are more men exercising unskilled activities. Women in the West of Germany are predominantly located in the group of specialist activities with at the same time lower shares in the upper two occupational levels compared to men. In contrast to this, women in the East of Germany show higher fractions in higher occupational activities compared to men. On average, men in the West of Germany work in firms with higher numbers of employees, whereas the opposite holds true for the East of Germany albeit with overall smaller values.

Characteristics of minimum wage workers. In advance to the empirical analyses, information on workers that are eligible to the wage floor before its introduction is presented in the following. Results of this analysis provide insights in groups of workers that are particularly affected by the introduction of the minimum wage. Estimating logit regression frameworks, where the dependent variable is a dummy variable being one if the observed worker earns less than the introduced minimum wage, several characteristics are taken into account. Table 4.A.1 in Appendix 4.A summarises the resulting average marginal effects of the whole sample and two subsamples differentiating between men and women.

The estimated effects of the overall sample provide evidence of a higher probability to be affected by the introduced minimum wage if workers are located in the East of Germany and are female. These results support the inference drawn from the descriptive

Table 4.1: Descriptive statistics by gender and region, 2013/14 and 2015/16

	2013/14				2015/16			
	West		East		West		East	
	Men	Women	Men	Women	Men	Women	Men	Women
Wages:								
Daily	137.48	103.76	96.28	87.89	141.12	107.98	100.59	91.83
	(91.15)	(55.34)	(61.44)	(47.99)	(94.19)	(58.21)	(62.83)	(47.22)
Age:								
	41.43	39.83	41.13	41.74	41.36	39.75	41.01	41.48
	(8.69)	(9.38)	(8.98)	(9.24)	(8.86)	(9.50)	(8.98)	(9.30)
Education:								
low	6.32	5.92	2.70	2.35	6.61	5.91	3.17	2.51
	(24.33)	(23.60)	(16.21)	(15.15)	(24.84)	(23.58)	(17.51)	(15.63)
middle	72.54	72.49	78.79	73.30	71.56	70.72	77.82	72.01
	(44.63)	(44.65)	(40.88)	(44.24)	(45.11)	(45.50)	(41.55)	(44.89)
high	21.14	21.59	18.51	24.35	21.83	23.37	19.02	25.49
	(40.83)	(41.14)	(38.43)	(42.92)	(41.31)	(42.32)	(39.24)	(43.58)
Foreign nationality:								
	9.65	7.44	2.85	2.56	10.73	8.36	3.89	3.34
	(29.53)	(26.23)	(16.63)	(15.79)	(30.94)	(27.67)	(19.35)	(17.98)
Tenure:								
Days in employment	6132.85	5483.14	5313.47	5314.24	6077.32	5469.17	5406.45	5423.40
	(3263.87)	(3135.73)	(2620.17)	(2536.72)	(3305.11)	(3179.48)	(2811.78)	(2734.45)
Days in job	2942.09	2472.80	2459.13	2543.14	2906.27	2430.50	2463.45	2522.77
	(2819.57)	(2495.70)	(2319.61)	(2379.97)	(2828.08)	(2502.21)	(2386.77)	(2451.16)
Occupational level:								
Unskilled activities	11.51	10.49	10.85	8.51	11.59	10.16	11.14	8.41
	(31.91)	(30.63)	(31.10)	(27.90)	(32.01)	(30.21)	(31.46)	(27.75)
Specialist activities	54.93	61.29	61.11	60.17	54.50	60.84	60.24	60.06
	(49.75)	(48.71)	(48.75)	(48.96)	(49.79)	(48.81)	(48.94)	(48.98)
Complex activities	17.21	14.79	13.92	15.64	17.30	15.08	14.16	15.60
	(37.74)	(35.50)	(34.62)	(36.33)	(37.82)	(35.78)	(34.86)	(36.29)
Highly complex activities	16.35	13.43	14.12	15.68	16.62	13.93	14.47	15.92
	(36.99)	(34.09)	(34.82)	(36.36)	(37.22)	(34.62)	(35.18)	(36.58)
Plant size:								
	1510.04	888.49	402.27	450.38	1577.18	931.25	429.55	482.43
	(5820.64)	(3789.07)	(1193.73)	(1146.79)	(6241.70)	(4040.08)	(1289.02)	(1272.71)
Number of observations	344,204	152,375	70,290	43,084	344,675	152,330	70,954	41,794

Source: SIAB7519, own calculations.
Notes: The table presents descriptive statistics for selected variables in 2013/14 and 2015/16 by gender and region. The wage variable presents information on gross daily wages and shares are multiplied by 100 for convenience.

statistics analyses before. For workers with a foreign nationality in the overall sample no clear effect is revealed. Regarding school education and the age of workers a clear trend towards a higher risk for less educated and older individuals is identified. Less tenure in the practised profession and few years of work experience as well increase the probability being a minimum wage worker. The practiced requirement level has a significant effect deteriorating the remuneration possibilities, especially being a worker exercising unskilled activities. Economic industries that noticeably increase the probability of being a minimum wage worker are in the field of food and hospitality, craft/trade, security, traffic and logistic as well as in the security sector. The plant size shows that the smaller the number of employees the higher the risk to be rewarded with the wage floor.

Having a look at men and women separately, overall similar results regarding the general trends can be seen. However, regarding the size of the respective effects differences emerge. For women in the East of Germany it is more likely to be affected by the wage floor than for their male counterparts. While there was no clear effect for foreign workers in the overall sample, the effects have opposing trends for women and men separately. However, both effects are relatively small. It also seems that lower educated women and older men are exposed to higher risk earning the introduced wage floor. Whereas the effects of years of job experience are more or less the same between men and women, it can be seen that fewer years of overall work experience for women pose a significantly higher risk on being a minimum wage worker. This observation also holds true for the exercised requirement level and especially for the plant size. When it comes to the economic sectors overall similar results are identified.

4.5 Empirical Approach

This section presents empirical approaches applied in the study. First of all, the reweighting procedure introduced by DiNardo et al. (1996) is defined in order to provide difference-in-differences estimations on unadjusted gender wage gaps. In this case, actual wage distributions before and after the minimum wage introduction as well as counterfactual wage distributions are estimated. In order to assess the effects on adjusted wage differentials between men and women in Germany, a reweighted Oaxaca-Blinder decomposition framework using recentered influence functions regressions is presented in a second part.

Counterfactual difference-in-differences analysis. The aim of this empirical analysis is to separate the effect of the minimum wage from the effect due to overall changes in observed characteristics on decreases in the gender wage gap. Estimating counterfactual wage distributions, it is possible to provide results on the effectiveness of the introduced wage floor in Germany with regards to reducing wage differentials.

First of all, the overall observed change in the gender wage gap, GWG, at a specific percentile, γ, between two points in time, $t = 0, 1$, is defined by:

$$\Delta GWG_{\gamma} = GWG_{\gamma,1} - GWG_{\gamma,0}, \tag{4.1}$$

where the gender wage gap in each point in time results of $GWG_{\gamma,t} = (w_{\gamma,t,M} - w_{\gamma,t,W})/w_{\gamma,t,M}$ with $w_{\gamma,t,g}$ being the wage of men, $g = M$, or women, $g = W$, at a specific wage percentile and point in time t.[20]

Observed wages of men and women are influenced by numerous factors. In the underlying analyses the estimated wage gaps are therefore a function of several explanatory variables, $X_{t,g}$, by time and gender as well as a policy measure, P_t, which is the introduced minimum wage in 2015. As a result, equation (4.1) can be rewritten as:

$$\Delta GWG_{\gamma} = GWG_{\gamma,1}(X_{1,M}; X_{1,W}; P_1) - GWG_{\gamma,0}(X_{0,M}; X_{0,W}; P_0). \tag{4.2}$$

From this equation it could be argued that if individual characteristics stay constant during the introduction of the minimum wage, the overall estimated change in the gender wage gap can be ascribed to the wage floor. However, due to possible changes in the composition of the workforce over time, this assumption does not hold true. Therefore, counterfactual estimations have to be added to the analysis.

In order to estimate counterfactual wages, $w^C_{\gamma,g}$, by gender and at a specific percentile, the procedure introduced by DiNardo et al. (1996) is applied. In this case, counterfactual wage distributions are estimated using a reweighting function. To start with, the actual densities of wages, $F(.)$, before and after the introduction of the minimum wage are observed. These are in general divided into a wage function $y(.)$ and a composition

[20]In order to present the gender wage gaps in percent, the defined expression is multiplied by 100.

function $h(.)$:

$$F(w|t_y = 0, t_h = 0)_g = \int y(w|X, t = 0)_g \; h(X|t = 0)_g \; dX \tag{4.3}$$
$$F(w|t_y = 1, t_h = 1)_g = \int y(w|X, t = 1)_g \; h(X|t = 1)_g \; dX, \tag{4.4}$$

where $y(w|X, t = 0, 1)_g$ is the density of wages and $h(X|t = 0, 1)_g$ defines the density of characteristics in a specific year of either men or women.

In order to get a counterfactual wage distribution $F^C(.)$, where the characteristics of point in time $t = 0$ are held constant and only the wage structure changes to point in time $t = 1$, a reweighting function $\hat{\psi}_g$ is applied:

$$\begin{aligned} F^C(w|t_y = 1, t_h = 0)_g &= \int y(w|X, t = 1)_g \; h(X|t = 0)_g \; dX \\ &= \int y(w|X, t = 1)_g \; \psi_g(X_g) \; h(X|t = 1)_g \; dX, \end{aligned} \tag{4.5}$$

where ψ_g is defined as the fraction $h(X|t = 0)_g/h(X|t = 1)_g$.

ψ_g is estimated as follows:

$$\begin{aligned} \hat{\psi}_g(X_g) &= \frac{h(X|t = 0)_g}{h(X|t = 1)_g} \\ &= \frac{Pr(t = 1)}{Pr(t = 0)} \frac{Pr(t = 0|X_g)}{Pr(t = 1|X_g)}, \end{aligned} \tag{4.6}$$

where $Pr(t = 0)$ and $Pr(t = 1)$ are the shares of the respective observations of one point in time in a pooled sample as well as $Pr(t = 0|X_g)$ and $Pr(t = 1|X_g)$ are estimated from a logit regression framework. With the estimated counterfactual wage distributions of men and women it is possible to estimate counterfactual wages, $w^C_{\gamma,1,g}$, and thus the counterfactual gender wage gap $GWG^C_{\gamma,1}$.

