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

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Abstract

We analyze how and through which channels wage inequality is affected by the rise in automation and robotization in the manufacturing sector in Germany from 1996 to 2017. Combining rich linked employer-employee data accounting for a variety of different individual, firm and industry characteristics with data on industrial robots and automation probabilities of occupations, we are able to disentangle different potential causes behind changes in wage inequality in Germany. We apply the recentered influence function (RIF) regression based Oaxaca-Blinder (OB) decomposition on several inequality indices and find evidence that besides personal characteristics like age and education the rise in automation and robotization contributes significantly to wage inequality in Germany. Structural shifts in the workforce composition towards occupations with lower or medium automation threat lead to higher wage inequality, which is observable over the whole considered time period. The effect of automation on the wage structure results in higher inequality in the 1990s and 2000s, while it has a significant decreasing inequality effect for the upper part of the wage distribution in the more recent time period.

JEL classification: J31, C21, D63, O30
Keywords: Wage Inequality, Automation, Robots, Decomposition Method, RIF-regression, Linked employer–employee data, Germany

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1 Introduction

During the last decades, Germany experienced increasing wage inequality like many other industrialized countries all over the world. The considerable rise in German wage dispersion since the 1990s is well documented by a vast literature (among others Dustmann et al. 2009, Card et al. 2013 & Antonczyk et al. 2018). The resulting debate on economic inequality and distribution of wealth not only attracted considerable attention of the general public, but also became a major issue of political concern. Many existing analyses examine potential causes behind changes in wage inequality. Labor market institutions and regulations such as the Hartz reforms, the decline in collective bargaining agreements, the impact of workplace heterogeneity and the introduction of a national statutory minimum wage play an important role when it comes to changes in the wage distribution (see for example Möller 2014, Felbermayr et al. 2014, Card et al. 2013 & Bossler and Schank 2020).

A more recently discussed explanatory factor for an increase in economic inequality is the rise in automation and robotization. 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 labor but on the other hand enable the substitution of labor, preferably unskilled labor. Frey and Osborne (2017) draw a dark picture of the employment effects from computerization. They estimate that around 47% of total US employment could be automated over the next two decades. Brzeski and Burk (2015) use the same method and show that even 59% of total employment in Germany can be replaced by automation. However, these large numbers are criticized by different economists. For example Autor (2015) argues that indeed automation substitutes labor but those effects are often overstated. It is widely ignored that automation complements labor and thus is even able to increase labor demand, raise productivity and by this lead to higher earnings. This view can be also supported by other studies which focus on the different tasks of occupational fields and their possibility to become automated. Arntz et al. (2016) estimate that on average merely 9% of all jobs in the 21 OECD countries are automatable. Dengler et al. (2014) estimate that 15% of employees in Germany have a high substitution potential, which means that more than 70% of the tasks in their occupation could already be automated.

Although the extent of automation and its final effects are strongly debated, automation will lead to a structural change in the economy that will create groups which gain from automation and some which will not. In this paper, we provide evidence for the relation between automation, robotization and wage inequality in Germany between 1996 and 2017, where we are able to obtain a quantification to which extent automation contributed to changes in the wage dispersion. We focus on men working full-time in the manufacturing sector in West Germany between 1996 and 2017. In order to evaluate the impact of a wide range of different individual, firm and industry characteristics on German wage inequality we use administrative linked employer–employee data provided by the Institute for Employment Research (IAB). Our measure of automation threat merges the information about occupation-specific scores of automation risk provided by Dengler and Matthes (2015) with the sectoral robot density in Germany provided by the International Federation of Robotics (IFR). We apply the recentered influence function (RIF) regression based Oaxaca Blinder (OB) decomposition introduced by Firpo et al. (2018), controlling for a variety of individual and firm characteristics, as well as sector and federal states fixed effects. Using this empirical strategy, we are able to quantify the relative importance of specific covariates regarding the observed developments in German wage inequality.

In our descriptive analysis we provide evidence of a trend towards medium automation threat, which is accompanied with a decline in the groups of high and low automation threat. It seems that workers are moving away from high automation risk jobs towards less automatable jobs, whereas at the same time more jobs are exposed to increasing automation and robotization. Due to the fact that within-group wage inequality is the lowest in the group with the highest automation threat, our RIF regression based decomposition analyses reveal that the observed compositional changes lead to an increase in wage inequality in the observed period between 1996 and 2017. This result is also supported by a counterfactual analysis on the wage distribution and commonly used inequality measures. Further, the distribution of wages is affected by changes in the relative wage differences between high-skilled workers with non-routine skills that are typically at low risk of automation and low-skilled workers with routine skills that are usually faced with higher risk of automation as predicted by skill-biased technological change. This development results in a positive wage structure effect of automation threat.

Our decomposition analyses yield that besides the usual demographic factors that enhance inequality, the increasing threat of automation has a positive, statistical significant impact on the wage dispersion in Germany. In addition, we show that different parts of the wage distribution are affected by increasing automation in different ways. Compositional changes affect the upper half of the wage distribution in the more recent time period to a larger extent than the lower half. In addition, we contribute to the literature by providing results for the latest period of steady or even declining inequality developments (see for example Möller 2016 and Baumgarten et al. 2020). Overall, our findings suggest inequality-increasing impact of automation and robotization in the German manufacturing sector for full-time working men.

The remainder of this paper proceeds as follows: the next section gives a short summary over current literature related to German wage inequality as well as literature that support the implementation of automation as a factor of rising wage dispersion. In Section 3 we describe the different data sets used in our empirical analysis. Section 4 provides information about the developments of wage inequality in Germany in the observed time period. Further, we give an overview of the evolution of automation in different areas in the world and in particular in Germany. In Section 5 we outline our empirical approach and define our proposed variable quantifying automation and robotization threat. Finally, we present our empirical results in Section 6 before we conclude in Section 7.

2 Related Literature

This analysis makes a contribution to the existing literature on wage inequality and the influence of automation and robotization. First, the article builds on the wide range of literature dealing with the causes of increasing wage inequality in Germany. After Germany has long been known for a rather constant wage distribution, see for example Steiner and Wagner (1996), Dustmann et al. (2009) provide evidence that wage inequality at the top of the wage distribution started to increase already in the 1980s with constant wage inequality at the bottom of the distribution in West Germany. In the 1990s wage inequality has increased at both, the top and the bottom of the wage distribution. Dustmann et al. (2009) emphasize the changes in the workforce composition and the decline in collective bargaining as important factors in rising German wage inequality. Moreover, they find evidence that technological change increases inequality at the top of the wage distribution.

Antonczyk et al. (2010), Biewen and Seckler (2019), Felbermayr et al. (2014) and Baumgarten et al. (2020) have implemented decomposition analyses of the wage distribution in Germany using linked employer-employee data. Antonczyk et al. (2010) analyze the increase in wage inequality in West Germany between 2001 and 2006 and show that firm effects, bargaining effects and personal characteristics mainly account for the rise in wage inequality. Biewen and Seckler (2019) analyze the wage distribution between 1995 and 2010 and find similar drivers of 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 like age, education and collective bargaining agreements play the most important role. Investment in new technologies as well as international trade had no significant influence on wage dispersion. Recently provided data indicates a reversal in trend after 2010. 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. They provide evidence that the main driving forces of the change in wage distribution are industry effects and collective bargaining effects. Similarly to this literature, we use linked employer-employee data to have a wide range of personal as well as plant characteristics as explanatory factors for the change in the wage distribution in Germany. Additionally, we extend the covered time period up to 2017 and focus on an additional variable, which captures the effect of automation and robotization on the wage distribution. We restrict our analysis to the manufacturing sector, because of the exceptional importance of automation and robotization to this sector and data availability.

There is a variety of theoretical and empirical literature that supports the implementation of automation as a factor of rising wage inequality. The endogenous growth model presented by Hémous and Olsen (2018) analyzes labor-saving innovation and the impact of such an innovation on income inequality. Horizontal innovation, modeled by an increase in the number of products similar to Romer (1990), increases wages for high-skilled as well as for low-skilled workers. Automation is implemented in a way that it allows to substitute low-skilled labor with machines and raise the productivity of the total economy. This results in increasing wages for high-skilled workers but leads to an ambiguous net effect on wages for low-skilled workers, which induces permanently increasing inequality. The growth model build by Acemoglu and Restrepo (2018) also involves automation and includes the creation of new tasks. However, in their model exists a balanced growth path because automation reduces the cost for using labor in production, leading to decreasing automation incentives and stimulates the introduction of new tasks. Thus, faster automation and the creation of new tasks lead to higher inequality during transitions, but in the long-run inequality stabilizes. The model of Prettner and Strulik (2019) is closely linked to those growth models, but additionally endogenizes education decisions of households in order to capture the race between education and technology. In line with the other two models, it predicts that automation increases inequality, because low-skilled workers do not benefit from automation.

Turning to empirical literature, Autor et al. (2003) show that an increase in computerization goes along with a relative shift in labor demand for college-educated workers. Furthermore, Acemoglu and Restrepo (2017) analyze the effect of robot density in the USA on wages and employment and find evidence that a rise in robot density reduces employment and wages between 1990 and 2007. In a similar way Dauth et al. (2017) analyze the effect of an increasing robot density in Germany and show that a rise in the robot density decreases wages and 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. Kaltenberg and Foster-McGregor (2020) implement a decomposition analysis of the wage distribution in 10 European countries and focus on the impact of automation risk of an occupation.[1] 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. Their results suggest that there is rising wage inequality between occupations that are at high automation risk and those that are not. Kaltenberg and Foster-McGregor (2020) use the automation probabilities estimated by Frey and Osborne (2017), which create several problems. In order to avoid those problems, we use data of automation risk for occupations in Germany. Additionally, we combine the risk of automation with the robot density in the corresponding sector. In a similar way, this approach is used in Anelli et al. (2019) in order to capture the individual exposure to automation.

[1] Germany is not included in their sample.

3 Data

3.1 Labor Market Data

We use German linked employer-employee data (LIAB), provided by the Research Data Center of the Institute for Employment Research (IAB).[2] The data set combines information of the yearly representative employer survey (IAB Establishment Panel) with the corresponding establishment and individual data, drawn from labor administration and social security. The IAB Establishment Panel has been conducted since 1993 in West Germany and 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 June 30th 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 workers characteristics and of the particular establishment in which they work. 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 about the establishments such as the classification of economic activities, total number of employees and region.

