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ORIGINAL ARTICLE

Automation, robots and wage inequality in Germany: A decomposition analysis

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Abstract

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

JEL CLASSIFICATION

J31, C21, O33

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 (see e.g., Antonczyk et al., 2018; Card et al., 2013 & Dustmann et al., 2009). At the same time, automation technologies have entered virtually every area in the economy. The manufacturing sector uses widely automated processes that on the one hand increase the productivity of labour but on the other hand also enable the substitution of labour.

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

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

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

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

Regarding the general empirical approach and the applied data, this paper is related to Antonczyk et al. (2010), Biewen and Seckler (2019), Felbermayr et al. (2015) and Baumgarten et al. (2020), who have implemented decomposition analyses of the wage distribution in Germany using linked employer–employee data. Antonczyk et al. (2010) and Biewen and Seckler (2019) analyse the increase in wage inequality in West Germany and show that firm effects, bargaining effects and personal characteristics mainly account for the rise in wage dispersion. Felbermayr et al. (2015) restrict the sample to the manufacturing sector and focus on the contribution of investment in new technologies and international trade to the increase in wage inequality from 1996 to 2010. Their results show that the change in the wage distribution can be explained to a large extent by composition effects, where the traditional factors such as age, education and collective bargaining agreements play the most important roles. Investment in new technologies as well as international trade had no significant influence on wage dispersion. More recently, Baumgarten et al. (2020) enlarge the covered time period up to 2014 and show that overall wage inequality in Germany has been rising up to 2010 before decreasing slightly thereafter.

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

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

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

The remainder of this paper proceeds as follows: Section 2 describes the different data sets used in our empirical analysis. In Section 3, we outline our empirical approach and define our variable quantifying automation threat. Descriptive evidence on the development of wage inequality and automation as well as descriptive statistics of our explanatory variables are revealed in Section 4. Finally, we present our empirical results in Section 5 before we conclude in Section 6.

2 | DATA

2.1 | Labour market data

We use German linked employer–employee data (LIAB), provided by the Research Data Center of the Institute for Employment Research (IAB).¹ The data set combines information on the yearly representative employer survey (IAB Establishment Panel) with the corresponding establishment and individual data, drawn from labour administration and social security. The IAB Establishment Panel has been conducted since 1993 in West Germany as well as since 1996 in East Germany and contains establishments with at least one employee subject to social security. The sample size of the IAB Establishment panel increased from roughly 4000 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 are employed. The data contains personal information of the workers such as gender, year of birth, nationality, vocational training, education and place of residence as well as information on their employment like daily wage, occupation, task level and number of days in employment. Moreover, the data set provides information on the establishments such as the classification of economic activities, total number of employees and region.

We restrict the data to male full-time workers in the manufacturing sector in their main employment between 18 and 65 years, who earned more than 10 Euros per day and consider the time period between 1996 and 2017.² Following the common literature on wage inequality in Germany, we restrict our analysis to West Germany, due to the fact that East and West Germany are still faced with significantly different labour market and wage structures (see e.g., Dustmann et al., 2009, Biewen and Seckler (2019) & Baumgarten et al., 2020). The wage earnings recorded by social security are right-censored at the contribution assessment ceiling of the social security system. To account for this problem, we use imputed wages following the approach by Gartner (2005).³ Non-censored and imputed wages are converted into constant 2015 Euros with the Consumer Price Index provided by the German Federal Statistical Office.

2.2 | Robot data

The data on industrial robots is obtained from the International Federation of Robotics (IFR), which is commonly used in recent analysis (see e.g., Acemoglu & Restrepo, 2020; Anelli et al., 2021; Dauth et al., 2021). The data contain the stock of industrial robots for 50 countries broken down at the industry level, where data availability differs across countries. German robot data is available from 1993 to 2017. An industrial robot is defined as ‘an automatically controlled, reprogrammable, multipurpose [machine]’ (International Federation of Robotics, 2018).⁴ The data rely on primary and secondary data sources. The primary source are yearly surveys of worldwide industrial robot suppliers that report their stock of industrial robots to the IFR. Additionally, the IFR uses secondary data collected by national robot associations to validate the survey data. Before 2004, the data on German industrial robots rely solely on collected data by national robot associations.