The combination of the two actual observed gender wage gaps before and after the minimum wage introduction with the estimated counterfactual wage gap leads then to a type of difference-in-differences estimation. Equation (4.2) can be thus divided into two parts:[21]

$$\Delta GWG_\gamma = \underbrace{GWG_{\gamma,1}(X_{1,M};X_{1,W};P_1) - GWG^C_{\gamma,1}(X_{0,M};X_{0,W};P_1)}_{Change\ due\ to\ changes\ in\ workers'\ characteristics} + \underbrace{GWG^C_{\gamma,1}(X_{0,M};X_{0,W};P_1) - GWG_{\gamma,0}(X_{0,M};X_{0,W};P_0)}_{Change\ due\ to\ minimum\ wage\ introduction}. \quad (4.7)$$

In the first part, the introduced policy measure is considered in both gender wage gap estimations and only the characteristics change, which results in the so-called endowment effect. The second part represents the effect that results due to the introduced minimum wage. Since the characteristics are held constant over time, the only part that changes is the status of the policy measure.

Estimating the impact of the introduced wage floor at different parts of the wage distribution enables to reveal specific consequences regarding the change in the gender wage gap for different wage groups. Thus, especially the effects on targeted groups in the low-paid sector, that should benefit from this policy measure, can be identified and quantified. Further, restricting on specific subgroups in the sample, effects depending on the observed region, age group, educational level and occupational activity can be computed.

Counterfactual decomposition of the gender wage gap. On the basis of the standard decomposition method introduced by Oaxaca (1973) and Blinder (1973) the following empirical analysis divides the overall, unadjusted, gender wage gap at the mean, $GWG_{\mu,t}$, into an explained and an unexplained effect.[22,23]

In a first step, earnings functions are estimated separately for men and women, where several explanatory variables, X_g, are considered. The linear wage setting regression

[21] In order to show the effect of a minimum wage on the gender wage gap, similar estimation procedures are proposed by Majchrowska and Strawiński (2018) and Bargain et al. (2019) using counterfactual distributions.

[22] In the following, the standard Oaxaca-Blinder decomposition at the mean is presented as a baseline model.

[23] In the majority of existing literature, this estimation strategy is referred to as the Oaxaca-Blinder decomposition. However, this overlooks the earliest contribution in this context made by Kitagawa (1955).

model is defined as follows:

$$ln(\bar{w})_{M,t} = \hat{\beta}^0_M + \hat{\beta}_M \bar{X}_M + v_M \tag{4.8}$$

$$ln(\bar{w})_{W,t} = \hat{\beta}^0_W + \hat{\beta}_W \bar{X}_W + v_W, \tag{4.9}$$

where $ln(\bar{w})_{M,t}$ and $ln(\bar{w})_{W,t}$ denote log daily average wages of men and women, respectively. Further, $\hat{\beta}^0_M$ and $\hat{\beta}^0_W$ define the respective constants and v_M and v_W are the residuals.

In a second step, after some transformation, the aggregate decomposition of the gender wage gap in point in time t is estimated by:

$$\begin{aligned} GWG_{\mu,t} &= ln(\bar{w})_{M,t} - ln(\bar{w})_{W,t} \\ &= \underbrace{(\bar{X}_{M,t} - \bar{X}_{W,t})\hat{\beta}_{M,t}}_{\substack{explained\\ effect}} + \underbrace{\bar{X}_{W,t}(\hat{\beta}_{M,t} - \hat{\beta}_{W,t}) + (\hat{\beta}^0_{M,t} - \hat{\beta}^0_{W,t})}_{\substack{unexplained\\ effect}}, \end{aligned} \tag{4.10}$$

where the first component of the equation defines the explained part of the gender wage gap. This endowment effect is the result of differences in observable characteristics between men and women. The second component represents the unexplained effect that arises on the one hand due to differences in remuneration between men and women despite the same endowment and on the other hand due to the constant term. The latter part results from factors that possibly describe the estimated gender wage gap but are not included in the dataset.[24]

In the context of an aggregate decomposition, the change in gender wage gaps between two points in time is then defined by:

$$\begin{aligned} GWG_{\mu,1} - GWG_{\mu,0} = {} & [(\bar{X}_{M,1} - \bar{X}_{W,1})\hat{\beta}_{M,1} + \bar{X}_{W,1}(\hat{\beta}_{M,1} - \hat{\beta}_{W,1}) + (\hat{\beta}^0_{M,1} - \hat{\beta}^0_{W,1})] \\ - {} & [(\bar{X}_{M,0} - \bar{X}_{W,0})\hat{\beta}_{M,0} + \bar{X}_{W,0}(\hat{\beta}_{M,0} - \hat{\beta}_{W,0}) + (\hat{\beta}^0_{M,0} - \hat{\beta}^0_{W,0})]. \end{aligned} \tag{4.11}$$

[24]The initial proposed decomposition analysis by Oaxaca (1973) and Blinder (1973) defines the male wage structure as the non-discriminatory wage structure. However, at the same time the wage structure of women or combined weighted wage structures as proposed by Reimers (1983) and Cotton (1988) can be used estimating the aggregate decomposition. Thus, the empirical analyses on the decomposition of gender wage gaps in Section 4.6 provide several robustness checks using alternative wage structures.

In a final step the counterfactual sample is added. Thus the type of difference-in-differences estimation strategy can be estimated in order to show the effect of the introduced minimum wage on the adjusted gender wage gap:

$$\begin{aligned} GWG_{\mu,1} - GWG_{\mu,0} &= \{GWG_{\mu,1} - GWG^{C}_{\mu,1}\} + \{GWG^{C}_{\mu,1} - GWG_{\mu,0}\} \\ &= \{[(\bar{X}_{M,1} - \bar{X}_{W,1})\hat{\beta}_{M,1} + \bar{X}_{W,1}(\hat{\beta}_{M,1} - \hat{\beta}_{W,1}) + (\hat{\beta}^{0}_{M,1} - \hat{\beta}^{0}_{W,1})] \\ &- \ [(\bar{X}_{M,0} - \bar{X}_{W,0})\hat{\beta}_{M,1} + \bar{X}_{W,0}(\hat{\beta}_{M,1} - \hat{\beta}_{W,1}) + (\hat{\beta}^{0}_{M,1} - \hat{\beta}^{0}_{W,1})]\} \\ &+ \ \{[(\bar{X}_{M,0} - \bar{X}_{W,0})\hat{\beta}_{M,1} + \bar{X}_{W,0}(\hat{\beta}_{M,1} - \hat{\beta}_{W,1}) + (\hat{\beta}^{0}_{M,1} - \hat{\beta}^{0}_{W,1})] \\ &- \ [(\bar{X}_{M,0} - \bar{X}_{W,0})\hat{\beta}_{M,0} + \bar{X}_{W,0}(\hat{\beta}_{M,0} - \hat{\beta}_{W,0}) + (\hat{\beta}^{0}_{M,0} - \hat{\beta}^{0}_{W,0})]\}. \end{aligned} \tag{4.12}$$

As in equation (4.7), the first component of the equation represents the effect due to changes in the composition of characteristics and the second component represents the effect of the minimum wage on the gender wage gap. Using the counterfactual sample, changes in the aggregate decomposition due to the introduction of the minimum wage can be revealed. Differentiating between the actual and counterfactual samples, it is possible to make statements how the binding wage floor might influence the unexplained wage gap and the relating thereto trend of discrimination.

In order to estimate gender wage gaps away from the mean, the recentered influence functions (RIF) regressions approach introduced by Firpo et al. (2018) is applied. In this case the standard Oaxaca-Blinder decompositions are estimated using coefficients of unconditional (quantile) partial regression models. The above presented estimation analyses are then adjusted accordingly.[25]

4.6 Empirical Results

This section presents the results of the estimated type of difference-in-difference analyses using counterfactual wage distributions on the impact of the introduced wage floor on the observed gender wage gap in Germany. Differentiating between various groups of workers, detailed responses of gender wage gaps on the implemented minimum wage can

[25]Detailed information on the estimation strategy of RIF-regressions and the relating thereto aggregate decomposition can be found in Fortin et al. (2011).

be assessed. Further, estimations on the impact of increases in the wage floor in 2017 and 2019 as well as counterfactual aggregate decomposition results are presented.

4.6.1 Gender Wage Gaps of the Overall Sample

Figure 4.4 shows the estimated results separately for the West and East of Germany as well as for different percentiles in the lower half of the wage distribution.[26,27,28] The gender wage gap at the 10th percentile overall decreases by 2.46 percentage points in the West of Germany and by 6.34 percentage points in the East of Germany between 2013/14 and 2015/16. Using the defined reweighting method in order to fix the distribution of characteristics at the level before the introduction of the wage floor, it is possible to divide the overall change on the one hand into an effect due to the binding minimum wage and on the other hand into an effect due to changes in the observed characteristics. As a result of this estimation strategy, it is revealed that around 60% in the decrease in wage differentials at the 10th percentile in the West of Germany are explainable by the minimum wage introduction. In contrast to this, in the East of Germany even 95% can be traced back to the effect resulting from the wage floor. A similar picture emerges for wages at the 25th percentile, where the gender wage gaps decrease by around 1.6 percentage points in both regions. However, whereas 72% of this decrease are traceable back to the wage floor in the East of Germany, the majority of the decline (59%) is explained by changes in the characteristics of the observed workers in the West of Germany between 2013/14 and 2015/16. Whereas for median wages no changes in the gender wage gap are observable in the East of Germany, wage differentials decrease by one percentage point in the West of Germany during the observed period of time. Again, the majority is explained by changes in characteristics (68%).

Table 4.A.2 in Appendix 4.A supports the above described trend with higher effects in

[26] All detailed results of Figures 4.4 to 4.8 are presented in Tables 4.A.4 to 4.A.8 in Appendix 4.A. For the sake of clarity, the group-specific results on age, educational level, occupational level and minimum wage increases only present the estimated gender wage gaps. The respective underlying percentile wages are all highly significant.

[27] Since the minimum wage addresses wages in the low-paid sector, the study is restricted to results of the gender pay gap up to the median as similarly done by Caliendo and Wittbrodt (2022).

[28] Additionally estimated RIF-regressions based Oaxaca-Blinder decompositions, where the dependent variable is the daily wage, support the presented estimation results of actual and counterfactual wages at different percentiles.