We restrict the data sample to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 Euros per day. We use the sample period from 1996 to 2017 and restrict our analysis to West Germany, due to different trends in wage dispersion between East and West Germany and for a better comparison with other studies. 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

[2] 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).

the approach by Gartner (2005).[3] We run a series of tobit regressions, controlling for five different age profiles, job tenure, nationality, occupational level, economic sector, plant size and federal state. This is done separately within each year and every educational level. We then replace the right-censored wages by the imputed wages drawn from the tobit regressions. Non-censored and imputed wages are converted into constant 2015 Euros with the Consumer Price Index provided by the German Federal Statistical Office.

3.2 Robot Data

The data on robot usage is obtained from the International Federation of Robotics (IFR). The data contain the stock of 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 manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (International Federation of Robotics, 2018). This definition excludes machines such as textile looms, cranes or transportation bands, because they cannot be reprogrammed to perform other tasks and/or need a human operator. Moreover, industrial robots eligible for a single industrial application, such as storage systems in automated warehouses, are excluded as well. This is a disadvantage of the IFR data, because such industrial machines might have a similar impact on employment and earnings as industrial robots.

The data rely on primary and 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 deepness of the industry classification in the IFR data differs between manufacturing sector and non-manufacturing sector. Outside the manufacturing sector, industries are aggregated to very broad groups, while inside the manufacturing sector the data are more disaggregated, reflecting the need for deeper analysis within this sector. Our analysis focuses on the manufacturing sector, because of better data availability and the predominant role of automation in this sector. The robot data reported by the IFR is mostly based on the International

[3]See Appendix A for a summary of the wage imputation procedure introduced by Gartner (2005).

Standard Industrial Classification of All Economic Activities (ISIC) Rev. 4.[4] In summary, 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.[5]

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. Thus, the robot data can be matched without using a crosswalk. 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).

3.3 Automation Risk Data

We use an occupation-specific score of automation risk. A commonly used measure is provided by Frey and Osborne (2017), which is also used in the decomposition analysis of Kaltenberg and Foster-McGregor (2020). Frey and Osborne (2017) estimate the probability of computerization 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

[4]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.

[5]As Dauth et al. (2017) 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.

classification.[6] 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).

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. Dengler et al. (2014) calculate the task composition for different occupations, based on BERUFENET Expert Database of the German Federal Employment Agency. The data set contains information of around 3,900 single occupations, like the required tasks, 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 these 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

[6]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 3-digit KldB 2010 classification, using the average of the automation probability, if the mapping is not unique.

[7]There is already an updated version of the automation probabilities based on the available technology in 2016, see Dengler and Matthes (2018). 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.

weights based on employment numbers from 2012. The weights ensure that single occupations with high employment are taken more into consideration, when determining the substitutability potential at the aggregated occupational level. The share of routine activities is used to determine the substitutability 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 task levels.[9] In summary, they estimate the substitutability potential for 131 occupation-task level combinations. The LIAB data contains occupation codes and task levels in the KldB 2010 classification. Thus, merging both data sets is possible without a crosswalk.

4 Trends in Wage Inequality, Automation and Robotization

The first subsection presents observable changes in the wage distribution of men working full-time in the manufacturing sector in West Germany between 1996 and 2017 using LIAB data. Different inequality indices and measures show the development of overall wage inequality and inequality at specific parts of the wage distribution. Moreover, shifts in the wage distribution over time are illustrated by kernel density estimations. The second subsection gives an overview of the evolution of industrial robots in different areas in the world and in particular in Germany. As another measure of automation, we depict the substitutability potential of different occupational sectors in Germany.

4.1 Wage Inequality in Germany

The development of wage inequality in the manufacturing sector defined by the gap between the 85th and 15th percentiles of the log real daily wages is displayed in Figure 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. In order to present a descriptive assessment about the development of wage inequality considering the whole wage distribution, the imputed daily wage data is used. Figure 2 illustrates the commonly used Gini

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

coefficient, which measures the normalised average absolute difference between all wage pairs in the workforce and takes on values between zero and one (Cowell, 2000). Again, a considerable increase in wage inequality until 2008 and a steady, slightly decreasing trend thereafter is shown. Thus, the development seen in Figure 1 is confirmed by the results for the Gini coefficient.

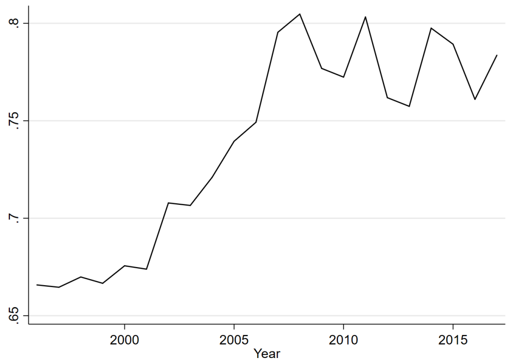

Figure 1: 85-15 log wage gap

Source: LIAB QM2 9317, own calculations.

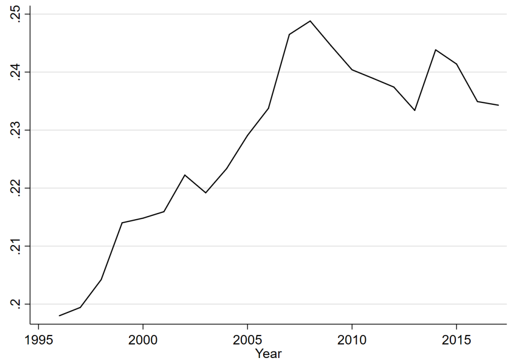

Figure 2: Gini coefficient

Source: LIAB QM2 9317, own calculations.

Since the 85-15 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 percentiles 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 Figure 3 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 becomes apparent. Figure 4 shows a noticeable increase between 2000 and 2008. However, in the following years inequality at the upper part of the wage distribution in the manufacturing sector 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.

In order to prepare for the detailed analysis of the change in wage inequality, we first examine the changes in the wage distribution over time. The descriptive analysis is conducted using kernel density estimations of the log wage distributions

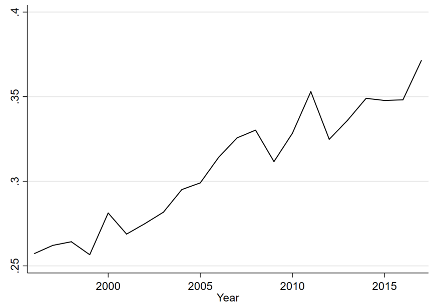

Figure 3: 50-15 log wage gap
Source: LIAB QM2 9317, own calculations.

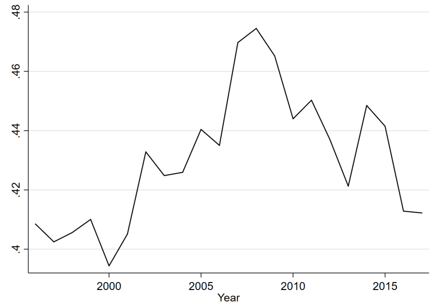

Figure 4: 85-50 log wage gap
Source: LIAB QM2 9317, own calculations.

of the respective years.[10] As it is evident from the previous part, major increases in wage inequality are observable until the late 2000s. Thereafter, a different development becomes apparent and no major increases in wage inequality are observed. Due to this result, we divide our whole period of observation into two subperiods, 1996-2010 and 2012-2017.[11]

Figure 5 presents the wage densities of 1996 and 2010 for full-time working men in the manufacturing sector in Germany. 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. This observation is also supported by the presented difference between the two wage distributions, which shows higher positive values in the second half of the wage distribution. This confirms the trend of an increasing wage gap in the upper half of the wage distribution, shown in Figure 4. However, it seems that especially in the middle of the distribution a shift to the right is the reason for changes in wage inequality. Thus, the more or less constant distribution at lower wages and the change in the middle of the distribution explain the increase in the 50-15 percentile wage gap, presented in Figure 3.

The changes in the wage distribution and the corresponding difference between 2012 and 2017 are illustrated in Figure 6. During this period a different development is confirmed. The shift of the wage distribution to the right is more

[10]Illustrating wage distributions using kernel density estimations demands two decisions. For one thing, as the kernel function the Gaussian kernel function is chosen. Apart from this, the bandwith, which influences the appearance of the density curve much more than the kernel function, has to be set (Kohler and Kreuter, 2012). The optimal value of the bandwidth is found by using a simple rule introduced by Silverman (1986): $0.9 * m * n^{-1/5}$, where m is the minimum standard deviation and n the number of observations (Schnell, 1994).

[11]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).

pronounced, since the displayed difference is either close to zero or negative in the lower half of the distribution. 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. This trend confirms the results of an increasing inequality in the lower half and a decreasing inequality of the upper half of the wage distribution illustrated in Figures 3 and 4.

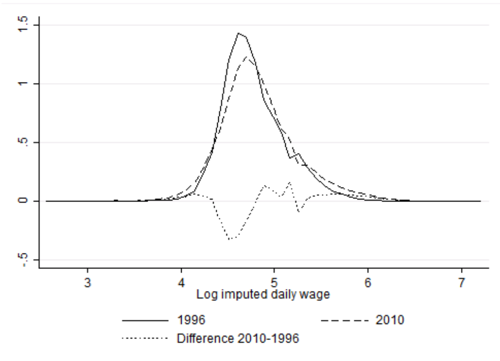

Figure 5: Change in wage distribution, 1996-2010

Source: LIAB QM2 9317, own calculations.

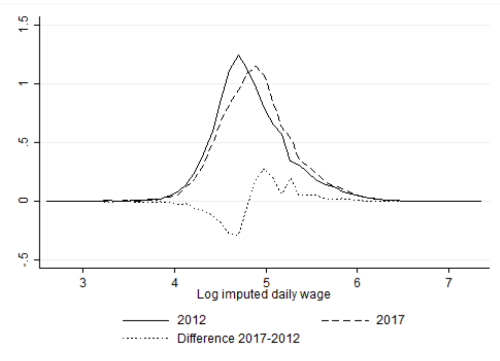

Figure 6: Change in wage distribution, 2012-2017

Source: LIAB QM2 9317, own calculations.

4.2 The Rise of Automation and Robotization

In order to give an overview of the evolution of automation and robotization, we use the number of operative industrial robots worldwide published by the International Federation of Robotics. Figure 7 illustrates the number of operative industrial robots worldwide from 1993 to 2017 and the corresponding contribution of Asia, Europe and North America. Particularly, in the last decade the number of operative industrial robots worldwide has doubled to almost 2.1 million in 2017. Hence, industrial robots grow by a much larger rate than the gross domestic product or the population worldwide leading to an increase in the robot density. Asia has by far the highest number of industrial robots in the world over the considered period. The operational stock of industrial robots in Asia increased from almost 400,000 in 1993 to 1,2 million in 2017. However, Asia's share of the global stock of robots declined from nearly 69% in 1993 to almost 59% in 2017. Europe was the second largest market in 1993 with a stock of 129,000 industrial robots, while the contribution of North America was rather small. In the last twenty-four years North America increased their share of robots from almost 8% in 1993 to more than 14% in 2017, while Europe stagnated with a share of more than 23%.