The industry classifications in the IFR data are very coarse and differ between the manufacturing and non-manufacturing sector, which is one of the main disadvantage of the data. Away from the manufacturing sector, industries are aggregated to very broad groups, while among the manufacturing sector the data are more disaggregated. Thus, our analysis focuses on the manufacturing sector in Germany due to better data availability and the predominant role of automation in this sector. Industrial robot data reported by the IFR is mainly based on the International Standard Industrial Classification of All Economic Activities (ISIC) Rev. 4.⁵ In total, we focus on eight different manufacturing sectors: 10–12 food products, beverages and tobacco products, 13–15 textiles, wearing apparel, leather and related products, 16–18 wood (including furniture) and paper products, printing and reproduction of recorded media, 19–23 coke and refined petroleum products, chemical products, pharmaceutical products, rubber and plastics products, and other non-metallic mineral products, 24–25 basic metals and fabricated metal products, 26–27 computer, electronic and optical products, electrical equipment, 28 industrial machinery and equipment n.e.c., 29–30 automotive and other vehicles.⁶ The IFR data can be matched with the LIAB data without any crosswalk, for further information see Appendix A.1.

2.3 | Automation risk data

We use an occupation- and requirement-specific score of automation risk. In contrast to the commonly used measure provided by Frey and Osborne (2017), we relate to specific estimations for occupations in Germany based on the task-based approach by Dengler and Matthes (2015). The resulting advantages are presented in the Appendix A.2. 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 3900 single occupations, such as the tasks to be performed in the respective occupation, the equipment or the working conditions. The so called requirement matrices classify 8000 different requirements to each single occupation. Dengler et al. (2014) assign to each requirement one task type (analytical non-routine tasks, interactive non-routine tasks, cognitive routine tasks, manual routine tasks and manual non-routine tasks). The central criterion whether the task is routine or non-routine is the substitutability of computers or computer-controlled machines, based on the available technology in 2013.⁷

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

The data is available in the 2-digit Classification of Occupations 2010 (Klassifizierung der Berufe 2010, KldB 2010). In addition, they distinguish for each 2-digit KldB 2010 code four different requirement levels.⁹ In total, they estimate substitution potentials for 131 occupation-requirement level combinations. The LIAB data contains occupation codes and requirement levels in the KldB 2010 classification.¹⁰ Therefore, merging both data sets is possible without any crosswalk.

3 | EMPIRICAL APPROACH

3.1 | Methods

3.1.1 | Oaxaca–Blinder decomposition

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

$$\begin{aligned}\widehat{\Delta}_O^\mu &= \bar{X}_1(\widehat{\beta}_1 - \widehat{\beta}_0) + (\bar{X}_1 - \bar{X}_0)\widehat{\beta}_0 \\ &= \widehat{\Delta}_S^\mu + \widehat{\Delta}_X^\mu.\end{aligned}\tag{1}$$

The first part of Equation (1) denotes the wage structure effect, $\widehat{\Delta}_S^\mu$, which is the result of holding the distribution of covariates constant and only modifying the conditional wage structure.¹¹ Thus, in other words this effect represents the differences in the estimated coefficients between the two groups and shows the way the specific characteristics are valued in the labour market. The second part is the composition effect, $\widehat{\Delta}_X^\mu$, where the conditional wage structure is held constant and the distribution of covariates varies according to the observed changes between the two points in time (Fortin et al., 2011). In other words, this effect presents the differences in the distribution of the explanatory factors between the two points in time.