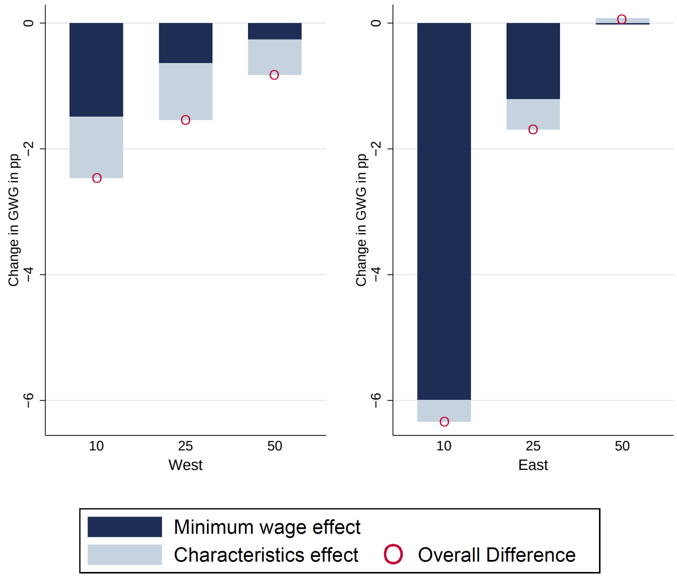


Figure 4.4: Change in gender wage gaps in the East and West of Germany

Source: SIAB7519, own calculations.
Note: The two subfigures present the estimated results of the difference-in-differences analysis using a reweighted distribution distinguishing between the East and the West of Germany.

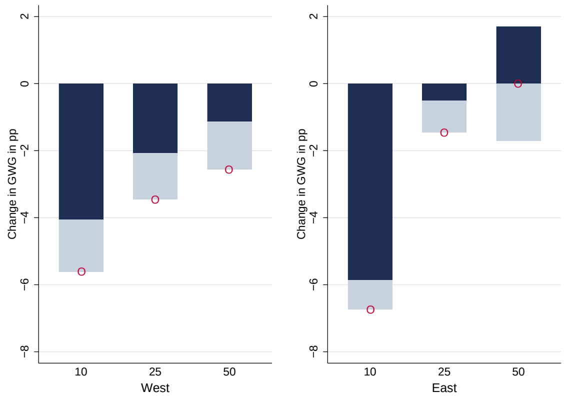
the East of Germany. Results of the counterfactual difference-in-differences estimation on the level of federal states show distinct differences in magnitudes. The highest reduction of the gender wage gap at the 10th percentile is seen in Saxony-Anhalt with -8.42 percentage points, where the minimum wage effect explains about 89%. Other federal states in the East of Germany (except Berlin) provide estimates between 5 and 7 percentage points in decreases of gender pay gaps at the lowest wage level. In contrast to this, estimates for the West of Germany range between -0.14 (Hamburg) and -4.84 (Saarland) percentage points, where between 25% and 81% of the reductions are impacted by the minimum wage. Exceptions are Bremen and Berlin, where gender wage gaps show no decreases at the 10th percentile.

Other regional differences are presented in Table 4.A.3, where it is differentiated between metropolitan and non-metropolitan areas.[29] In general, higher values of decreases are identified for non-metropolitan areas in both the East and the West of Germany at the 10th percentile. Further, the effects resulting from the minimum wage are as well higher

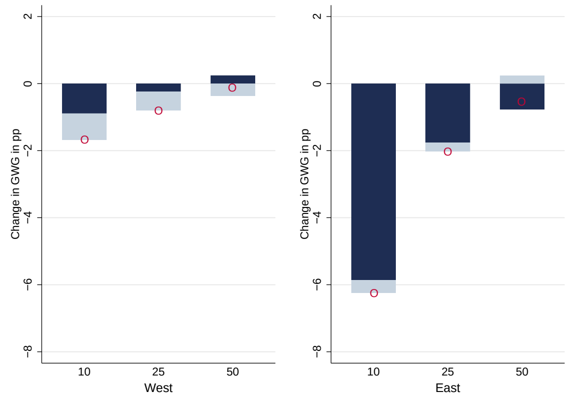
[29] The definition of metropolitan regions in 2008 is based on the information provided by the Initiative Circle European Metropolitan Regions in Germany (IKM) (2022) and Kawka (2016).

in rural areas (West Germany: 65%, East Germany: 93%) leading to larger reductions of differences in pay. Whereas at higher wage levels this relationship is also seen in the East of Germany, the results for metropolitan and non-metropolitan areas in the West of Germany are more or less similar.

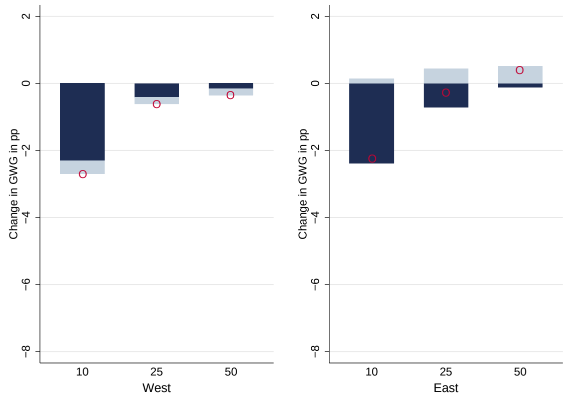
4.6.2 Gender Wage Gaps Among Specific Groups



(a) Low



(b) Medium



(c) High

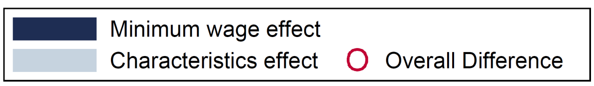


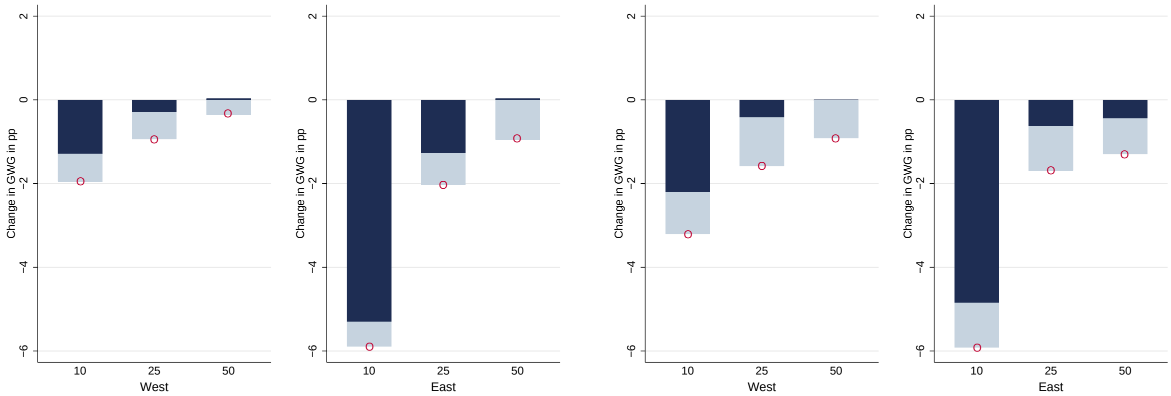
Figure 4.5: Change in gender wage gaps in the East and West of Germany by educational levels

Source: SIAB7519, own calculations.
Notes: The different subfigures present the estimated results of the difference-in-differences analysis using a reweighted distribution distinguishing between different educational levels.

As presented in the descriptive section on the characteristics of minimum wage workers (see Table 4.A.1), there are specific groups of workers that are at higher risk to be affected by the implemented wage floor. Therefore, the following analyses focus on particular groups of the workforce in order to show possible varied responses. At first, Figure 4.5 presents the results on the counterfactual estimations separately for workers of three educational levels. Again, it can be seen that the highest overall decreases of wage differentials are observable at the lowest wages. Further, on average, the highest declines are identified for the group of the lowest educational level. In particular, gender wage gaps at the 10th percentile decrease around 6 percentage points in both regions. At higher wages for the lowest educational group wage differentials between men and women decline mainly in the West of Germany, where at the same time the effect due to changes in the characteristics is more pronounced. The decrease in wage gaps in the East of Germany is either less or non-existent. At the medium educational level, overall decreases in wage differentials are higher for the East of Germany compared to the West. Regarding the former, the observed gender wage gap decreases by around 6 percentage points at the 10th percentile and around 2 percentage points at the 25 percentile. In both cases, around 90% of the drop is traced back to changes in the wage structure due to the introduced wage floor. Wage differentials at the 10th percentile for the highest educational group decrease by more than 2 percentage point in both regions, which occurs mainly due to the minimum wage effect. Wage gaps at the 25th percentile and median only slightly go back or exhibit no change at all. However, inequality increasing tendencies between men and women are identified resulting from changes in the observed characteristics in the East of Germany, which are either totally or partly balanced out by the introduced wage floor.[30]

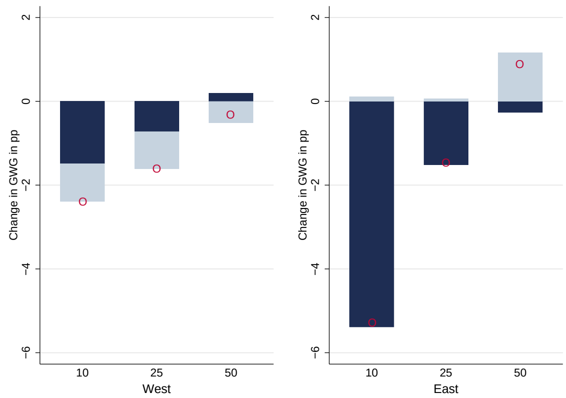
The next subgroups that are taken into account are workers of different age, divided into three groups: (1) 25-34 years, (2) 35-44 years and (3) 45-55 years. Figure 4.6 shows that on average the highest decreases in gender wage gaps, around 6 percentage points,

[30] The presented results might be counterintuitive to the observed descriptive statistics of Table 4.1, where the highest fraction of highly educated workers is revealed for women in the East of Germany and the share of least educated women in the West is higher compared to the East of Germany. However, it has to be kept in mind that there are considerable differences in the observed group-specific wage growth of women after the introduction of the minimum wage. While in the West of Germany wages at the 10th percentile for the least and medium educated women increase by 12% and 5%, the corresponding wages increase by 25% and 17% for women in the East of Germany. Female wages for the highest educational group rise by around 5% in both regions. Thus, the highest reductions of gender wage gaps are identified for educational groups in the East of Germany.