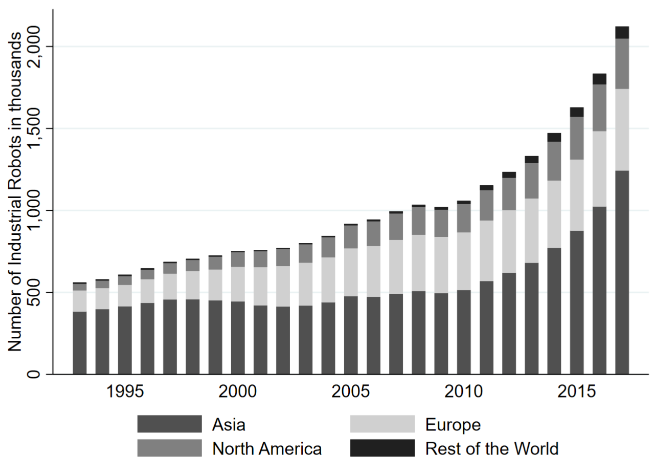

Figure 7: Operational stock of industrial robots worldwide from 1993 to 2017
Source: International Federation of Robotics (2018).

The total number of robots might be an inappropriate measure when comparing countries with different economic size. Thus, we have a closer look on the robot density which is the number of robots relative to the number of workers. Figure 8 compares the robot density in the German and US-American industry and separably in the corresponding manufacturing sector. While in both countries the robot density in the whole economy and in the manufacturing sector is increasing, Germany faces a much higher robot density than the United States. The robot density in German overall industries increased from almost 2 robots per thousand workers in 1997 to around 5 robots per thousand workers in 2017, whereas the robot density in the United States increased from 0.5 up to almost 1.8 robots per thousand workers. In both countries the robot density is higher in the manufacturing sector compared to the overall economy. This points to the fact that automation plays a predominant role in the manufacturing sector. The robot density in Germany in the manufacturing sector increased from 8.9 robots per thousand workers in 1997 to nearly 23 robots per thousand workers in 2017. While the robot density in the manufacturing sector in the United States in 2004 is almost equal to the robot density in the total economy, the robot density in the manufacturing sector rises much stronger from 0.9 up to almost 19 robots per thousand workers.[12]

Another dimension to measure the effect of automation is the substitutability potential of occupations. In order to have a closer look at different occupations, we aggregate the substitutability potential provided by Dengler and Matthes (2015)

[12]The IFR does not provide robot data at the industry level in the United States until 2004.

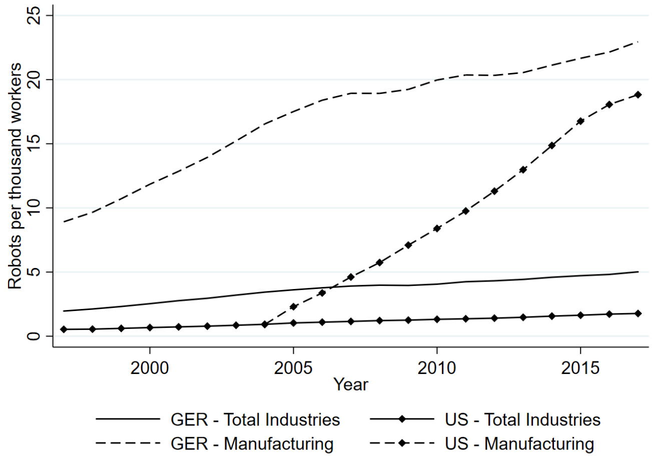

Figure 8: Industrial robot density in Germany and USA from 1997 to 2017

Source: International Federation of Robotics (2018) and Stehrer et al. (2019), own calculations.

to five occupational sectors.[13] Due to the fact that the effect of automation differs to a large extent between task levels, we provide the substitutability potential of occupational sectors for each task level, see Figure 9. In general the task levels with higher educational requirements are faced with a lower potential of substitution. One exception is the substitutability potential in production and personal service occupations. At first glance it seems to be implausible that specialist activities which require at least two years of vocational training are more affected by digitalisation than unskilled or semi-unskilled activities. However, it may be more easy to code specialist activities into programmable algorithms than tasks of unskilled workers who perform to a large extent non-routine activities that cannot be easily automated, see Dengler and Matthes (2015).

The substitutability potential in production occupations, such as agricultural occupations, manufacturing occupations or construction occupations, is between 36% for highly complex activities and 63% for specialist activities. Employees in a personal service occupation are faced with a much less potential of substitution between 5% and 25%. Service occupations in the business sector are more affected by digitalization. The substitutability potential lies between 23% for highly complex activities and 56% for unskilled activities. Turning to the IT and scientific occupations, it seems to be surprising that those occupations are faced with very high substitutability potentials. One reason is that there are only few occupations with unskilled activities. In this occupational sector unskilled activities occur only

[13]Matthes et al. (2015) provide different aggregation levels of the occupation classification KldB 2010 in Germany.

in chemical and pharmaceutical engineering which have a substitutability potential of 83%. Another reason is that, beside experts, the IT and scientific occupations in particular have rather high potential of substitution because many activities are turned into routine activities. IT specialists are already writing algorithms which are able to write algorithms on itself and thus relieve them of simple programming activities, see Dengler and Matthes (2015). The last occupational sector combines other economic service occupations like security occupations, transport and logistic occupations and cleaning occupations. Disregarding from unskilled activities with 48% the substitutability potential of the other task levels are relatively low between 20% and 26%.

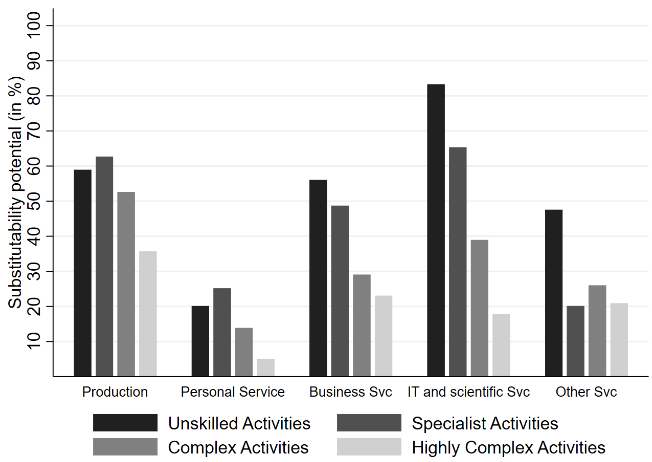

Figure 9: Substitutability potential of each occupation sector by task levels in Germany

Source: Dengler and Matthes (2015), own aggregation based on employment numbers on 30th of June 2014 provided by the German Federal Employment Agency, see `https://statistik.arbeitsagentur.de/Statistikdaten/Detail/201406/iiia6/beschaeftigung-sozbe-bo-heft/bo-heft-d-0-201406-xlsx.xlsx?__blob=publicationFile&v=1`.

5 Empirical Approach

The RIF regression approach introduced by Firpo et al. (2018) provides an intuitive way of estimating a detailed decomposition of the overall change in wage inequality over time. It is possible to account for several covariates and their respective influence on the outcome variable for which an influence function can be computed. Further, it allows us to make a distinction between a composition effect and a wage structure effect. This method is closely linked to the well-known decomposition method introduced by Oaxaca (1973) and Blinder (1973) and can be regarded as an extension of it. While in the standard approach the mean of the distribution is the variable of interest, using RIF regressions allows to account for changes in percentile wage gaps, the variance or the Gini coefficient. In the following, we present in the first subsection a short summary of the standard OB decomposition and the details of the RIF regression approach. In the second subsection, we describe the applied covariates and introduce our automation threat variable in more detail.

5.1 Method

Oaxaca-Blinder Decomposition. The standard OB decomposition divides the overall mean wage gap between two defined groups, in our case two points in time, into a composition effect and a wage structure effect. The first effect is linked to changes in the covariates over time and the latter effect to changes in the conditional wage distribution over time (Oaxaca 1973 & Firpo et al. 2018).

In general, a linear wage equation is assumed:

$$w_t = X'\beta_t + v_t, \tag{1}$$

where w_t denotes the log wage, X' a vector of covariates and $E[v_t|X] = 0$. Further, two points in time are considered, either $t = 0$ or $t = 1$.

The overall mean wage gap is given by $\hat{\Delta}^{\mu}_{O}$:

$$\begin{aligned} \hat{\Delta}^{\mu}_{O} &= \bar{X}_1\hat{\beta}_1 - \bar{X}_0\hat{\beta}_0 + \bar{X}_1\hat{\beta}_0 - \bar{X}_1\hat{\beta}_0 \\ &= \bar{X}_1(\hat{\beta}_1 - \hat{\beta}_0) + (\bar{X}_1 - \bar{X}_0)\hat{\beta}_0 \\ &= \hat{\Delta}^{\mu}_{S} + \hat{\Delta}^{\mu}_{X}. \end{aligned} \tag{2}$$

The first part of equation (2) denotes the wage structure effect, $\hat{\Delta}^{\mu}_{S}$, which is the result of holding the distribution of covariates constant and only modifying the conditional wage structure. The second part is the composition effect, $\hat{\Delta}^{\mu}_{X}$, 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 order to quantify the specific effect of each covariate relative to the other included factors, the wage structure effect and the composition effect can be written in terms of sums over the explanatory variables to compute the detailed decomposition:

$$\hat{\Delta}_S^{\mu} = (\hat{\beta}_{10} - \hat{\beta}_{00}) + \sum_{k=1}^{M} \bar{X}_{1k}(\hat{\beta}_{1k} - \hat{\beta}_{0k}) \tag{3}$$

$$\hat{\Delta}_X^{\mu} = \sum_{k=1}^{M} (\bar{X}_{1k} - \bar{X}_{0k})\hat{\beta}_{0k}, \tag{4}$$

where $(\hat{\beta}_{10} - \hat{\beta}_{00})$ represents the constant and thus the omitted group effect.[14] $\bar{X}_{tk}$ and $\hat{\beta}_{tk}$ represent the kth element of $\bar{X}_t$ and $\hat{\beta}_t$, respectively. This procedure is valid under the additive linearity assumption, which makes the detailed decomposition possible. In other words, the two terms $\bar{X}_{1k}(\hat{\beta}_{1k} - \hat{\beta}_{0k})$ and $(\bar{X}_{1k} - \bar{X}_{0k})\hat{\beta}_{0k}$ are the respective contributions of the kth covariate on the wage structure effect and the composition effect (Firpo et al. 2018 & Fortin et al. 2011).