3.1.2 | 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). Thus, the dependent variable, w , is replaced by

the recentred 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 conditional expectation of the $RIF(w,v)$ can be estimated using a linear function of the explanatory variables, i.e., $E[RIF(w,v)|X] = X\gamma$, where the parameters γ can be estimated by OLS (Fortin et al., 2011).

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

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

$$\begin{aligned}\hat{\Delta}_O^\tau &= \bar{X}_1(\hat{\gamma}_{1,\tau} - \hat{\gamma}_{0,\tau}) + (\bar{X}_1 - \bar{X}_0)\hat{\gamma}_{0,\tau} \\ &= \hat{\Delta}_S^\tau + \hat{\Delta}_X^\tau,\end{aligned}\quad (2)$$

where $\hat{\Delta}_O^\tau$ defines the wage gap at the τ th unconditional quantile. The first term of Equation (2) corresponds to the wage structure effect that is obtained by holding the distribution of the covariates constant and only modifying the conditional wage structure represented by the RIF coefficients. The second term represents the composition effect, which is the result of holding the conditional wage structure constant and changing the distribution of the covariates according to the observed change between the points in time $t = 0$ and $t = 1$. The detailed decomposition can be computed similarly as in the case of the mean (Fortin et al., 2011).

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

$$\begin{aligned}\hat{\Delta}_{X,R}^\tau &= (\bar{X}_{01} - \bar{X}_0)\hat{\gamma}_{0,\tau} + \bar{X}_{01}(\hat{\gamma}_{01,\tau} - \hat{\gamma}_{0,\tau}) \\ &= \hat{\Delta}_{X,p}^\tau + \hat{\Delta}_{X,e}^\tau,\end{aligned}\quad (3)$$

where the first part of the right-hand side of Equation (3) corresponds to the pure composition effect, while the second part represents the specification error.

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

$$\begin{aligned}\hat{\Delta}_{S,R}^\tau &= \bar{X}_1(\hat{\gamma}_{1,\tau} - \hat{\gamma}_{01,\tau}) + (\bar{X}_1 - \bar{X}_{01})\hat{\gamma}_{01,\tau} \\ &= \hat{\Delta}_{S,p}^\tau + \hat{\Delta}_{S,e}^\tau,\end{aligned}\quad (4)$$

where the first term of the right-hand side of Equation (4) defines the pure wage structure effect and the second part denotes the reweighting error. Since the counterfactual sample $t = 01$ is used to imitate the sample of point in time $t = 1$, in large samples it should be $plim(\bar{X}_{01}) = plim(\bar{X}_1)$.

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

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

The fact that the method uses simple regressions that are easy to interpret provides a straightforward way of a detailed decomposition. Compared with the sequential decomposition introduced by DiNardo et al. (1996) (DFL-method), the RIF-regressions based detailed decomposition does not suffer from path dependence. However, the RIF-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.

3.2 | Model specification

The decomposition analyses consider a wide range of covariates that are determinants to changes in the wage distribution. Besides the commonly used personal and plant characteristics, we propose a measure of automation threat that is described in more detail below. The personal characteristics include the individual's age (five categories)¹³; education (three categories)¹⁴; tenure (five categories)¹⁵; and a dummy variable capturing German or foreign citizenship. Furthermore, we consider the following two plant characteristics: plant size (six categories)¹⁶; and the bargaining regime (three categories).¹⁷ In addition, we control for fixed effects of eight different manufacturing sectors and include federal state dummies to capture regional shifts.¹⁸