(a) 25-34 Years

(b) 35-44 Years



(c) 45-55 Years

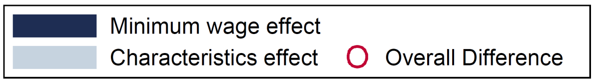
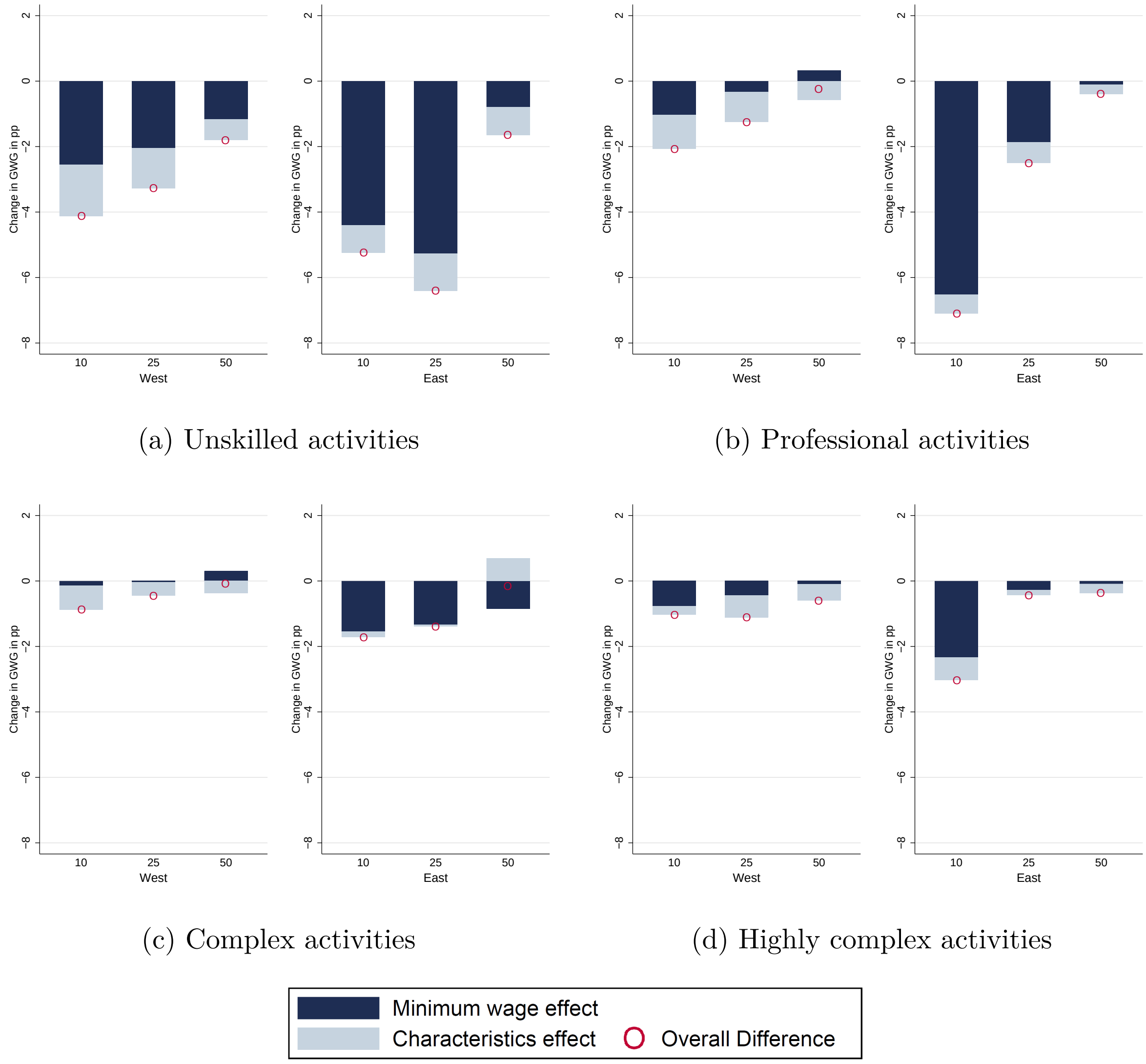


Figure 4.6: Change in gender wage gaps in the East and West of Germany by age groups
Source: SIAB7519, own calculations.
Notes: The different subfigures present the estimated results of the difference-in-differences analysis using a reweighted distribution distinguishing between different age groups.

are estimated for the lowest wages in the East of Germany, regardless the age. The most significant drop in wage differentials between men and women in the West of Germany is revealed for the medium age group. Decreases by more than 3 percentage points at the 10th percentile, by around 1.6 percentage points at the 25th percentile and 1 percentage point at median wages are estimated. When it comes to the division into the effect due to the minimum wage and the effect resulting from changes in the characteristics a more diverse picture emerges. Whereas the majority of decreases in the youngest and oldest groups of workers at lower wages in the East of Germany is explained by the effect that comes from the wage floor, larger parts of the declines in the West of Germany are explained again by changes in the observed endowments of the workers. The identified development in the median wage gap in the East of Germany for the oldest group shows an overall increase in wage differentials driven by the characteristics effect. For the medium age group, wage gaps at the 25th percentile and the median decrease for both regions mainly due to differences in characteristics between 2013/14 and 2015/16 (between 63% and 99%).



(a) Unskilled activities

(b) Professional activities

(c) Complex activities

(d) Highly complex activities

Figure 4.7: Change in gender wage gaps in the East and West of Germany by occupational activities

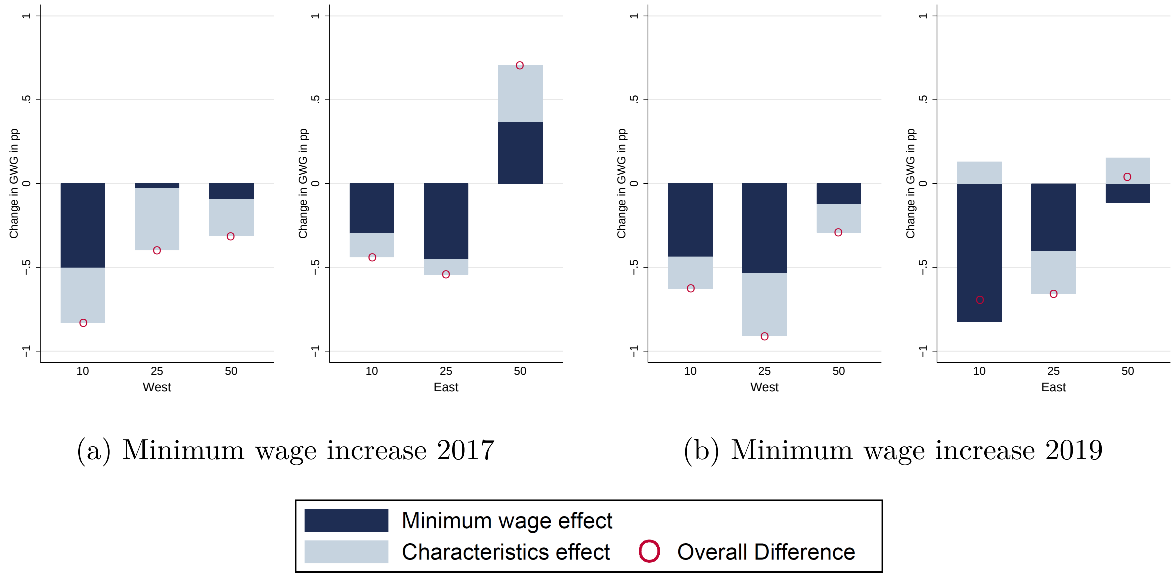
Source: SIAB7519, own calculations.
Notes: The different subfigures present the estimated results of the difference-in-differences analysis using a reweighted distribution distinguishing between different occupational levels.

The last subgroups of workers that are taken into account in more detail are the four occupational levels, (1) unskilled activities, (2) professional activities (3) complex activities and (4) highly complex activities (Figure 4.7). Overall, wage gaps between men and women are in particular reduced in the lowest two occupational groups. Wage differentials for the most likely affected workers at the 10 percentile decrease in the West of Germany between 2.1 and 4.1 percentage points, whereas in the East of Germany the magnitudes rage between 5.2 and 7.1 percentage points. Again, the proportions of effects due to changes in characteristics have higher values for the West of Germany (38% and 50%) compared to the East (16% and 8%). Looking at wage gaps at the 25th percentile and the median, decreases are on average higher for the lowest occupational level with larger values for the East of Germany. For the second occupational level, declines in these wage gaps mainly occur due to changes in the characteristics in the West of Germany and in the East of Germany due to the wage floor effect. Wage gaps between men and women at the highest occupational levels exhibit either small or no decreases for the West of Germany. If there are any drops in wage differentials in the East of Germany, they mainly result from the minimum wage effect with values between 1.7 and 2.2 percentage points.

4.6.3 Gender Wage Gaps After Minimum Wage Increases

As presented in the descriptive statistics in Figure 4.2, the minimum wage increases in the years 2017 and 2019 possibly influence the observed gender wage gaps in the East and West of Germany as well. Thus, the reweighted difference-in-differences analysis is applied for the years 2016 and 2017 as well as 2018 and 2019 in Figure 4.8.[31] Despite the fact that there are noticeable decreases in wage differentials between men and women in both time points, there is no significant difference between the West and the East of Germany observable. Further, the magnitudes of declines are significantly smaller compared to the effects resulting from the introduction of the minimum wage. Overall, in particular wage gaps at the bottom of the wage distribution are influenced by wage floor

[31] Due to the close consecutive years of minimum wage introduction and minimum wage increases, no pooled time points are used in these sub-analyses.



(a) Minimum wage increase 2017 (b) Minimum wage increase 2019

Figure 4.8: Change in gender wage gaps in the East and West of Germany after minimum wage increases

Source: SIAB7519, own calculations.
Notes: The different subfigures present the estimated results of the difference-in-differences analysis using a reweighted distribution for the minimum wage increases in 2017 and 2019.

rises, where mainly the minimum wage effect is decisive (between 0.5 and 0.8 percentage points). Regarding the division into the wage floor effect and characteristics effect at the 25th percentile and the median, again higher shares for the latter effect in the West of Germany are revealed (between 41% and 94%). For median wage gaps in the East of Germany even increasing tendencies for both effects (2017) or due to the characteristics effect (2019) are identified.