RIF Regression Approach. The RIF regression 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). This implicates that estimating the regression, the dependent variable, w, is replaced by the recentered influence function of the statistic of interest. The influence function, $IF(w; v)$, 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 recentered influence function is the sum of the distributional statistic and the influence function, $RIF(w; v) = v(F_w) + IF(w; v)$, so that it aggregates back to the statistic of interest, $\int RIF(w; v)dF(w) = v(F_w)$. The conditional expectation of the $RIF(w; v)$ can be estimated using a linear function of the explanatory variables:

$$E[RIF(w; v)|X] = X\gamma, \tag{5}$$

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 co-

[14]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).

variates (Firpo et al., 2009). Using the RIF regression 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.[15] The influence function, $IF(w, Q_\tau)$, is given by $(\tau - \mathbb{1}(w \leq Q_\tau))/f_w(Q_\tau)$, where $\mathbb{1}(\cdot)$ is an indicator function, $f_w(\cdot)$ is the density of the marginal distribution of w and Q_τ is the population τ-quantile of the unconditional distribution of w. Therefore, $RIF(w; Q_\tau)$ is equal to the sum of the population τ-quantile and the influence function:

$$\begin{aligned} RIF(w; Q_\tau) &= Q_\tau + IF(w, Q_\tau) \\ &= Q_\tau + \frac{\tau - \mathbb{1}(w \leq Q_\tau)}{f_w(Q_\tau)} && (6) \\ &= c_{1,\tau}\mathbb{1}(w \geq Q_\tau) + c_{2,\tau}, && (7) \end{aligned}$$

where $c_{1,\tau} = 1/f_w(Q_\tau)$ and $c_{2,\tau} = Q_\tau - c_{1,\tau}(1-\tau)$. From equation (7) it follows that the RIF for a quantile is, except for the two constants, $c_{1,\tau}$ and $c_{2,\tau}$, simply the indicator variable $\mathbb{1}(w \geq Q_\tau)$ for whether the outcome variable is smaller or equal to the quantile Q_τ (Fortin et al. 2011 & Firpo et al. 2018).

Thus, in a first step the sample quantiles, $\hat{Q}_\tau$, are estimated, where the density at this point is computed using kernel methods. These estimates, $\hat{Q}_\tau$ and $\hat{f}_w(\hat{Q}_\tau)$, are then inserted into equation (6) to obtain an estimate of the RIF for each observation, $\widehat{RIF}(w_i; Q_\tau)$. With the estimated coefficients of the unconditional quantile regressions, $\hat{\gamma}_{t,\tau}$[16], for each group of $t = 0, 1$ the OB decomposition of equation (2) can be written as:

$$\begin{aligned} \hat{\Delta}_O^\tau &= \bar{X}_1(\hat{\gamma}_{1,\tau} - \hat{\gamma}_{0,\tau}) + (\bar{X}_1 - \bar{X}_0)\hat{\gamma}_{0,\tau} && (8) \\ &= \hat{\Delta}_S^\tau + \hat{\Delta}_X^\tau, \end{aligned}$$

where $\hat{\Delta}_O^\tau$ defines the wage gap at the τth unconditional quantile. The first term of equation (8) 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

[15] While the conditional quantile regressions estimate the return to a specific variable, where the return varies between the different conditional quantiles, the unconditional quantile regressions estimate the impact on a specific point of the wage distribution if a factor changes for everyone of the distribution. Further information on the difference between the two regression methods can be found in Fournier and Koske (2012).

[16] The coefficients of the unconditional quantile regressions for each group are defined as: $\hat{\gamma}_{t,\tau} = (\sum X_i X_i')^{-1} \sum \widehat{RIF}(w_{ti}; Q_{t,\tau}) X_i$, where $t = 0, 1$.

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 (see equations (3) and (4)) (Fortin et al., 2011).

However, as in the standard OB decomposition it could be the case that the linearity assumption does not hold.[17] 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 using the familiar reweighting function introduced by DiNardo et al. (1996).[18] Using the reweighting function the hypothetical 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:

$$\begin{aligned}\hat{\Delta}^{\tau}_{X,R} &= (\bar{X}_{01}\hat{\gamma}_{01,\tau} - \bar{X}_{0}\hat{\gamma}_{0,\tau}) + (\bar{X}_{01}\hat{\gamma}_{0,\tau} - \bar{X}_{01}\hat{\gamma}_{0,\tau}) \\ &= (\bar{X}_{01} - \bar{X}_{0})\hat{\gamma}_{0,\tau} + \bar{X}_{01}(\hat{\gamma}_{01,\tau} - \hat{\gamma}_{0,\tau}) \\ &= \hat{\Delta}^{\tau}_{X,p} + \hat{\Delta}^{\tau}_{X,e},\end{aligned} \tag{9}$$

where the first part of the right-hand side of equation (9) corresponds to the pure composition effect, while the second part represents the specification error. The latter one denotes the difference between the total wage structure effect in the initial OB decomposition and the reweighted regression decomposition.

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

[17] 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.

[18] The reweighting function introduced by DiNardo et al. (1996) is defined as:

$$\hat{\psi}_X(X) = \frac{Pr(t_X = 0)}{Pr(t_X = 1)}\frac{Pr(t_X = 1|X)}{Pr(t_X = 0|X)},$$

where $Pr(t_X = 0)$ and $Pr(t_X = 1)$ denote the sample proportions of observations of the respective point in time in the pooled data. The proportions $Pr(t_X = 0|X)$ and $Pr(t_X = 1|X)$ are reminiscent of a standard binary dependent variable. Therefore, the likelihood that an observation is at point in time $t = 0$ conditional on the covariate X can be estimated using a logit or a probit model based on the pooled sample (Fortin et al., 2011).

and the counterfactual sample $t = 01$:

$$\begin{aligned}\hat{\Delta}^{\tau}_{S,R} &= (\bar{X}_1\hat{\gamma}_{1,\tau} - \bar{X}_{01}\hat{\gamma}_{01,\tau}) + (\bar{X}_1\hat{\gamma}_{01,\tau} - \bar{X}_1\hat{\gamma}_{01,\tau}) \\ &= \bar{X}_1(\hat{\gamma}_{1,\tau} - \hat{\gamma}_{01,\tau}) + (\bar{X}_1 - \bar{X}_{01})\hat{\gamma}_{01,\tau} \\ &= \hat{\Delta}^{\tau}_{S,p} + \hat{\Delta}^{\tau}_{S,e},\end{aligned} \tag{10}$$

where the first term of the right-hand side of equation (10) defines the pure wage structure effect and the second part denotes the reweighting error. Thus, the first part ensures that the difference $(\hat{\gamma}_{0,\tau} - \hat{\gamma}_{01,\tau})$ represents the true underlying difference between the two groups regarding the wage structure. The latter part is defined as the difference between the total explained effect across the initial OB decomposition and the reweighting regression decomposition. In other words, 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 regression 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. For the two distributional statistics, variance and Gini coefficient, the RIF-regressions have to be adjusted accordingly (see Firpo et al., 2018).

The RIF regression based decomposition method has several advantages. The fact that the method uses simple regressions that are easy to interpret provides a straightforward way of a detailed decomposition. Moreover, the underlying linearity of RIF-regressions is an important factor of this procedure and guarantees monotonicity. Compared to the sequential decomposition introduced by DiNardo et al. (1996) (DFL-method), the RIF regression based detailed decomposition does not suffer from path dependence. Further, since this method makes it possible to conduct the OB decomposition at other parts than the mean of the wage distribution, the property of censored wage observations should not pose severe problems in this analysis.

However, the RIF regression assumes 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. Compared to the DFL-method, using the RIF regression approach it is not possible to distinguish between explained inequality and residual wage inequality.

Thus, the estimated wage structure effect reflects both the change in wage differentials between different groups as well as the change in wage inequality within groups. As the detailed decomposition is based on the OB decomposition, the estimation of the different contributions to the wage structure effect is sensitive to the base group (Firpo et al., 2018). This has to be kept in mind when it comes to interpretations of categorical variable effects.

5.2 Choice of Explanatory Variables

In our decomposition analysis we 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)[19]; education (three categories)[20]; tenure (five categories)[21]; and a dummy variable capturing German or foreign citizenship. Furthermore, we consider the following two plant characteristics: plant size (six categories)[22]; and the bargaining regime (three categories)[23]. In addition, we control for fixed effects of 8 different manufacturing sectors and include federal state dummies to capture regional shifts.[24]

Our measure of automation threat merges the data on the substitutability 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

[19](1) 18-25 years; (2) 26-35 years; (3) 36-45 years; (4) 46-55 years; (5) 56-65 years.

[20](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.

[21](1) 0-2 years; (2) 2-4 years; (3) 4-8 years; (4) 8-16 years; (5) >16 years.

[22](1) 1-9 employees; (2) 10-49 employees; (3) 50-199 employees; (4) 200-999 employees; (5) 1000-4999 employees; (6) $\geq$5000 employees.

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

[24]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.

the number of robots per 1,000 workers:[25]

$$automation\ threat_{j,s,t} = \theta_j * \frac{Robots_{s,t}}{emp_{s,1995}}. \tag{11}$$

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.[26] 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. 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.

For our decomposition analysis we have to define several groups of automation on the basis of our variable in order to ensure the common support assumption.[27] For this reason, we divide the total number of observations of our automation variable for each year in three equally large groups and define respective cut-off points. As a consequence, we are able to assign every individual to either low, middle or high automation threat in a given year. Detailed descriptive information about our proposed variable is presented in the following.

6 Empirical Analysis

At first we provide results of a descriptive analysis, where we reveal different trends and dynamics in the composition of the workforce and present the sectoral development of the estimated automation threat variable. Moreover, we get a first glance on the contribution of automation to rising wage inequality in Germany.

[25]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.

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

[27]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).

Afterwards we conduct a counterfactual analysis and present our decomposition results in order to identify the importance of specific factors, especially automation, to observed changes in wage inequality.

6.1 Descriptive Analysis

Since one important part of the OB decomposition are changes in the composition of workers, we present in Table 1 the descriptive statistics of our considered explanatory variables. We provide information about four years, because in the subsequent analysis we consider two time periods, 1996-2010 and 2012-2017. 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. In the used data set 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.

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.

Turning to the plant characteristics, one striking development is presented when it comes to the 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, different developments become apparent. On the one hand, there are sectors that shrink over time. The textiles sector decreased significantly between 1996 and 2017 as well as the plastic and chemical products sector and the metal products sector. More or less stable developments are presented for the electronic products sector and the industrial machinery sector. On the other hand, a slight increase in employment share is shown for the food and beverages sector. However, the most striking increase is displayed for the automotive and other vehicles sector. Between 1996 and 2017, the employment share increased from 15% to 23% and is therefore in the last year of observation the largest sub-sector in the manufacturing sector. Regarding the regional developments no major changes are observed. However, two federal states show noticeable developments. Whereas the employment share of North Rhine-Westphalia decreased by around 8 percentage points, the share of workers increased in Bavaria by more than 12 percentage points between 1996 and 2017.