The main factor of interest is our new introduced measure of automation threat, which captures two dimensions of automation. On the one hand, we take the various evolution of the sectoral robot density into account, which is often used as an approximation of automation exposure. On the other hand, we consider the different automation risk of workers due to the task content of their occupation. Therefore, we merge data on the substitution potential of an occupation provided by Dengler and Matthes (2015), which we interpret as a proxy variable for the automation probability of an occupation, with the IFR robot data. This procedure combines the occupational information about the automation probability with the time varying sectoral information about the number of robots per 1000 workers¹⁹:

$$\text{automationthreat}_{j,s,t} = \theta_j \times \frac{\text{Robots}_{s,t}}{\text{emp}_{s,1995}}, \quad (5)$$

where θ_j is the automation probability of occupation j , $\text{Robots}_{s,t}$ is the stock of operational robots in sector s in year t and $\text{emp}_{s,1995}$ is the number of employees in thousands in the corresponding sector s in the base year 1995.²⁰ Thus, each individual working in occupation j and sector s is confronted with the corresponding automation probability of its occupation and a specific sectoral robot density of a given year t .

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

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

The necessity of the combination between automation probabilities and sector specific robots densities is shown in Table B1 in Appendix B. Here the distribution of the different economic sectors within the three groups of automation threat is compared with the shares of economic sectors within the groups based on the automation probabilities by Dengler and Matthes (2015).²³ The first thing that becomes apparent is the fact that in the medium and especially in the high automation threat group not all economic sectors are represented. Looking at the robot densities reveals that the missing sectors (textiles and wood, furniture and paper) indeed exhibit the lowest values. The low robot density weights the automation probability down, which leads to the result that no employee within this sector is faced with a high (or even medium) automation threat. Another striking feature is the relatively low share in the low and medium automation threat group within the automotive sector. This is due to the fact that the automotive sector is faced with a very high robot density which leads to an upweight of the automation probabilities. This takes into account that working in a sector with higher robot density is associated with a higher automation threat than working in a sector with lower robot density, regardless of the occupation. These findings validate the combination of automation probabilities of occupations and sector specific robot densities. Further descriptive information about our proposed variable is presented in the following.

4 | DESCRIPTIVE EVIDENCE

4.1 | Developments in wage inequality

The development of wage inequality in the German manufacturing sector defined by the difference between the 85th and 15th percentiles of log real daily wages for men working full-time is

displayed in Panel (a) of Figure 1. Starting with a short period of moderate increase in wage inequality, a significant rise in the wage gap is observable between 2001 and 2008. In the subsequent years, wage inequality shows an alternating behaviour but is not subjected to major increases as before. A similar pattern is observable by having a look at the development of the Gini coefficient, which measures the normalized average absolute difference between all wage pairs in the workforce. As a result of these observations, we divide our overall period of observation into two subperiods, 1996–2010 in which wage inequality is overall increasing and 2012–2017 in which wage inequality more or less stagnates.²⁴

Since the 85–15 percentile wage gap only takes the top and bottom percentiles into account, developments in the middle of the distribution are omitted. Therefore, the wage gaps between the 50th and 15th percentiles as well as between the 85th and 50th 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 Panel (b) of Figure 1 suggest that in the manufacturing sector a significant increase in inequality at the lower part of the wage distribution is observable. This development is seen throughout the whole period of observation. Regarding the findings of the wage gap in the upper half of the distribution a different pattern is identified. Panel (c) of Figure 1 shows a noticeable increase between 2000 and