4.6.4 Minimum Wage and the Decomposition of Wage Gaps

Until now, the counterfactual type of difference-in-differences analyses identify effects resulting from the introduced minimum wage on the overall unadjusted gender wage gap in Germany. However, decomposing wage differentials between men and women into explained and unexplained effects, as described by the Oaxaca-Blinder decomposition, is a crucial factor in the debate on gender wage gaps. Thus, in Table 4.2 the Oaxaca-Blinder decomposition results for wage differentials at different percentiles for the West and the East of Germany are presented.

Beginning with the observed subsamples in 2013/14 and 2015/16, the overall decrease in wage differentials over time as well as higher magnitudes of drops for the East of Germany compared to the West of Germany are confirmed. The results of the decomposition analyses reveal that in the underlying data wage gaps are mainly traced back to unexplained effects. Differences in the observed characteristics between men and women reveal positive and highly statistically significant explained effects that account for up to 20% at the 10th percentile as well as around 10% at the 25th percentile and the median in the West of Germany. In contrast to this, in the East of Germany explained effects at the lowest wages are very small and only weakly statistically significant. Further, for higher wages the effects turn negative and provide high statistical significance. These results reveal that for wages at the 25th percentile and the median, women in the East of Germany exhibit better endowments and considering only these characteristics they would earn more than men. When it comes to unexplained effects, these can be further divided on the one hand into the impact due to differences in remuneration for women, despite the same observed characteristics as men, and on the other hand the constant. The latter summarises all effects resulting from factors that cannot be observed in the data. The constant defines between 64% and 83% of the unexplained effect in the West and between 60% and 98% of the unexplained effect in the East of Germany.[32]

In order to show how the introduction of the national minimum wage influenced the decomposition of the gender wage gap, the estimation results of the counterfactual sample are additionally presented in Table 4.2. When it comes to the aggregate decomposition in the explained and unexplained effect no major differences between the actual observable sample in 2015/16 and the counterfactual sample are revealed. However, having a closer look at the division of the unexplained part observable differences emerge. For wage gaps at the 10th percentile in the West of Germany the constant explains around 64% of the unexplained part in 2013/14. This effect increases up to 72% in 2015/16. For the counterfactual sample in 2015/16 with the distribution of characteristics fixed at the level of 2013/14, the proportion is almost as high as in the actual sample after the introduced

[32]Using administrative data with limited availability of explanatory variables in the context of gender wage gap decompositions, these results are confirmed by the existing literature (see e.g. Fuchs et al., 2019; Weyh et al., 2022).

wage floor. From this observed trend it can be concluded that the share of the unexplained wage gap, that is traced back to differences in remuneration for women despite the same observed characteristics as men, decreases due to the introduced minimum wage in 2015. In other words, it seems that possible discrimination against women regarding observable characteristics that are available in the underlying data is restricted by the binding wage floor in the West of Germany. For other wage levels, the division of the unexplained effects into the constant and the part, where women earn differently than men despite the same characteristics, either stays constant or the latter effect slightly increases. This holds also true for all wage levels for the East of Germany. However overall, no major changes regarding the shares of explained and unexplained effects in the aggregate decomposition of wage gaps are identified after the introduction of the minimum wage in Germany.

Table 4.2: Actual and counterfactual aggregate decomposition results

	West of Germany			East of Germany		
Percentile	Explained effect	Unexplained effect	Constant	Explained effect	Unexplained effect	Constant
2013/14						
10	5.80***	22.97***	14.70***	0.52*	15.59***	16.97***
25	3.07***	19.84***	16.47***	−2.48***	13.73***	21.08***
50	2.39***	15.47***	12.25***	−10.91***	10.39***	28.58***
2015/16						
10	4.47***	21.21***	15.32***	0.26	8.66***	8.84***
25	2.07***	18.91***	13.04***	−2.74***	12.13***	20.02***
50	2.04***	14.85***	11.60***	−10.13***	9.67***	26.91***
2015/16 counterfactual						
10	4.88***	21.51***	15.26***	0.42*	8.70***	7.90***
25	2.36***	19.19***	13.11***	−2.60***	12.26***	19.84***
50	2.32***	14.61***	11.29***	−10.25***	9.78***	26.68***

Source: SIAB7519, own calculations.
Notes: The table presents the counterfactual aggregate decomposition of gender wage gaps at different percentiles (10th, 25th and 50th percentile) using the RIF-regressions based Oaxaca-Blinder method. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively.

As described in Section 4.5 there are several ways to define the non-discriminatory wage structure estimating the aggregate decomposition. Thus, in Tables 4.A.9 and 4.A.10 in Appendix 4.A robustness checks on alternative definitions of the non-discriminatory wage structure are provided. Applying the weighted wage structure approach by Reimers (1983), where female and male wage structures get the same weight, it can be seen that no major changes arise. The same holds true for the approach proposed by Cotton (1988), where the two different wage structures are weighted according the actual share of the two groups in the underlying data. In this case, as well no changes in the relative size of the different components are observable. As a result, the presented results are robust to different estimation strategies of the non-discriminatory wage structure.

4.7 Discussion and Conclusion

This study analyses the effects of the implemented statutory minimum wage in 2015 on the observed gender wage gap in Germany. Descriptive analyses show significant wage differentials between men and women in the West of Germany between 25.11% and 15.53% along the lower half of the wage distribution between 2013/14 and 2015/16. In contrast to this, gender wage gaps in the East of Germany are considerably lower in size with a maximum of 14.87% at the 10th percentile before the introduction of the binding wage floor. At the same time, workers in the East of Germany exhibit a significantly higher probability to be affected by the introduced minimum wage estimated by regional-specific minimum wage bites. In particular, it is revealed that women benefit highly from the defined wage floor in the East of Germany.

Using administrative data provided by the German Institute for Employment Research, the study provides yearly information and thus assessments of the effects resulting from the introduction of the minimum wage but also from its subsequent increases can be estimated separately. The applied estimation strategy with counterfactual wage distributions, where the distribution of characteristics is fixed at the level before the minimum wage introduction, allows divided analyses of different sources of effects.

The results reveal significant decreases of wage differentials between men and women that can be traced back to the introduced statutory wage floor. Among low-paid jobs, wage differentials exhibit on average the highest declines. At the 10th percentile wage gaps decrease by 2.46 percentage points in the West and by 6.34 percentage points in the East of Germany. Thereby, respectively around 60% and 95% can be explained by the introduction of the minimum wage. For higher wage levels at the 25th percentile and the median decreases in the observed gender wage gaps can be seen as well, although smaller in size. Thus, this separate analysis for the East and the West of Germany reveals two main conclusions. On the one hand, higher impact on wage gaps in regions, where women are significantly more affected by the minimum wage than their male counterparts, is identified. Thus, the effectiveness of the wage floor and the suitability of this policy measure in reducing wage differentials in these regions are confirmed. On the other hand, it is revealed that for the West of Germany changes in the distribution of characteristics as well play a substantial role. As a result, it seems that in the West of Germany, where in general significantly higher wage gaps are identified, still considerable differences in the endowment between women and men exist and reducing them is decisive in the fight against gender-specific wage differentials. Therefore, it needs further targeted efforts in the West of Germany in order to guarantee equal remuneration for women and men.

Differentiating between several groups of the workforce by educational level, age and occupational activity the analysis provides detailed information on the effectiveness of the wage floor for different target groups. In particular, at lower wage levels for the least educated and middle aged workers the introduction of the minimum wage is the driving factor that significantly lowers group-specific gender wage gaps. In the context of increasing wage gaps between men and women after the age of 30, as presented by Schrenker and Zucco (2020), the latter response indicates an effective mechanism of the introduced minimum wage in reducing distinct age-specific wage differentials. Further, looking at occupational levels, it can be seen that in particular wage gaps in the lower half of the distribution among the least demanding occupational activities benefit from the binding wage floor. Again, higher effects due to the minimum wage are identified in the East of Germany, in contrast to higher shares resulting from changes in observable characteristics in the West of Germany. The consecutive rises in the level of minimum wages in the years 2017 and 2019 are also considered in the counterfactual difference-in-difference analyses. Revealing significantly smaller impact on decreases in the gender wage gap and no observable regional-specific difference, these increases in the wage floor can rather be assessed as compensation of inflation.

The presented results on the effect of the minimum wage in Germany are in line with literature on the evaluation of the implemented minimum wage in relation to resulting developments in wage inequality. Thus, the wage floor not only considerably leads to a reduction in overall wage inequality in recent years as presented by Bossler and Schank (2020), but also is a valid measure for diminishing wage differentials between men and women as generally shown by Caliendo and Wittbrodt (2022). Therefore, the underlying study once more supports, with its detailed regional and group-specific analyses, the importance and effectiveness of the binding minimum wage as well as its significant effects on wage gaps between men and women in Germany.

The added counterfactual decomposition analyses, where unadjusted wage differentials are divided into an explained and an unexplained effect, provide first evidence on how the introduced minimum wage affects the adjusted gender wage gap. Overall, the estimated results suggest that for the lowest wage level in the West of Germany, the share of differences in wages between men and women, that cannot be traced back to different endowment, decreases due to the introduced wage floor. This means, possible discrimination against women on the basis of observable characteristics in the underlying data seems to be restricted by the minimum wage. For wage gaps in the East of Germany, no major effects can be observed. Further, in general, the shares of the components in the aggregate decomposition are not affected by the introduction of the wage floor. On this basis, it would be interesting to extend the number of factors that explain wage differentials between men and women in order to provide further evidence whether and how the minimum wage possibly limits discriminatory remuneration structures in Germany. Due to data availability restrictions and the applied estimation design, it was not feasible in this study and thus remains an important issue for future research.