Going into more detail of our automation threat variable, we first take a look at the sectoral development of the estimated automation variable. Figure 10 illustrates the automation threat in Germany across sectors in the manufacturing industry from 1996 to 2017. It is striking that the automotive and other vehicles sector was faced with an extraordinarily 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. Beside the automotive and other vehicles sector, the plastic and chemical products sector and the metal products sector experienced a substantial increases in automation threat between 1996 and 2017. Moderate increases in automation threat can be seen in the industrial machinery sector, the food and beverages sector and the electronic products sector. However, two sectors were faced with a decrease in automation threat over the period of observation. Despite an initial increase in the wood, furniture and paper sector, automation

Table 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, standards errors are given in parentheses. All variables, except the real wage, are reported in percent. Sampling weights are employed.

threat decreased slightly. The second sector with a small reduction in automation threat is the textiles sector, which remains in total more or less stable.

In order to understand the dynamics behind the effect of automation and robotization on changes in wage inequality, we provide descriptive evidence of differences in within-group wage inequality. In Figure 11 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 inequality between

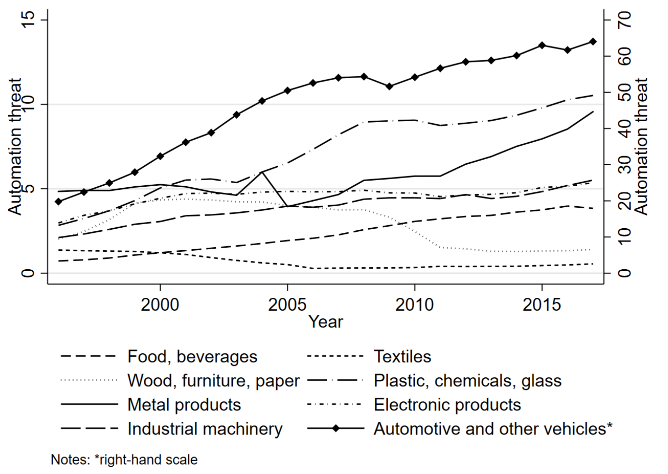

Figure 10: Automation threat in Germany across sectors in the manufacturing industry from 1996 to 2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

1996 and 2008 and the stagnation thereafter becomes apparent. However, there is a substantial difference in the level of inequality between the high automation threat group and the groups with middle and low automation threat. The lowest inequality is found in the highest group of automation threat. In contrast to this, significantly higher wage dispersion is found in the medium and low automation threat groups. Table B.1 in Appendix 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. 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 B.1 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 occupational levels a similar picture emerges. A significant clustering of workers in the second occupational level of specialist activities in the highest group of automation threat becomes apparent. Other levels are much less present. Again the lowest and medium group of automation threat exhibits a more varied distribution of occupational levels and no extremely 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.

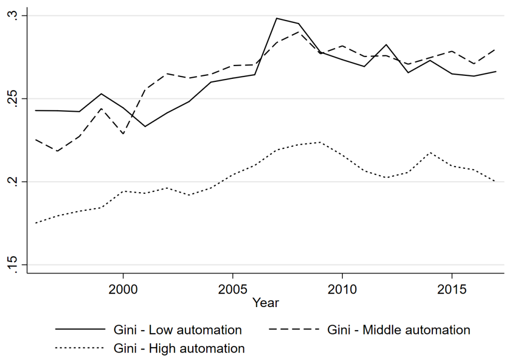

Figure 11: Within inequality of automation threat groups, 1996-2017
Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

6.2 Decomposition Analysis

Due to the observable trends in wage inequality between 1996 and 2017 in Germany, we define two time periods (1996-2010 and 2012-2017) during which wage inequality seems to exhibit different trends. The goal of this section is to identify the importance of specific factors and their respective contributions to observed changes in wage inequality. Our primary focus lies in quantifying the effect of increasing automation and robotization on the wage gap using our proposed variable. In order to get a first impression of the potential impact of automation threat on wage inequality, we conduct a counterfactual analysis looking especially at changes in the wage distribution. Using the RIF regression based OB decomposition allows us then a specific quantification of the automation effect on wage inequality.

1996-2010

Counterfactual Analysis. Since we are mainly interested in the effects 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.[28]

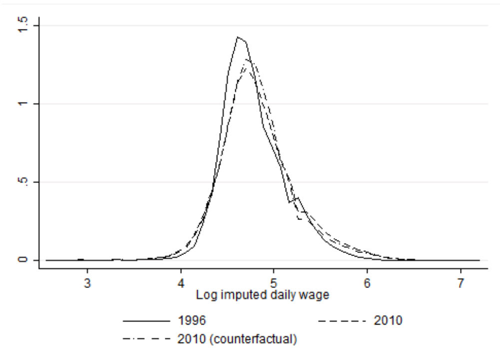

Figure 12: Actual and counterfactual wage distributions, 1996-2010
Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

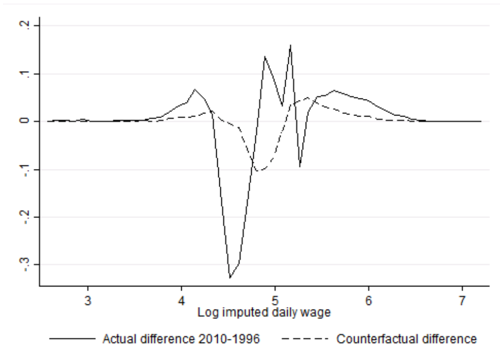

Figure 13: Actual and counterfactual differences, 1996-2010
Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

Figure 12 illustrates the actual wage distributions of 1996 and 2010, which are already presented in Figure 5. 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 reduces inequality if the composition of the automation groups would have been the same in 2010 as in 1996. The distributional change that results by only changing the automation threat is shown in Figure 13. The actual observed change in the wage distribution between 1996 and 2010 (already shown in Figure 5) is compared to the difference between the counterfactual and actual wage distribution in 2010 (dashed line). The analysis shows that the observed trend regarding the automation threat can explain to a certain extent the shift in the upper half of the wage distribution. However, since the counterfactual

[28] The counterfactual distribution, where the distribution of automation groups, r, is shifted back to that of point in time 0, but everything else is fixed at the point in time 1 level, is given by $f_1(w|t_r = 0) = \sum_{r=1}^{3} \omega_{0r} f_{1r}(w)$, where ω_{0r} defines the counterfactual weights for each group of automation r and f_{1r} is the initial wage distribution of point in time 1. For further information see Appendix A.

difference stays close to zero up to the middle of the distribution, a smaller effect on lower wages is assumed. In Figures C.1 and C.7 we re-estimate the 85-15 log wage gap and the Gini coefficient using our counterfactual weights. Indeed, we are able to show that compositional changes in the automation threat groups led to inequality increases between 1996 and 2010 since the counterfactual estimates are at all time below the actual outcomes. Further, Figures C.3 and C.5 confirm 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 of the distribution indicating a higher effect that increases inequality.

Decomposition Results. We conduct the first RIF regression based OB decomposition for the period 1996 and 2010 for men working full-time in the manufacturing sector in West Germany. Table 2 represents the estimated results using the 85-15 percentile wage gap and the Gini coefficient as measures of inequality. Between 1996 and 2010 the wage gap between the 85th and the 15th percentile increased by 10.67 log points, which is almost completely explained by the positive aggregate composition effect. Thus, the increase in inequality is mainly driven by changes in the underlying employment structure. In contrast to this, 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.

The detailed decomposition reveals that changes in the distribution of educational levels and changes in the age structure explain up to 41%[29] 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 specific impact on the composition effect of the automation threat variable accounts for roughly 10%. Thus, we find evidence that automation has a medium positive, highly significant effect on wage inequality in the manufacturing sector during the observed time period. Less pronounced but still significant effects that increase inequality are driven by changes in the composition of the sectors and the nationality variables. A small significant negative effect on inequality is provided by the changes in the composition of the firm size variable, which accounts for roughly 5%.

[29]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%.

Table 2: Decomposition of the 85-15 log 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	1.93	(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.

When we consider the detailed results of the wage structure effects, very different implications become evident. As already described above, the interpretation of the wage structure effects of the respective factors depends on the choice of the base category. Due to this, the specific impact 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. Inequality-increasing wage structure effects occur mainly due to the age, sector and automation covariates. In this case, automation threat belongs to the major driving forces of the aggregate wage structure effect that increase inequality and is statistically significant at the 5% level. Applying the same interpretation as before, we see that the relative importance of automation and robotization regarding the wage structure effect is similar to the composition effect. The observed positive effect could be the result of changes in relative wage returns between workers in high and low automation jobs, as predicted by skill-biased technological change. This would suggest an increase in the relative wage of non-routine skills that are typically at low risk of automation compared to routine skills that are usually faced with higher risk of automation. In this case, a change in between groups wage inequality would be observed. However, all effects that increase inequality are fully compensated by negative effects related especially to tenure and collective bargaining.

As a result of the decomposition of our main inequality measure, 85-15 log wage gap, we conclude that increasing automation and robotization contribute to an increasing wage inequality in the manufacturing sector between 1996 and 2010 by around 10%.

The second inequality measure used for the RIF regression based decomposition is the Gini coefficient, which is presented in the second column of Table 2. Since this measure considers the whole wage distribution, an appropriate comparison with the results of the 85-15 wage gap can be made. 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. However, the same covariates like age and educational levels exhibit the largest statistically significant composition effects that increase inequality. Inequality-decreasing effects are mainly insignificant. Further, the automation threat variable again contributes to inequality and has a positive significant composition effect. Using the Gini coefficient makes it easier to explain the movements behind the effect of automation on inequality in the following. The positive effect stems from the compositional change in the workforce regarding the three automation threat groups. As seen in the descriptive analysis, in the observed period between 1996 and 2010 there is a trend towards the medium automation risk group, accompanied by decreasing high and low automation threat groups. 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 risk groups are mainly negative (see Table B.5)[30]. 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 increase inequality. In other words, in this case the composition effect consists of two negative components, which build together a positive effect on inequality. As a result of this analysis we provide evidence that increasing automation and robotization cause distributional shifts in the composition of the workforce, which result in an inequality-increasing outcome.