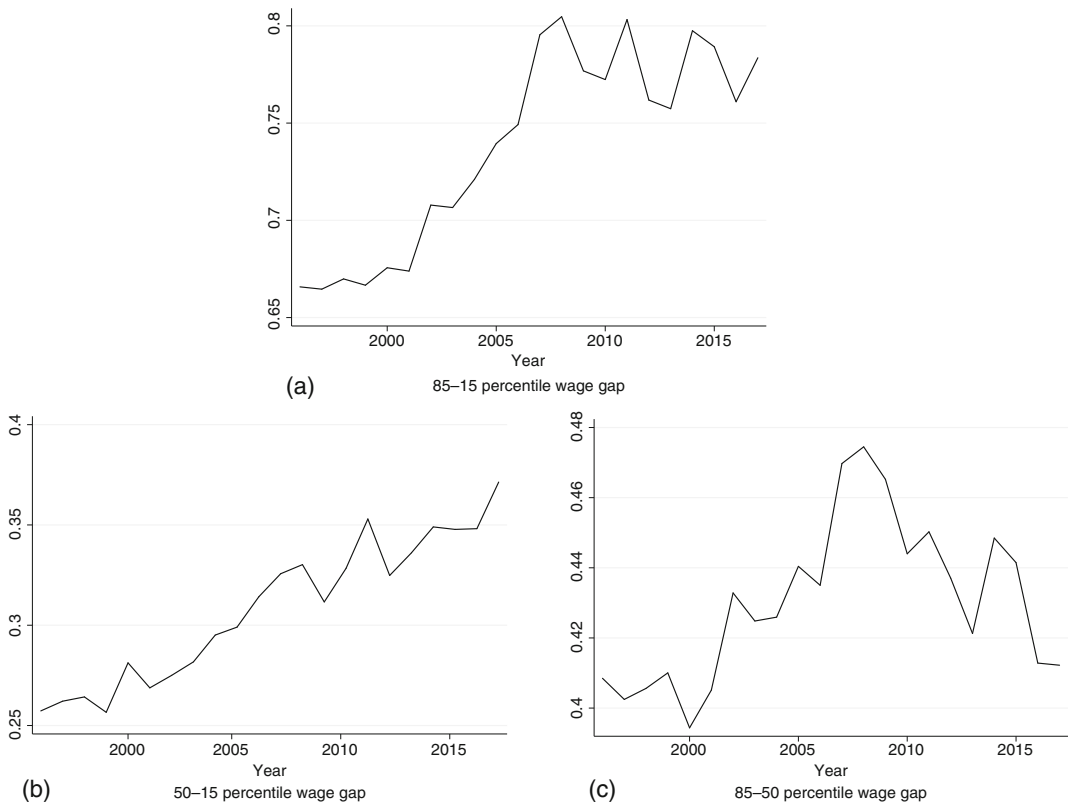


FIGURE 1 The evolution of the 85–15, 50–15 and 85–50 percentile wage gap between 1996 and 2017. The figure presents the evolution of the 85–15, 50–15 and 85–50 percentile wage gap between 1996 and 2017 for men working full-time in the manufacturing sector in Germany. The results are based on imputed real daily wages. Sampling weights are employed. *Source:* LIAB QM2 9317, own calculations.

2008. However, in the following years inequality at the upper part of the wage distribution decreased significantly and ends up in 2017 almost at the same level as in 1996. These trends result in the consistent increase of the overall wage inequality until 2008. Thereafter, the observed developments in wage inequality at the lower and upper parts of the wage distribution balance each other out.

4.2 | The rise of automation

At the same time, automation technology accelerated since the 1990s. This increase is also captured by our automation threat variable, despite sectoral differences. Figure C1 in Appendix C illustrates the estimated automation threat variable in Equation (5) summarized over all occupations in each manufacturing sector in Germany from 1996 to 2017. While most sectors experienced an increase in automation threat, the wood, furniture and paper sector and the textiles sector have seen a slight decrease in automation threat. It is striking that the automotive and other vehicles sector was faced with an extraordinarily increase compared with the other sectors. Automation threat in the automotive and other vehicles sector was eight times higher in 1996 compared with the average of automation threat in the other manufacturing sectors. In 2017 automation threat was even almost 12 times higher than in the other sectors.

4.3 | Descriptive statistics of explanatory variables

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 for the years 1996, 2010, 2012 and 2017. The first column of each year gives the mean of the respective variable, whereas in the second column the corresponding SD 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 per cent and between 2012 and 2017 an increase by 7 per cent 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 per cent in 1996 to more than 15 per cent in 2017, whereas at the same time the low skilled group is halved, from 12 to 6 per cent. In addition, workers tend to have a higher tenure. The group of workers with more than 16 years of employment increased by more than 16 percentage points over the whole period of observation, whereas all other groups decreased in size over time. Workers are denoted as foreigners or natives based on their nationality. During the observed time span the amount of workers with a foreign nationality decreased, which is presumably the result of a change in the German nationality law.