Appendix 4.A

Table 4.A.1: Characteristics of minimum wage workers - logit estimations

	Whole sample	Male sample	Female sample
East Germany	0.040***	0.032***	0.055***
Women	0.041***		
Foreign Nationality	0.001	0.005***	-0.009***
Educational level:			
Low	0.020***	0.015***	0.023***
High	-0.022***	-0.011***	-0.040***
Age:			
25-35 Years	-0.020***	-0.008***	-0.045***
45-55 Years	0.010***	0.012***	0.007***
Job experience:			
0-2 years	0.012***	0.011***	0.013***
4-8 years	-0.002*	-0.002**	-0.003
8-16 years	-0.009***	-0.010***	-0.011***
$\geq$ 16 years	-0.025***	-0.018***	-0.040***
Work experience:			
0-2 years	0.017***	0.007***	0.040***
4-8 years	-0.013***	-0.009***	-0.015***
8-16 years	-0.024***	-0.020***	-0.023***
$\geq$ 16 years	-0.048***	-0.041***	-0.058***
Requirement level:			
unskilled activities	0.033***	0.022***	0.052***
complex activities	-0.028***	-0.020***	-0.045***
highly complex activities	-0.043***	-0.027***	-0.081***
Occupations:			
Food, agriculture and forestry	0.042***	0.021***	0.068***

Continued on next page

Table 4.A.1 – *Continued from previous page*

	Whole sample	Male sample	Female sample
Manufacturing	0.026***	0.015***	0.031**
Technical production	0.009***	0.005***	0.000
Food and hospitality industry	0.070***	0.054***	0.072***
Health care	0.035***	0.021***	0.023**
Social and cultural service	0.031***	0.039***	0.004
Craft/trade	0.051***	0.026***	0.059***
Company organisation	0.027***	0.022***	0.005
Service sector	0.018***	0.022***	-0.016
IT and scientific service	-0.001	0.001	-0.039***
Security	0.058***	0.042***	0.057***
Traffic and logistic	0.050***	0.036***	0.040***
Cleansing service	0.075***	0.042***	0.106***
Plant size:			
1-9 employees	0.084***	0.054***	0.145***
10-49 employees	0.045***	0.027***	0.084***
50-199 employees	0.024***	0.015***	0.038***
1000-4999 employees	-0.025***	-0.017***	-0.042***
$\geq$ 5000 employees	-0.031***	-0.018***	-0.057***
N	304,710	207,204	97,506

Source: SIAB7519, own calculations.

Notes: The table presents the estimated average marginal effects of logit regression frameworks with a dummy variable that is equal to one if the worker earns less than €8.50 as the dependent variable. The base category of the estimation is a male worker in the West of Germany with German citizenship and medium education between 35 and 44 years. The time in employment and in job is between 2 and 4 years exercising specialist activities in a construction occupation at a plant with between 200 and 999 employees. In column (1) estimates on the overall sample are provided, whereas in columns (2) and (3) subsamples differentiating between men and women are used. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively.

Table 4.A.2: Total change in gender wage gaps and effects of the minimum wage at the federal state level

Percentile	Total change	Minimum wage effect	Total change	Minimum wage effect
	Saxony-Anhalt		Hamburg	
10	−2.53	−2.04	−0.14	0.77
25	−2.04	−0.66	−0.61	0.25
50	−0.52	−0.18	−0.97	−0.94
	Lower Saxony		Bremen	
10	−2.40	−1.82	0.28	0.84
25	−1.14	−0.47	−1.82	−1.56
50	−0.77	−0.31	−0.40	0.00
	North Rhine-Westphalia		Hesse	
10	−2.83	−1.66	−2.05	−0.51
25	−1.59	−0.66	−1.79	−0.23
50	−0.89	−0.24	−1.57	−0.61
	Rhineland-Palatinate		Baden-Wuerttemberg	
10	−3.17	−1.78	−2.39	−1.22
25	−1.94	−0.86	−1.20	−0.31
50	−0.39	0.50	−0.48	−0.06
	Bavaria		Saarland	
10	−2.37	−1.51	−4.84	−3.17
25	−1.41	−0.62	−2.31	−1.07
50	−0.88	−0.45	−0.35	0.84
	Berlin		Brandenburg	
10	0.20	0.68	−4.83	−4.10
25	−0.46	−0.03	−2.53	−1.24
50	0.09	−0.17	−1.15	−0.56
	Mecklenburg-Western Pomerania		Saxony	
10	−5.28	−4.84	−6.61	−6.36
25	−2.49	−1.94	−1.38	−1.45
50	0.30	0.20	−0.26	−0.82
	Saxony-Anhalt		Thuringia	
10	−8.42	−7.48	−6.87	−6.30
25	−3.34	−2.79	−2.14	−2.52
50	0.48	0.24	−1.24	−1.35

Source: SIAB7519, own calculations.

Notes: The table presents the change in the observed gender wage gaps in percentage points and the results of the counterfactual difference-in-differences estimations for federal states in the East and the West of Germany.

Table 4.A.3: Total change in gender wage gaps and effects of the minimum wage for metropolitan and non-metropolitan areas

	West of Germany		East of Germany	
Percentile	Total change	Minimum wage effect	Total change	Minimum wage effect
Metropolitan area				
10	−2.09	−1.03	−4.60	−4.34
25	−1.59	−0.67	−0.50	−0.09
50	−0.78	−0.25	0.38	0.28
Non-metropolitan area				
10	−3.13	−2.04	−6.59	−6.11
25	−1.33	−0.50	−2.66	−2.32
50	−0.33	−0.24	−0.13	−0.20

Source: SIAB7519, own calculations.

Notes: The table presents the change in the observed gender wage gaps in percentage points and the results of the counterfactual difference-in-differences estimations for metropolitan and non-metropolitan areas in the East and the West of Germany.

Table 4.A.4: Actual wages and gender wage gaps in 2013/14 and 2015/16 as well as counterfactual wages and gender wage gaps in 2015/16, overall sample

	West of Germany			East of Germany		
Percentile	Women	Men	Wage gap	Women	Men	Wage gap
2013/14						
10	49.57***	66.18***	25.10%	41.59***	48.85***	14.87%
	(0.0853)	(0.0796)		(0.1264)	(0.0818)	
25	68.13***	85.68***	20.48%	53.22***	59.57***	10.66%
	(0.1620)	(0.0690)		(0.1771)	(0.1036)	
50	94.75***	113.28***	16.36%	78.69***	78.29***	−0.51%
	(0.1263)	(0.1031)		(0.3406)	(0.2188)	
2015/16						
10	52.45***	67.81***	22.64%	48.14***	52.63***	8.53%
	(0.0963)	(0.0985)		(0.0684)	(0.0881)	
25	70.88***	87.43***	18.94%	57.28***	62.93***	8.96%
	(0.1195)	(0.0920)		(0.1381)	(0.0986)	
50	98.02***	116.05***	15.53%	82.03***	81.66***	−0.45%
	(0.1278)	(0.1128)		(0.2345)	(0.1460)	
2015/16 counterfactual						
10	52.11***	68.29***	23.61%	48.00***	52.72***	8.87%
	(0.0111)	(0.0115)		(0.0120)	(0.0113)	
25	70.28***	87.72***	19.84%	56.91***	62.87***	9.45%
	(0.0180)	(0.0125)		(0.0211)	(0.0114)	
50	97.32***	116.05***	16.09%	81.67***	81.19***	−5.29%
	(0.0221)	(0.0167)		(0.0352)	(0.0261)	

Source: SIAB7519, own calculations.

Notes: The table presents the observed wages and gender wage gaps in 2013/14 and 2015/16 as well as the counterfactual wages and gender wage gaps in 2015/16 at different wage percentiles, separately for the East and West of Germany. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Bootstrap standard errors are in parentheses.

Table 4.A.5: Actual gender wage gaps in 2013/14 and 2015/16 as well as counterfactual gender wage gaps in 2015/16, by educational groups

	West of Germany			East of Germany		
Percentile	2014/15	2015/16	2015/16 counterfactual	2014/15	2015/16	2015/16 counterfactual
Educational group						
Low						
10	17.45%	11.83%	13.39%	4.29%	−2.45%	−1.57%
25	18.99%	15.54%	16.91%	2.21%	0.76%	1.70%
50	16.10%	13.54%	14.96%	−3.41%	−3.41%	−1.70%
Medium						
10	25.66%	23.98%	24.77%	16.58%	10.34%	10.72%
25	21.07%	20.27%	20.83%	13.66%	11.64%	11.90%
50	15.22%	15.11%	15.47%	3.45%	2.92%	2.69%
High						
10	30.26%	27.56%	27.96%	20.57%	18.32%	18.19%
25	27.50%	26.89%	27.09%	21.19%	20.92%	20.47%
50	28.49%	28.14%	28.34%	20.44%	20.85%	20.33%

Source: SIAB7519, own calculations.

Notes: The table presents the observed gender wage gaps in 2013/14 and 2015/16 as well as the counterfactual gender wage gaps in 2015/16 at different wage percentiles, separately for the East and West of Germany by educational groups.

Table 4.A.6: Actual gender wage gaps in 2013/14 and 2015/16 as well as counterfactual gender wage gaps in 2015/16, by age groups

	West of Germany			East of Germany		
Percentile	2014/15	2015/16	2015/16 counterfactual	2014/15	2015/16	2015/16 counterfactual
Age group						
25-34 Years						
10	13.21%	11.26%	11.93%	11.35%	5.50%	6.05%
25	10.71%	9.77%	10.42%	8.06%	6.04%	6.79%
50	7.76%	7.43%	7.79%	0.56%	−0.36%	0.59%
35-44 Years						
10	29.32%	26.11%	27.12%	17.70%	11.79%	12.85%
25	22.54%	20.96%	22.12%	13.99%	12.30%	13.37%
50	16.72%	15.80%	16.71%	4.38%	3.08%	3.93%
45-55 Years						
10	31.89%	29.50%	30.40%	15.79%	10.51%	10.40%
25	26.18%	24.57%	25.46%	10.12%	8.67%	8.61%
50	19.76%	19.45%	19.96%	−3.78%	−2.89%	−4.05%

Source: SIAB7519, own calculations.

Notes: The table presents the observed gender wage gaps in 2013/14 and 2015/16 as well as the counterfactual gender wage gaps in 2015/16 at different wage percentiles, separately for the East and West of Germany by age groups.

Table 4.A.7: Actual gender wage gaps in 2013/14 and 2015/16 as well as counterfactual gender wage gaps in 2015/16, by occupational activities

	West of Germany			East of Germany		
Percentile	2014/15	2015/16	2015/16 counterfactual	2014/15	2015/16	2015/16 counterfactual
Occupational level						
Unskilled activities						
10	18.87%	14.76%	16.33%	14.11%	8.87%	9.70%
25	20.93%	17.66%	18.89%	13.63%	7.22%	8.36%
50	22.43%	20.63%	21.27%	15.43%	13.79%	14.64%
Professional activities						
10	24.78%	22.71%	23.75%	17.12%	10.01%	10.59%
25	18.77%	17.53%	18.44%	12.53%	10.03%	10.66%
50	12.06%	11.82%	12.39%	−0.60%	−0.99%	−0.70%
Complex activities						
10	26.49%	25.61%	26.35%	16.46%	14.75%	14.91%
25	23.04%	22.59%	23.01%	18.06%	16.67%	16.73%
50	22.36%	22.89%	22.66%	15.13%	14.97%	14.28%
Highly complex activities						
10	27.87%	26.84%	27.11%	17.34%	14.31%	15.01%
25	24.62%	23.51%	24.18%	14.77%	14.34%	14.50%
50	24.97%	24.37%	24.87%	12.19%	11.82%	12.10%

Source: SIAB7519, own calculations.