Looking at the wage structure effect, the same covariates enhance inequality, where automation threat exhibits the largest significant positive effect. Again, a closer look at the results of the RIF regressions explains this result (see Table B.5). 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 would decrease 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 regression estimates for the medium and high automation risk group either decrease in absolute terms or even get positive. This means that in 1996 the two groups decreased inequality more than in 2010, when everything else being 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 wage structure effect of automation threat is estimated. However, on the opposite there are also wage structure effects that reduce inequality. For example, the negative wage structure effect from tenure completely offsets the positive automation effect. Other inequality-decreasing wage structure effects are either weakly or not statistically significant (nationality and regional effects). 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 for the Variance in the Appendix in order to make it comparable to other existing studies using this inequality measure (see Table B.7). Again, automation threat has a positive and significant composition and wage structure effect using this inequality

[30]In Appendix B, all RIF regression estimation results of the applied inequality measures and percentiles are presented, see Tables B.2 - B.6.

measure.

Table 3: Decomposition of the 50-15 and the 85-50 log wage gap, 1996-2010

Wage differential	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 3 displays 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. 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. When it comes to our proposed automation threat variable we see that in both parts of the wage distribution automation and robotization have the same relative importance of around 10%. In contrast to this, regarding the wage structure effect a different outcome become apparent. The automation threat has a clear positive and significant wage effect on the 50-15 percentile wage gap. As a result of this, evidence for skill-biased technological change especially for the lower half of the wage distribution can be found. In contrast to this, there is a medium negative wage structure effect of automation threat, that is statistically insignificant, in the upper part of the wage distribution.

2012-2017

Counterfactual Analysis. Until now, we examined in more detail the first period accompanied with a significant increase in wage inequality and analyzed the corresponding driving forces behind it. In the recent years a different development is observed, where the wage dispersion seems to remain constant or even decreases over time. In the following the same analysis as before is done for the second period.

Figure 14 again shows the actual wage distributions in 2012 and 2017 as well as the counterfactual distribution in 2017, where the composition of the automation threat groups is shifted back to 2012. 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 15. The observed trend, where less workers are exposed to a high threat of automation explains very well the small shift of the upper half of the wage distribution. 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. Again, the standard inequality measures are re-estimated accounting for counterfactual weights (see Appendix C). In this case, we also find supporting results of the above described findings.

Decomposition Results. In the more recent time period the increase in the wage gap between the 85th and the 15th percentile is less pronounced and increased by

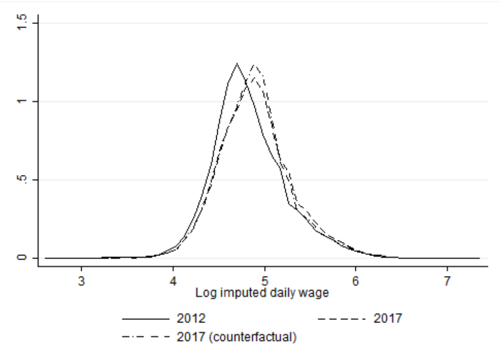

Figure 14: Actual and counterfactual wage distributions, 2012-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

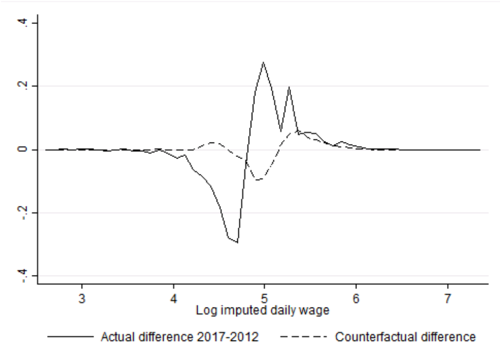

Figure 15: Actual and counterfactual differences, 2012-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

only 2.17 log points, see the first column of Table 4. This is due to the opposing effects of the positive aggregate composition effect and the negative aggregate wage structure effect.

In comparison to the first time period the change in the age structure is no more statistically significant in explaining the composition effect. Changes in the distribution of educational levels explain around 27% of the composition effect. The effect of automation is much more pronounced in the actual time period. The impact on the composition effect of automation threat accounts for around 41%. Hence, we find evidence that automation is one of the major driving forces behind positive significant effects on wage inequality in the manufacturing sector. Small but still significant effects that increase inequality are driven by changes in the composition of the sector, firm size and nationality variables. Tenure and the bargaining regime have a small significant negative effect on inequality due to changes in their composition. In comparison to the time period between 1996 and 2010, 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 is the major effect. Inequality-increasing wage structure effects occur mainly from the nationality and collective bargaining variable. Negative wage structure effects appear especially from age, tenure, education and regional differences.

The decomposition results for the Gini coefficient show a slightly decrease in the overall wage inequality during the considered time period, see the second column of Table 4. The aggregate composition effect is positive and significant but quite small with 0.77 points. Educational levels, automation and the plant size are the largest statistically significant composition effects that raise inequality. Automation explains one quarter of the aggregate composition effect and is highly

Table 4: Decomposition of the 85-15 log 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.

significant. These findings are supported by the observed shift from 2012 to 2017 towards 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 B.5). Thus, we see here the same dynamics behind the inequality-increasing effect through automation. Small but still significant effects that decrease inequality are driven by changes in the composition of tenure and the bargaining regime. The results of the detailed wage structure effect are more or less equal to the results of the 85-15 percentile wage gap, although we find a statistically significant inequality-decreasing effect driven by automation. This finding is supported by the decomposition result for the Variance in the Appendix (see Table B.7).

Table 5 depicts the decomposition results of the 50-15 and the 85-50 percentile wage gaps. 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 point. The reason for this is the large negative wage structure effect for the 85-50 percentile wage gap. Age, tenure, education, automation and regional differences are the largest statistically significant inequality-decreasing wage structure effects at the upper part of the wage distribution. Thus, automation threat accounts as a significant inequality-decreasing wage structure effect for the upper end of the wage distribution. In contrast to this, the wage structure effect of automation threat is statistically insignificant for the 50-15 percentile wage gap.

Turning to the detailed composition effect, automation has a positive and highly significant effect on wage inequality at the upper and lower end of the wage distribution. It is evident that workers at the upper part of the wage distribution are more affected by automation (41%) then the lower part of the wage distribution (26%). This observed difference in the relative importance of automation and robotization along the wage distribution confirms the results of the graphical representation from the counterfactual analysis done before.

6.3 Robustness Check

To further support our results concerning the effect of automation and robotization on wage inequality, we implement two robustness checks.

Alternative Automation Variable. One might worry about the use of robots as a proxy variable for automation. In a robustness check, we exclude the sectoral developments of operational robots in our automation threat variable. Based on the automation probabilities for occupation-task level combinations by Dengler and Matthes (2015), we use three automation risk categories. Low automation risk is given if a maximum of 30% of the occupation could be performed by computers, which is the base category in the decomposition regression. Middle automation

Table 5: Decomposition of the 50-15 and the 85-50 log 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.

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.[31] The decomposition results are depicted in Table B.8 and Table B.9 in the Appendix. The results for the composition effect of the automation variable are similar, although a bit less pro-

[31]Kaltenberg and Foster-McGregor (2020) use a similar measure of automation risk, but in contrast to our analysis the authors use automation probabilities provided by Frey and Osborne (2017).

nounced. The only difference in the results is the contribution of the automation variable to the wage structure effect between 2012 and 2017. Using the alternative measure, automation has a positive and significant effect on the 85-15 and 85-50 percentile wage gap. Nevertheless, our main results are not solely driven by the sectoral evolution of robots.

Automotive and other Vehicles Sector. The automotive and other vehicles sector is by far the most affected sector by automation threat, see Figure 10. In order to check whether our results are mainly driven by the development in this sector, we exclude the automotive and other vehicles sector in Table B.10 and Table B.11 in the Appendix. The main results for the automation threat variable are more or less the same. One difference becomes apparent by considering the wage structure effect of the automation variable from 2012 to 2017. By excluding the automotive and vehicles sector, automation has now a positive and significant wage effect on the 85-15 percentile wage gap. This is due to the fact that automation has a large positive and highly significant wage effect on the 50-15 percentile wage gap, while automation has no more a highly significant negative wage effect on the upper end of the wage distribution. However, our results are not driven by the dynamic trend in the automotive and other vehicles sector.

7 Conclusion

An increase in wage inequality during the last decades in many industrialized countries accompanied with a rise in automation lead to a widely discussion if automation causes rising wage inequality. Germany is faced with one of the highest industrial robot density in the world, thus the impact of automation on wage inequality, if there is one, should be observable in Germany. In this paper we focus on the specific quantification of the effect of increasing automation and robotization on wage dispersion in the German manufacturing sector between 1995 and 2017. We find evidence that automation has a positive and highly significant effect on wage inequality in the manufacturing sector during the considered time period.

We construct an automation threat variable, where we combine occupation-specific scores of automation risk with yearly sector-specific robot densities. Using rich linked employer-employee data (LIAB data) we are able to account for a variety of different individual, firm and industry characteristics. In order to quantify the actual contribution of automation on increasing wage inequality in Germany, we apply the RIF regression based Oaxaca-Blinder decomposition on several inequality indices. Regarding our main inequality measure, the 85-15 log wage gap, we see that automation and robotization contribute by around 10% to the total increase in wage inequality between 1996 and 2010. Both, the composition and wage structure effect, play a significant role on how automation and robotization affect wage inequality. First, there is an observable trend towards the medium automation threat group, accompanied by decreasing high and low automation threat groups. Due to the fact that within-group wage inequality is the lowest in the group with the highest automation threat, those compositional changes lead to an increase in wage inequality. This result is also supported by a counterfactual analysis, where a graphical representation provides empirical evidence of a clear inequality-increasing effect of the rise of automation and robotization. Second, we find evidence that changes in relative wage returns between workers with high and low automation threat lead to rising wage inequality. As predicted by skill-biased technological change, we find evidence that the relative wage of non-routine skills that are typically at low risk of automation are increasing compared to routine skills that are usually faced with higher risk of automation. Increasing wage inequality driven by changes in the relative wages between the three automation threat groups occurs at the lower part of the wage distribution and plays no significant role at the upper part of the wage distribution.

In the more recent period, the inequality-increasing effect due to compositional changes in automation threat is much more pronounced. Workers at the upper part of the wage distribution are more affected by automation then workers at the lower part of the wage distribution. The impact on the wage structure effect of automation threat differs across the considered inequality measures. While the automation related wage structure effect for the 85-15 percentile wage gap is no more significant, we find evidence that automation has a decreasing effect on the Gini coefficient. Further, automation seems to have a decreasing wage inequality effect on the upper part of the wage distribution due to changes in the relative wages between the three automation threat groups.