Regarding plant characteristics, one striking development is presented when it comes to collective bargaining coverage. Between 1996 and 2017 the group of workers that is not covered by any sort of collective bargaining agreement increased from 8 to 29 per cent, whereas the group with sector level agreements decreased from 82 to 58 per cent. 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 5000 employees increased by 9 percentage points. Looking at compositional changes of the sectors and changes in employment shares of the different federal states no major differences over the years appear.

TABLE 1 Descriptive statistics

	1996		2010		2012		2017	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
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: ≥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: ≥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)

TABLE 1 (Continued)

	1996		2010		2012		2017	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Plant size: 1000–4999 employees	17.14	(37.68)	18.48	(38.82)	16.68	(37.28)	13.59	(34.27)
Plant size: ≥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	(29.09)	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	

Note: The table presents the descriptive statistics for four time points, SDs are given in parentheses. All variables, except the real wage, are reported in per cent. Sampling weights are employed.

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

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

To get a first impression about the relation between automation threat and changes in wage inequality, we provide descriptive evidence of differences in within-group wage inequality. In Figure 2 the estimated Gini coefficients for the respective groups of automation threat for the whole period of observation are illustrated. In all three groups the significant increase of wage inequality between 1996 and 2008 and the stagnation thereafter becomes apparent. However, there is a substantial difference in the level of wage inequality between the high automation threat group and the groups with middle and low automation threat. The lowest wage inequality is found in the highest group of automation threat. Table B2 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 B2 in Appendix B shows that the highest automation threat group exhibits a mainly similar level of education with more than 80 per cent 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

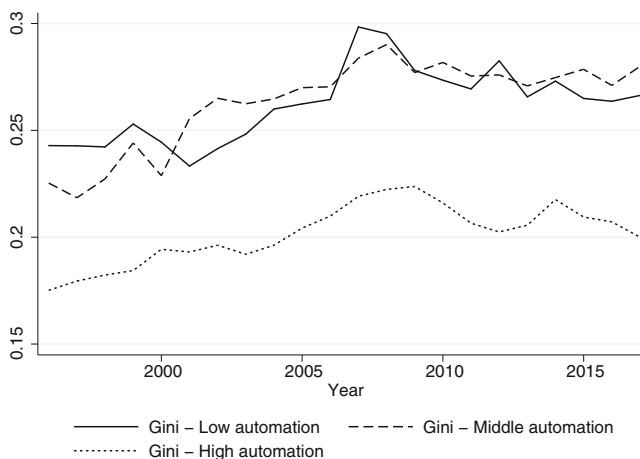


FIGURE 2 Gini coefficients in different automation threat groups, 1996–2017. The figure presents the evolution of the group-specific Gini coefficient estimations between 1996 and 2017. We distinguish between low, medium and high automation threat. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

emerges when it comes to the medium and lowest groups of automation threat. Although the medium educational level still makes up the largest group in both cases, especially the highest educational level plays a more important role and therefore leads to a more diverse structure. When it comes to the requirement levels a similar picture emerges. A significant clustering of workers in the second requirement level of specialist activities in the highest group of automation threat is revealed. Other levels are much less present. Again the low and medium group of automation threat exhibit a more varied distribution of requirement levels and no 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.