Notes: The table presents the observed gender wage gaps in 2013/14 and 2015/16 as well as the counterfactual gender wage gaps in 2015/16 at different wage percentiles, separately for the East and West of Germany by occupational activities.

Table 4.A.8: Actual and counterfactual gender wage gaps before and after minimum wage increases

	West of Germany			East of Germany		
Percentile	Before	After	Counterfactual	Before	After	Counterfactual
Minimum wage increase						
2017						
10	22.36%	21.52%	21.85%	9.57%	9.13%	9.27%
25	18.47%	18.07%	18.44%	8.30%	7.76%	7.85%
50	15.22%	14.90%	15.12%	−0.57%	0.14%	−0.20%
2019						
10	21.75%	21.12%	21.31%	10.27%	9.58%	9.45%
25	18.05%	17.14%	17.52%	7.42%	6.76%	7.02%
50	14.84%	14.54%	14.71%	0.49%	0.53%	0.37%

Source: SIAB7519, own calculations.

Notes: The table presents the results of the counterfactual difference-in-differences analyses between 2016 and 2017 as well 2018 and 2019 at different wage percentiles, separately for the East and West of Germany.

Table 4.A.9: Actual and counterfactual aggregate decomposition results using alternative non-discriminatory wage structure, by Reimers (1983)

	West of Germany			East of Germany		
Percentile	Explained effect	Unexplained effect	Constant	Explained effect	Unexplained effect	Constant
Non-discriminatory wage structure proposed by Reimers (1983)						
2013/14						
10	5.21***	23.56***	14.70***	−0.27	16.38***	16.97***
	(0.0021)	(0.0030)	(0.0274)	(0.0033)	(0.0045)	(0.0366)
25	3.11***	19.80***	16.47***	−4.48***	15.73***	21.08***
	(0.0017)	(0.0022)	(0.0203)	(0.0033)	(0.0040)	(0.0331)
50	1.93***	15.92***	12.25***	−12.33***	11.82***	28.58***
	(0.0014)	(0.0016)	(0.0146)	(0.0040)	(0.0043)	(0.0350)
2015/16						
10	3.43***	22.24***	15.32***	−0.27	9.18***	8.84***
	(0.0019)	(0.0027)	(0.0244)	(0.0023)	(0.0032)	(0.0250)
25	2.02***	18.96***	13.04***	−4.29***	13.68***	20.02***
	(0.0017)	(0.0021)	(0.0195)	(0.0028)	(0.0035)	(0.0291)
50	1.44***	15.44***	11.60***	−11.47***	11.02***	26.91***
	(0.0014)	(0.0016)	(0.0144)	(0.0036)	(0.0040)	(0.0321)
2015/16 counterfactual						
10	3.81***	22.58***	15.26***	−0.09	9.21***	7.90***
	(0.0018)	(0.0026)	(0.0235)	(0.0021)	(0.0031)	(0.0234)
25	2.38***	19.17***	13.11***	−4.16***	13.82***	19.84***
	(0.0017)	(0.0021)	(0.0183)	(0.0028)	(0.0037)	(0.0283)
50	1.74***	15.49***	11.29***	−11.59***	11.11***	26.68***
	(0.0014)	(0.0016)	(0.0148)	(0.0037)	(0.0041)	(0.0325)

Source: SIAB7519, own calculations.

Notes: The table presents the counterfactual aggregate decomposition of gender wage gaps at different percentiles (10th, 25th and 50th percentile) using the RIF-regressions based Oaxaca-Blinder method. The non-discriminatory wage structure is calculated using the estimation strategy suggested by Reimers (1983). ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Robust standard errors are presented in parentheses.

Table 4.A.10: Actual and counterfactual aggregate decomposition results using alternative non-discriminatory wage structure, by Cotton (1988)

	West of Germany			East of Germany		
Percentile	Explained effect	Unexplained effect	Constant	Explained effect	Unexplained effect	Constant
Non-discriminatory wage structure proposed by Cotton (1988)						
2013/14						
10	5.44***	23.33***	14.69***	−0.08	16.18***	16.97***
	(0.0019)	(0.0028)	(0.0275)	(0.0030)	(0.0043)	(0.0367)
25	3.10***	19.81***	16.47***	−3.98***	15.23***	21.08***
	(0.0015)	(0.0020)	(0.0203)	(0.0029)	(0.0038)	(0.0331)
50	2.11***	15.75***	12.25***	−11.98***	11.46***	25.58***
	(0.0013)	(0.0015)	(0.0146)	(0.0036)	(0.0041)	(0.0350)
2015/16						
10	3.83***	21.84***	15.32***	−0.14	9.05***	8.84***
	(0.0017)	(0.0026)	(0.0244)	(0.0021)	(0.0031)	(0.0250)
25	2.04***	18.94***	13.04***	−3.90***	13.29***	20.02***
	(0.0015)	(0.0020)	(0.0195)	(0.0025)	(0.0034)	(0.0291)
50	1.67***	15.21***	11.60***	−11.14***	10.68***	26.91***
	(0.0013)	(0.0015)	(0.0144)	(0.0034)	(0.0038)	(0.0321)
2015/16 counterfactual						
10	4.22***	22.17***	15.26***	0.04	9.09***	7.90***
	(0.0017)	(0.0026)	(0.0235)	(0.0020)	(0.0030)	(0.0234)
25	2.37***	19.18***	13.11***	−3.77***	13.43***	19.84***
	(0.0014)	(0.0020)	(0.0183)	(0.0025)	(0.0034)	(0.0283)
50	1.96***	15.27***	11.29***	−11.25***	10.78***	26.68***
	(0.0014)	(0.0016)	(0.0148)	(0.0034)	(0.0039)	(0.0325)

Source: SIAB7519, own calculations.

Notes: The table presents the counterfactual aggregate decomposition of gender wage gaps at different percentiles (10th, 25th and 50th percentile) using the RIF-regressions based Oaxaca-Blinder method. The non-discriminatory wage structure is calculated using the estimation strategy suggested by Cotton (1988). ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Robust standard errors are presented in parentheses.

References

Ahlfeldt, G. M., Roth, D., and Seidel, T. (2018). The regional effects of Germany's national minimum wage. *Economics Letters*, 172:127–130.

Antonczyk, D., Fitzenberger, B., and Sommerfeld, K. (2010). Rising wage inequality, the decline of collective bargaining, and the gender wage gap. *Labour Economics*, 17(5):835–847.

Bargain, O., Doorley, K., and Van Kerm, P. (2019). Minimum Wages and the Gender GAP in Pay: New Evidence from the United Kingdom and Ireland. *Review of Income and Wealth*, 65(3):514–539.

Bauer, T. K., Schaffner, S., Kluve, J., and Schmidt, C. M. (2009). Fiscal effects of minimum wages: An analysis for Germany. *German Economic Review*, 10(2):224–242.

BBSR Bonn (2019). Laufende Raumbeobachtung des BBSR https://www.bbsr.bund.de/BBSR/DE/forschung.html (access on 01-12-2020).

Berge, P. v., Frodermann, C., Graf, T., Grießemer, S., Kaimer, S., Köhler, M., Lehnert, C., Oertel, M., Schmucker, A., Schneider, A., and Seth, S. (2021). Stichprobe der Integrierten Arbeitsmarktbiografien (SIAB) 1975 - 2019. *FDZ Datenreport, 01/2021 (de), Nürnberg.*

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

Blömer, M. J., Guertzgen, N., Pohlan, L., Stichnoth, H., and Van den Berg, G. J. (2018). Unemployment effects of the German minimum wage in an equilibrium job search model. In *Proceedings. Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association*, volume 111, pages 1–60. JSTOR.

Boll, C. and Lagemann, A. (2019). The gender pay gap in EU countries—new evidence based on EU-SES 2014 data. *Intereconomics*, 54(2):101–105.

Börschlein, B. and Bossler, M. (2019). Eine Bilanz nach fünf Jahren gesetzlicher Mindestlohn: Positive Lohneffekte, kaum Beschäftigungseffekte. IAB-Kurzbericht 24/2019.

Bosch, G. (2007). Mindestlohn in Deutschland notwendig: kein Gegensatz zwischen sozialer Gerechtigkeit und Beschäftigung. *Zeitschrift für Arbeitsmarkt Forschung-Journal for Labour Market Research*, 40(4):421–430.

Bossler, M. and Gerner, H.-D. (2020). Employment effects of the new German minimum wage: Evidence from establishment-level microdata. *ILR Review*, 73(5):1070–1094.

Bossler, M. and Schank, T. (2020). Wage inequality in Germany after the minimum wage introduction. *IZA Discussion Paper*.

Caliendo, M. and Wittbrodt, L. (2022). Did the minimum wage reduce the gender wage gap in Germany? *Labour Economics*, 78:102228.

Caliendo, M., Wittbrodt, L., and Schröder, C. (2019). The causal effects of the minimum wage introduction in Germany–an overview. *German Economic Review*, 20(3):257–292.

Cotton, J. (1988). On the decomposition of wage differentials. *The Review of Economics and Statistics*, 70(2):236–243.

Destatis (2016). 4 Millionen Jobs vom Mindestlohn betroffen. *Statistisches Bundesamt Press Release, no. 121.*

Dex, S., Sutherland, H., and Joshi, H. (2000). Effects of minimum wages on the gender pay gap. *National Institute Economic Review*, 173(1):80–88.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64(5):1001–1044.

Dustmann, C., Lindner, A., Schönberg, U., Umkehrer, M., and Vom Berge, P. (2022). Reallocation effects of the minimum wage. *The Quarterly Journal of Economics*, 137(1):267–328.

Eurostat (2022). Gender pay gap statistics https://ec.europa.eu/eurostat/statistics-explained (access on 13-01-2023). *Statistics Explained.*

Firpo, S. P., Fortin, N. M., and Lemieux, T. (2018). Decomposing Wage Distributions Using Recentered Influence Function Regressions. *Econometrics*, 6(2):1–40.

Fortin, N., Lemieux, T., and Firpo, S. (2011). Decomposition Methods in Economics. In *Handbook of Labor Economics*, volume 4, pages 1–102. Elsevier.