Those findings are in line with the decomposition results of Kaltenberg and Foster-McGregor (2020), who implement a simpler variable of automation risk of an occupation. They find evidence that the composition effect of increasing automation contributes to a large part to wage inequality in 10 European countries, while the wage effect explains automation related inequality in half of the countries. Moreover, in line with our findings in the more recent time period, Kaltenberg and Foster-McGregor (2020) show that the automation related composition effect occur mainly at the upper part of the wage distribution.

Our analysis contributes to a better understanding of the influence of automation and robotization on wage inequality in Germany. Especially structural shifts in the workforce composition towards occupations with lower automation threat lead to higher wage inequality. Due to our data structure we are not able to analyze if workers are forced into unemployment as a result of increasing automation in their occupational field. Future research could examine whether this possible circumstance is able to increase overall inequality even further.

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Appendix A

Wage Imputation proposed by Gartner (2005). The main intuition behind all imputation approaches is the assumption that the log wage, w, for every person i is given by

$$w_i = x_i'\beta + v_i,\ i = 1, ..., n \tag{A.1}$$

where x_i are covariates and $v_i \sim N(0, \sigma^2)$ is the error term. For censored data, wage observations lower than the contribution limit, a, are given as their actual value, $w_{obs,i} = w_i$. In contrast, wages that are greater or equal to a are denoted as the limit a instead of the true value w_i. This results in:

$$w_i = \begin{cases} w_{obs,i} \text{ if } w_i < a \\ a \text{ if } w_i \geq a. \end{cases} \tag{A.2}$$

In order to analyse the whole wage distribution, wages above a have to be imputed. For this, $w^{imp} = (w_{obs}, z)$ is defined, where z is a truncated variable in the range of (a, ∞) (Büttner and Rässler, 2008). Since it is known that the true value of censored wages is above the contribution limit, the imputed wage should be grater than a. According to the imputation method introduced by Gartner (2005) the imputed wage, $ln(w^{imp})$, is a random value drawn from a normal distribution $N(x_i'\hat{\beta}, \sigma^2)$. This means that to the expected wage, $x_i'\hat{\beta}$, an error term η is added:

$$ln(w_i^{imp}) = x_i'\hat{\beta} + \eta_i, \tag{A.3}$$

where η has the standard deviation σ, which is estimated from a tobit estimation (Büttner and Rässler, 2008). In order to estimate wage observation above the social security contribution ceiling, a drawing of a random variable from a truncated distribution has to be made. The standard core of the upper limit and the imputed wage is then given as $\alpha = \dfrac{(a - \mu)}{\sigma}$ and $\epsilon = \dfrac{(ln(w_i)^{imp} - \mu)}{\sigma}$, where ϵ is standard normal distributed $g(\epsilon) = \phi(\epsilon)$. In order to draw a random value from this distribution the condition $\epsilon > \alpha$ must hold. As a result of this, the truncated standard normal distribution is defined as:

$$g(\epsilon|\epsilon > \alpha) = \frac{f(\epsilon)}{1-\Phi(\alpha)}, \epsilon > \alpha. \tag{A.4}$$

The truncated distribution function $G(\epsilon)\epsilon \to Y$ with $Y \in [0,1]$ is then given by:

$$G(\epsilon) = \int_{\alpha}^{\epsilon} \frac{\phi(z)}{1-\Phi(\alpha)} dz \tag{A.5}$$

Splitting the integral leads to:

$$G(\epsilon) = \frac{1}{1-\Phi(\alpha)} \left(\int_{-\infty}^{\epsilon} \phi(t)dt - \int_{-\infty}^{\alpha} \phi(t)dt \right) \tag{A.6}$$

$$G(\epsilon) = \frac{1}{1-\Phi(\alpha)} (\Phi(\epsilon) - \Phi(\alpha)). \tag{A.7}$$

Since ϵ is the variable of interest, the inverse function $G^{-1}(Y)$, where $Y = \frac{1}{1-\Phi(\alpha)}(\Phi(\epsilon) - \Phi(\alpha))$ is needed. $\Phi(\epsilon)$ is then defined as $\Phi(\epsilon) = Y(1-\Phi(\alpha)) + \Phi(\alpha)$. Taking on both sides the inverse Φ^{-1} the following results:

$$\epsilon = \Phi^{-1}(Y(1-\Phi(\alpha)) + \Phi(\alpha)). \tag{A.8}$$

Assuming a truncated standard normal distribution the imputed log wage, $ln(w^{imp})$, can be estimated as follows:

$$ln(w_i^{imp}) = \epsilon_i \hat{\sigma} + x_i' \hat{\beta}. \tag{A.9}$$

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:

$$f_1(w|t_r = 0) = \sum_{r=1}^{3} \omega_{0r} f_{1r}(w), \tag{A.10}$$

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.

Appendix B

Table B.1: Descriptive statistics of the automation threat variable

	1996	2010	2012	2017
Automation Threat: low				
Real daily wage	127.62	141.74	143.28	140.54
Education: low	12.58	8.67	6.13	4.55
Education: middle	75.48	71.60	72.33	76.98
Education: high	11.94	19.73	21.55	18.47
Occupational level: unskilled activities	0.78	0.79	9.11	10.21
Occupational level: specialist activities	67.82	56.24	44.95	52.64
Occupational level: complex activities	17.25	15.78	25.12	20.51
Occupational level: highly complex activities	14.15	27.19	20.82	16.64
Automation Threat: middle				
Real daily wage	147.36	145.86	158.28	160.45
Education: low	9.60	7.56	4.86	4.88
Education: middle	68.56	70.59	65.93	66.37
Education: high	21.84	21.85	29.21	28.74
Occupational level: unskilled activities	1.07	2.77	10.92	12.42
Occupational level: specialist activities	55.65	59.56	36.35	36.24
Occupational level: complex activities	25.86	23.67	26.58	26.83
Occupational level: highly complex activities	17.43	14.01	26.15	24.52
Automation Threat: high				
Real daily wage	121.20	133.85	128.65	143.43
Education: low	12.78	9.06	8.25	6.80
Education: middle	81.44	81.03	83.63	83.69
Education: high	5.78	9.92	8.12	9.51
Occupational level: unskilled activities	3.10	1.16	16.34	12.61
Occupational level: specialist activities	83.53	84.88	68.39	68.86
Occupational level: complex activities	9.40	7.76	10.51	11.58
Occupational level: highly complex activities	3.98	6.19	4.75	6.94

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. Sampling weights are employed.

Table B.2: 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	0.0997***	0.0984***	0.1237***	0.0993***
years	(0.0219)	(0.0232)	(0.0179)	(0.0222)
Tenure: 4-8	0.2144***	0.1975***	0.1875***	0.2661***
years	(0.0189)	(0.0241)	(0.0177)	(0.0231)
Tenure: 8-16	0.2721***	0.3239***	0.2938***	0.3606***
years	(0.0189)	(0.0267)	(0.0187)	(0.0240)
Tenure: $\geq$ 16	0.3412***	0.4645***	0.4519***	0.4806***
years	(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	0.0021	-0.0563***	-0.0042	-0.0350
threat: middle	(0.0099)	(0.0117)	(0.0097)	(0.0244)
Automation	-0.0180*	-0.0673***	-0.0314***	-0.0191
threat: high	(0.0108)	(0.0109)	(0.0097)	(0.0221)
Firm level agree-	-0.0097	0.1666***	0.1377***	0.1274***
ment	(0.0198)	(0.0072)	(0.0069)	(0.0090)
Sector level	0.0379**	0.1762***	0.1781***	0.1863***
agreement	(0.0172)	(0.0071)	(0.0066)	(0.0074)
Plant size: 1-9	-0.3037***	-0.6222***	-0.6038***	-0.5561***
employees	(0.0320)	(0.0358)	(0.0365)	(0.0481)

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Table B.2 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
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: $\geq$ 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)
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)

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Table B.2 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
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 B.3: 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)

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Table B.3 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
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: ≥ 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)
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: ≥ 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)

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Table B.3 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
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)
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 B.4: 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)
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)

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Table B.4 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
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: ≥ 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)
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)

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Table B.4 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
Hesse	0.0045	-0.0313***	-0.0214**	0.0129
	(0.0137)	(0.0072)	(0.0085)	(0.0083)
Rhineland-	-0.1184***	-0.0664***	-0.0317***	-0.0189**
Palatinate	(0.0123)	(0.0066)	(0.0082)	(0.0090)
Baden-	-0.0088	0.0319***	0.0879***	0.0679***
Wuerttemberg	(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 B.5: 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	-0.0139***	-0.0326***	-0.0332***	-0.0325***
years	(0.0014)	(0.0028)	(0.0023)	(0.0027)

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Table B.5 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
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)
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)

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Table B.5 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
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)
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 B.6: 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)
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)

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Table B.6 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
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)
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)

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Table B.6 – *Continued from previous page*