5 | DECOMPOSITION ANALYSIS AND DISCUSSION

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

5.1 | 1996–2010

5.1.1 | Counterfactual analysis

Since we are mainly interested in the contribution of automation on changes in wage inequality, we first provide results of a *ceteris paribus* analysis. Multinomial logit estimations are used in order to derive counterfactual weights by which a counterfactual wage distribution is estimated. This distribution reflects the case where the distribution of all covariates is as in point in time 1 except for the distribution of the automation threat groups, which is shifted to that of point in time 0. This procedure is different to that proposed by DiNardo et al. (1996), where a counterfactual distribution is estimated shifting all available covariates. Thus, the conducted analysis makes it possible to show graphically the effect of a compositional change of one specific covariate. The multinomial logit model that estimates the possibility of belonging to one of the three possible types of automation threat is estimated accounting for all remaining covariates we used in the decomposition (for further information see Appendix A.3).

Figure 3 illustrates the actual wage distributions of 1996 and 2010 using kernel density estimations of the log wage distributions of the respective years. In 2010 a lower peak and fatter tails compared with the one in 1996 are observed. Moreover, the widening of the wage distribution is not symmetric, since more mass is shifted to the upper half of the wage distribution. In addition, the counterfactual wage distribution of 2010 with the composition of the automation threat groups shifted back to 1996 is shown. We observe that the counterfactual distribution approaches the density in 1996. A higher peak and a narrower tail at the upper half of the distribution suggest an impact that contributes to a reduction in wage inequality if the composition of the automation threat groups would have been the same in 2010 as in 1996. The actual observed change in the wage distribution between 1996 and 2010 is compared with the difference between the counterfactual and the actual wage distribution in 2010 in Figure C2 in Appendix C.

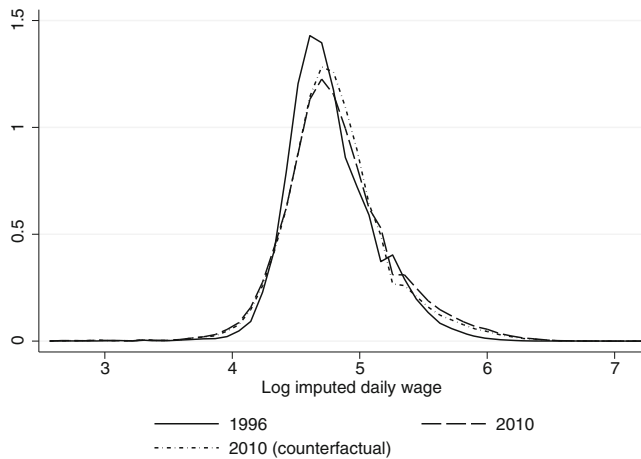


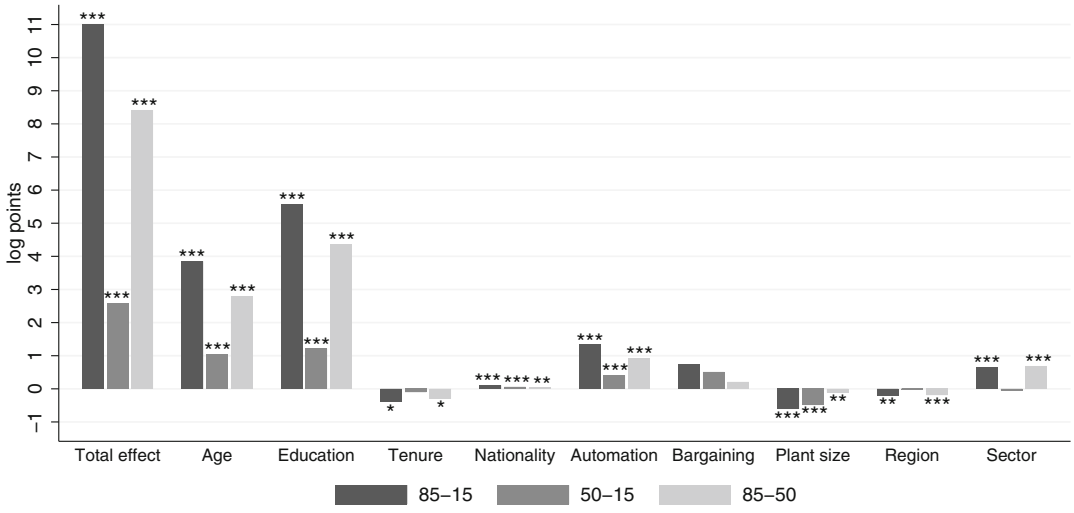
FIGURE 3 Actual and counterfactual wage distributions, 1996–2010. The figure presents the actual wage distributions in 1996 and 2010 as well as the counterfactual wage distribution that would have prevailed if automation and robotization had remained at the level of 1996. Counterfactual weights are estimated using multinomial logit estimations, see Appendix A.3. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