Friedrich, M. (2020). Using occupations to evaluate the employment effects of the German minimum wage. *Jahrbücher für Nationalökonomie und Statistik*, 240(2-3):269–294.

Fuchs, M., Rossen, A., Weyh, A., and Wydra-Somaggio, G. (2019). Why do women earn more than men in some regions? Explaining regional differences in the gender pay gap in Germany. IAB-Discussion Paper 11/2019, Nürnberg.

Gartner, H. (2005). The Imputation of Wages Above the Contribution Limit with the German IAB Employment Sample. *FDZ Methodenreport 02/2005, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.*

Grabka, M. M. and Schröder, C. (2018). Ungleichheit in Deutschland geht bei Stundenlöhnen seit 2014 zurück, stagniert aber bei Monats- und Jahreslöhnen. DIW Wochenbericht 9, Berlin.

Grabka, M. M. and Schröder, C. (2019). The low-wage sector in Germany is larger than previously assumed. DIW Weekly Report 14, Berlin.

Grandner, T. and Gstach, D. (2015). Decomposing wage discrimination in Germany and Austria with counterfactual densities. *Empirica*, 42(1):49–76.

Initiative Circle European Metropolitan Regions in Germany (IKM) (2022). https://deutsche-metropolregionen.org (access on 02-02-2022).

Kalina, T. and Weinkopf, C. (2014). Niedriglohnbeschäftigung 2012 und was ein gesetzlicher Mindestlohn von 8,50 Euro verändern könnte. *IAQ-Report*, 2(2014):1–15.

Kawka, R. (2016). Metropolregionen–Kooperation und Wettbewerb in Deutschland und Europa. *Informationen zur Raumentwicklung*, (5).

Kitagawa, E. M. (1955). Components of a difference between two rates. *Journal of the American Statistical Association*, 50(272):1168–1194.

Knabe, A. and Schöb, R. (2009). Minimum wage incidence: the case for Germany. *FinanzArchiv/Public Finance Analysis*, pages 403–441.

Knabe, A., Schöb, R., and Thum, M. (2014). Der flächendeckende Mindestlohn. *Perspektiven der Wirtschaftspolitik*, 15(2):133–157.

Kubis, A., Rebien, M., and Weber, E. (2015). Neueinstellungen im Jahr 2014: Mindestlohn spielt schon im Vorfeld eine Rolle. IAB-Kurzbericht 12/2015, IAB-Kurzbericht, Nürnberg.

Majchrowska, A. and Strawiński, P. (2018). Impact of minimum wage increase on gender wage gap: Case of Poland. *Economic Modelling*, 70:174–185.

MiLoG (2022). Gesetz zur Regelung eines allgemeinen Mindestlohns (Mindestlohngesetz - MiLoG) http://www.gesetze-im-internet.de/milog/ (access on 01-11-2022).

Mindestlohnkommission (2016). Beschluss der Mindestlohnkommission nach § 9 MiLoG. Berlin, June.

Mindestlohnkommission (2018). Beschluss der Mindestlohnkommission nach § 9 MiLoG. Berlin, June.

Müller, K.-U. and Steiner, V. (2008). Would a legal minimum wage reduce poverty? A microsimulation study for Germany. DIW Diskussionspapier 791.

Müller, K.-U. and Steiner, V. (2011). Beschäftigungswirkungen von Lohnsubventionen und Mindestlöhnen–Zur Reform des Niedriglohnsektors in Deutschland. *Zeitschrift für Arbeitsmarktforschung*, 44(1):181–195.

Müller, K.-U. and Steiner, V. (2013). Distributional effects of a minimum wage in a welfare state–The case of Germany. *SOEP Papers on Multidisciplinary Panel Data Research*, (617).

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

Ohlert, C. (2018). Gesetzlicher Mindestlohn und der Gender Pay Gap im Niedriglohnbereich: Ergebnisse aus der Verdienststrukturerhebung 2014 und der Verdiensterhebung 2015. *Zeitschrift für amtliche Statistik Berlin Brandenburg*, 2:26–31.

Reimers, C. W. (1983). Labor market discrimination against Hispanic and black men. *The Review of Economics and Statistics*, pages 570–579.

Schrenker, A. and Zucco, A. (2020). Gender Pay Gap steigt ab dem Alter von 30 Jahren stark an. DIW Wochenbericht 10.

Selezneva, E. and Van Kerm, P. (2016). A distribution-sensitive examination of the gender wage gap in Germany. *The Journal of Economic Inequality*, 14(1):21–40.

Weyh, A., Hennig, D., Fuchs, M., and Rossen, A. (2022). Geschlechtsspezifische Lohnunterschiede in Sachsen in Zeiten der Corona-Pandemie. Technical report, IAB-Regional. IAB Sachsen.

Chapter 5

Conclusion

Increasing unequal distribution of income and wealth is one of the most pressing social and economic problems of our time. Being closely related to the economic well-being of individuals and overall satisfaction of the society, scientific research in the field of economic inequality is of high importance. Economic and political challenges, technological change and impacts from changes in policies are essential to be considered in this context. Therefore, this thesis analyses wage inequality in the light of three challenges of the German labour market and contributes to existing literature extensive new insights in these areas of research. In particular, it identifies how increasing automation and robotization affected the observed wage dispersion in the manufacturing sector during the last decades. Further, it examines immigrant-native wage gaps and related driving forces in the face of increasing migration and regional differences. Lastly, the effect of an introduced policy measure, the minimum wage, on observed differences in pay between men and women is assessed. In all three studies, the research questions are addressed by applying extensive decomposition methods that cover all parts of the wage distribution and provide detailed information about the driving forces behind changes in unequal remuneration.

Chapter 2 provides evidence on the impact of automation and robotization on wage inequality in the German manufacturing sector. In view of considerable concerns on how new automation technologies impact the labour market outcomes employment and wages, the presented study makes a pivotal contribution to existing literature. With considerable increases in wage inequality since the mid-1990s and at the same time with one of the highest robot densities worldwide, Germany is an interesting and insightful case. Detailed decomposition analyses on the basis of RIF-regressions consider a new introduced automation threat variable. With this, occupation- and requirement-specific scores of automation risk and yearly sector-specific robot densities are combined in order to capture the effects of automation and robotization. The estimation results reveal two channels through which the considered technologies contribute to increases in wage inequality. On the one hand, the first effect results through compositional changes in the workforce with a trend towards occupations with medium automation threat. As a result of this development, the automation-related composition effect explains roughly 10% of the overall composition effect in the increase of wage inequality between 1996 and 2010. This impact even increases up to 41% in the second observed time period until 2017. On the other hand, a rise in wage dispersion between occupations with low automation threat, that especially relate to non-routine tasks, and occupations with high automation threat, that especially relate to routine tasks, is identified in the first period of observation. These findings support the concept of routine-biased technological change, where technology increases the relative demand, and thus the relative wages, for non-routine tasks compared to routine tasks. With regard to current major advances in artificial intelligence, machine learning and new manufacturing technologies, future research in this field remains an important and required challenge.

Chapter 3 analyses wage differentials between immigrant and native workers in Germany. Gaps in remuneration provide information on the effectiveness of immigration and labour market policies as well as identify the degree of economic integration of foreign workers. Between 2000 and 2019, significant changes in wage gaps between German and Non-German workers along the entire wage distribution are identified. With a reversal in trend after 2012, a considerable increase in median wage gaps and regional-specific differences between metropolitan and non-metropolitan areas, decomposition analyses based on RIF-regressions are applied in order to provide evidence on driving forces along the whole wage distribution. Aggregate decomposition results support the hypothesis that the majority of wage differentials can be explained by differences in observed characteristics. Separate detailed analyses at different points in time show that the effects of explanatory factors not only change over time but the sources of gaps also vary along the wage distribution. The traditionally assumed main driving factor education is seen to have decreasing impact over time. In contrast, the economic sector affiliation at the bottom of the distribution and working in a specific occupation at the top, decisively affect wage differentials to the detriment of foreign workers. With considerable changes in the composition of the foreign workforce regarding labour market experience after 2015, the study reveals inequality increasing sources that need to be addressed by political measures. Considering differences in the presence of foreign population, increasing tendencies in wage differentials are especially identified for lower wage levels. Further, differentiating between urban and rural areas, the study provides evidence of significantly higher immigrant-native wage gaps in large cities and metropolitan areas in Germany, where as well on average a higher share of foreign population is encountered. In this context, structural differences regarding educational attainment to the detriment of Non-German workers are identified. In times of a shrinking overall population and skills shortage that requires skilled immigration from abroad, the underlying results make an essential contribution to related research and political discussion in Germany.

Chapter 4 assesses the effectiveness of the introduced national binding minimum wage in 2015 on wage differentials between men and women in Germany. With a considerable extent of the gender wage gap and high female employment rates in the low-wage sector, the study provides substantial results. Regional-specific analyses support evidence of higher minimum wage bites for women and workers in the East of Germany. At the same time, significant variation in wage differentials are revealed with on average higher gender wage gaps in the West of Germany. The empirical analyses are based on a difference-in-differences estimation strategy using counterfactual wage distributions and gender wage gaps. As a result of this procedure, changes in observed wage gaps between men and women are segmented into an effect due to changes in endowments and into an effect resulting from the introduced wage floor. Overall, differences in remuneration at the 10th percentile decrease by around 2.5 percentage points in the West and more than 6 percentage points in the East of Germany after the introduction of the wage floor. Thereby, respectively around 60% and 95% are traced back to the introduction of the minimum wage. Thus, the study supports the hypothesis that there is higher impact on wage differentials in regions, where women are significantly more affected by the minimum wage than their male counterparts. Differentiating between several group-specific dynamics, it is revealed that especially lower educated and medium aged female workers benefit from the introduction of the wage floor, which leads to a significant reduction in the related wage gaps. Combining counterfactual wage distributions with RIF-regressions based Oaxaca-Blinder decompositions finally provides first evidence that in the West of Germany possible discrimination against women at the lowest wage level is restricted by the wage floor. Moreover, the study reveals structural wage differentials that could not be reduced by the wage floor for the West of Germany and thus shows the necessity for further action against unequal remuneration between men and women in this area.

As concluding remarks, the presented empirical results of the three underlying studies show the importance to consider different aspects in analysing inequalities in remuneration. Being a complex area, research on different determinants and driving factors of wage inequality stays an important and essential channel through which a contribution for a more satisfactory distribution of resources, incomes and opportunities in a society can be made. Especially in view of current global developments, it remains interesting to see how changes in inequality, related policy actions and the public interest will interact in the future.