	1996	**2010**	**2012**	**2017**
Hesse	0.0228***	0.0171***	0.0119***	0.0265***
	(0.0010)	(0.0020)	(0.0017)	(0.0020)
Rhineland-	-0.0121***	-0.0103***	0.0015	-0.0192***
Palatinate	(0.0013)	(0.0021)	(0.0020)	(0.0022)
Baden-	0.0067***	0.0113***	0.0151***	0.0196***
Wuerttemberg	(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 B.7: 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 B.8: Decomposition results of the alternative measure of automation, 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***	(0.43)	4.24***	(0.11)	7.11***	(0.34)	3.56***	(0.27)	5.58***	(0.20)
Pure composition effect										
Age	3.73***	(0.22)	0.68***	(0.05)	1.03***	(0.17)	2.70***	(0.15)	0.73***	(0.07)
Education	4.90***	(0.29)	1.45***	(0.08)	1.05***	(0.07)	3.85	(0.24)	1.48***	(0.09)
Tenure	−0.44*	(0.25)	−0.04	(0.05)	−0.13	(0.19)	−0.31**	(0.15)	−0.05	(0.07)
Nationality	0.07**	(0.03)	0.01	(0.01)	0.04**	(0.02)	0.03	(0.02)	0.03	(0.02)
Automation threat	0.62***	(0.11)	0.08***	(0.02)	0.22***	(0.03)	0.40***	(0.08)	0.10***	(0.02)
Collective bargaining	0.87*	(0.51)	0.39***	(0.12)	0.57	(0.43)	0.30	(0.35)	0.98***	(0.23)
Plant size	−0.57***	(0.11)	−0.20***	(0.03)	−0.49***	(0.08)	−0.08	(0.06)	−0.23***	(0.04)
Region	−0.18***	(0.06)	−0.02	(0.02)	0.00	(0.04)	−0.18***	(0.05)	−0.06***	(0.02)
Sector	0.09	(0.07)	0.04**	(0.02)	−0.20***	(0.05)	0.11**	(0.05)	0.03	(0.03)
Total	8.91***	(0.64)	2.38***	(0.16)	2.10***	(0.44)	6.81***	(0.47)	2.99***	(0.24)
Specification error	−0.34	(0.54)	−0.36***	(0.10)	0.71**	(0.36)	−1.05**	(0.44)	−0.31**	(0.14)
Pure wage structure effect										
Age	4.92***	(1.83)	1.52***	(0.44)	−0.15	(1.63)	5.08***	(1.28)	2.66***	(0.73)
Education	1.65***	(0.52)	0.91***	(0.12)	−0.59***	(0.16)	2.24***	(0.52)	1.39***	(0.15)
Tenure	−16.17***	(4.88)	−2.94***	(1.12)	−15.29***	(4.00)	−0.88	(2.28)	−9.00***	(2.61)
Nationality	−0.39**	(0.18)	−0.03	(0.04)	−0.09	(0.14)	−0.31**	(0.14)	−0.01	(0.07)
Automation threat	2.20	(2.26)	−1.23	(0.82)	4.76***	(1.29)	−6.96***	(2.07)	−1.54	(1.31)
Collective bargaining	−7.53***	(1.22)	−1.16***	(0.26)	−5.48***	(0.88)	−2.06**	(1.04)	0.02**	(0.45)
Plant size	2.42***	(0.68)	0.36**	(0.18)	3.10***	(0.61)	−0.68	(0.58)	1.72***	(0.28)
Region	−0.72	(0.96)	−0.25	(0.24)	−0.91	(0.73)	0.19	(0.76)	−0.74*	(0.40)
Sector	2.87**	(1.33)	0.37	(0.29)	1.86**	(0.95)	1.01	(1.01)	0.71	(0.53)
Constant	18.10***	(5.67)	4.83***	(1.50)	17.14***	(4.05)	0.96	(3.57)	7.91**	(3.14)
Total	2.94***	(0.59)	2.38***	(0.18)	4.37***	(0.48)	−1.42***	(0.47)	3.13***	(0.26)
Reweighting error	−0.84***	(0.16)	−0.16***	(0.05)	−0.06	(0.09)	−0.78***	(0.10)	−0.23***	(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 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 B.9: Decomposition results of the alternative measure of automation, 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***	(0.56)	−0.31***	(0.11)	4.66***	(0.47)	−2.48***	(0.27)	−0.19	(0.20)
Pure composition effect										
Age	−0.05	(0.08)	0.00	(0.02)	-0.03	(0.04)	−0.02	(0.06)	0.01	(0.03)
Education	1.08***	(0.18)	0.30***	(0.05)	0.19***	(0.04)	0.89***	(0.15)	0.35***	(0.07)
Tenure	−0.18***	(0.04)	−0.04***	(0.01)	−0.13***	(0.03)	−0.05**	(0.02)	−0.09***	(0.02)
Nationality	0.01	(0.01)	0.00	(0.00)	0.01	(0.01)	0.01***	(0.00)	0.00	(0.00)
Automation threat	1.24***	(0.12)	0.11***	(0.02)	0.55***	(0.05)	0.69***	(0.09)	0.20***	(0.03)
Collective bargaining	−0.11***	(0.04)	−0.02**	(0.01)	−0.09***	(0.03)	−0.02**	(0.01)	−0.03***	(0.01)
Plant size	−0.51***	(0.12)	0.21***	(0.03)	0.40***	(0.09)	0.12*	(0.07)	0.31***	(0.05)
Region	−0.09	(0.06)	0.00	(0.01)	−0.11***	(0.04)	0.01	(0.04)	−0.03	(0.03)
Sector	0.29***	(0.09)	0.03	(0.02)	0.36***	(0.05)	−0.64**	(0.06)	0.08***	(0.03)
Total	2.12***	(0.25)	0.58***	(0.06)	1.14***	(0.13)	0.98***	(0.20)	0.80***	(0.09)
Specification error	1.47***	(0.12)	−0.07***	(0.01)	0.02	(0.09)	1.45***	(0.10)	−0.08***	(0.01)
Pure wage structure effect										
Age	−6.51***	(1.64)	−1.44***	(0.26)	−0.16	(1.29)	5.35***	(1.07)	−2.10**	(0.49)
Education	−3.31***	(0.52)	−0.41***	(0.06)	0.26	(0.18)	−3.57***	(0.49)	−0.55***	(0.12)
Tenure	−9.08**	(4.23)	−1.83**	(0.90)	−4.05	(3.21)	−5.03**	(2.10)	−1.11	(2.00)
Nationality	0.56***	(0.17)	0.06**	(0.03)	0.41***	(0.13)	0.15*	(0.09)	0.12**	(0.06)
Automation threat	6.26***	(1.74)	−0.29	(0.27)	1.22	(0.99)	5.04***	(1.61)	0.12	(0.39)
Collective bargaining	2.31**	(0.94)	0.49***	(0.16)	1.90**	(0.76)	0.40	(0.60)	1.06***	(0.32)
Plant size	−1.22**	(0.56)	−0.34***	(0.11)	−1.00**	(0.46)	−0.22	(0.36)	−0.50**	(0.20)
Region	−4.03***	(0.84)	−0.90***	(0.18)	−1.28**	(0.65)	−2.75***	(0.68)	−1.36***	(0.39)
Sector	3.22***	(0.91)	0.59***	(0.19)	1.19	(0.80)	2.03***	(0.64)	0.51	(0.38)
Constant	10.83**	(4.63)	3.31***	(1.01)	6.04*	(3.53)	4.79*	(2.50)	2.97	(2.12)
Total	−0.99*	(0.57)	−0.74***	(0.10)	3.53***	(0.45)	−4.52***	(0.29)	−0.84***	(0.18)
Reweighting error	−0.43***	(0.06)	−0.08***	(0.01)	−0.03	(0.02)	−0.40***	(0.05)	−0.08***	(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, 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 B.10: 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 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 B.11: 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 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 C

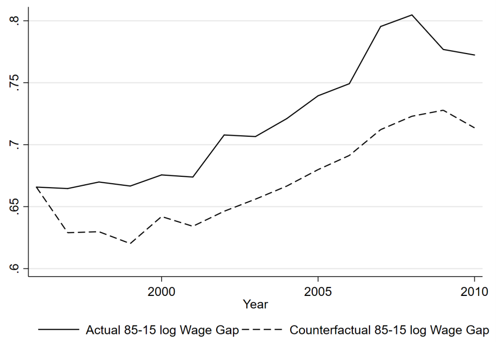

Figure C.1: Actual and counterfactual 85-15 log wage gap, 1996-2010

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

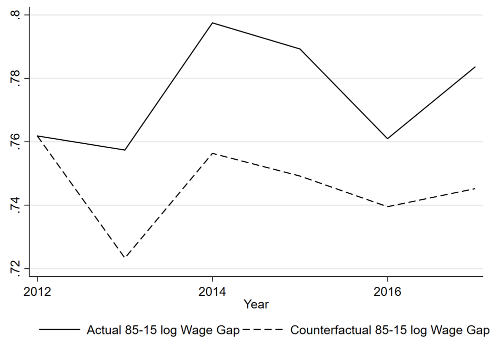

Figure C.2: Actual and counterfactual 85-15 log wage gap, 2012-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

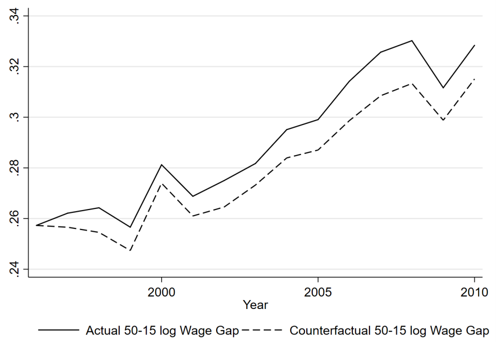

Figure C.3: Actual and counterfactual 50-15 log wage gap, 1996-2010

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

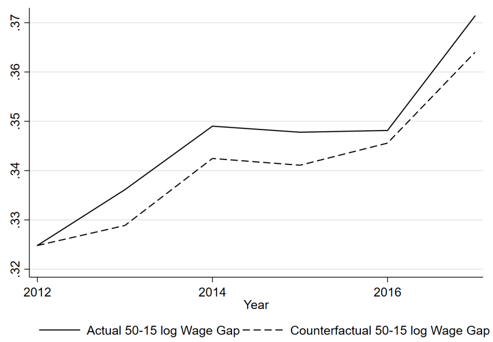

Figure C.4: Actual and counterfactual 50-15 log wage gap, 2012-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

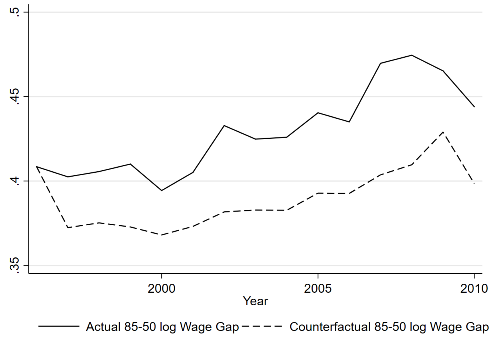

Figure C.5: Actual and counterfactual 85-50 log wage gap, 1996-2010

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

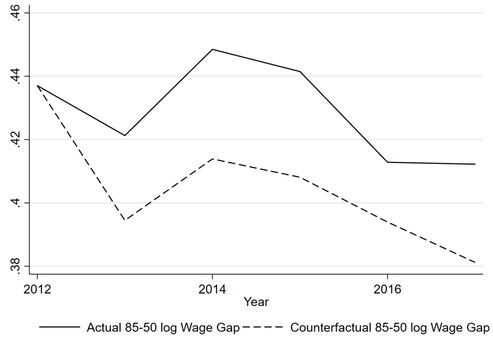

Figure C.6: Actual and counterfactual 85-50 log wage gap, 2012-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

Figure C.7: Actual and counterfactual Gini coefficient, 1996-2010

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

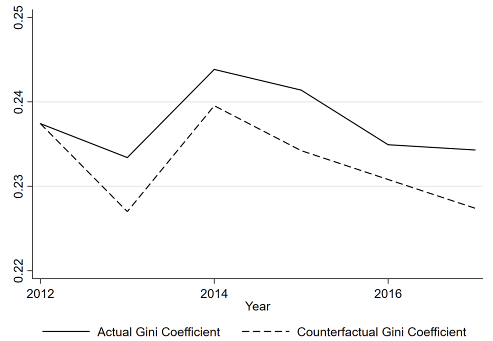

Figure C.8: Actual and counterfactual Gini coefficient, 2012-2017

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

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