The analysis shows that the observed trend in automation threat contributes to the shift in the upper half of the wage distribution. However, since the counterfactual difference stays close to zero up to the middle of the distribution, a smaller contribution on lower wages is assumed. In Figure C3, we re-estimate the 85–15 percentile wage gap and the Gini coefficient using our counterfactual weights. Indeed, we are able to show that compositional changes in the automation threat groups have played an important role in the rise in wage inequality between 1996 and 2010 since the counterfactual estimates are at all time below the actual outcomes. Further, Figure C4 confirms the different impact along the wage distribution. Whereas the counterfactual line stays close to the actual line at the lower half of the distribution, a substantial gap between the two lines is shown for the upper half revealing a higher impact of automation to increasing wage inequality at this part of the wage distribution.

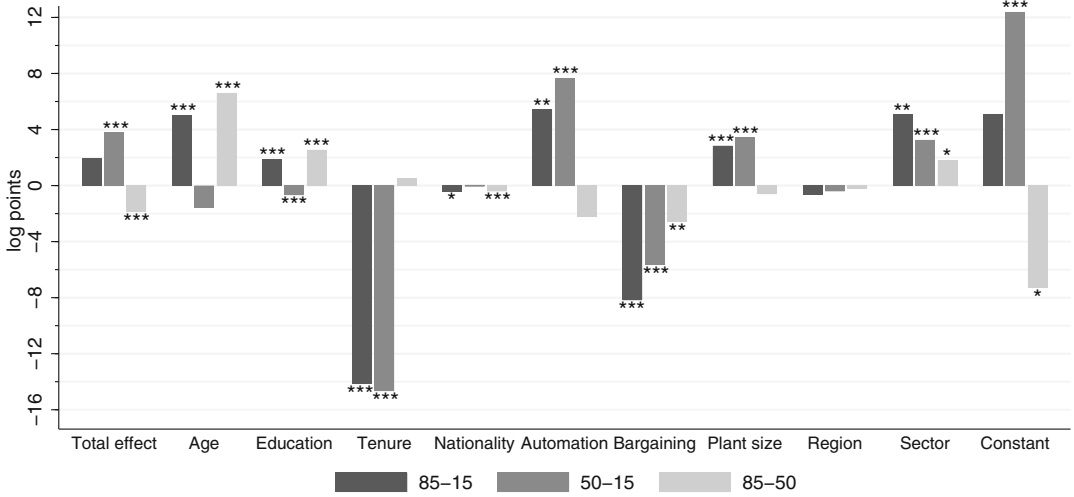
5.1.2 | Decomposition results

We now turn to the results of the RIF-regressions based OB decomposition for the period 1996 and 2010 for men working full-time in the manufacturing sector in West Germany. Figure 4 presents graphically the estimated results of different percentile wage gaps for the composition effect, see Panel (a), and the wage structure effect, see Panel (b).²⁵ First of all, we turn to the decomposition results of the wage gap between the 85th and the 15th percentile, which increased by 10.67 log points between 1996 and 2010. The aggregate composition effect mainly contributes to the increase in the wage gap, while the aggregate wage structure effect is not statistically different from zero. The estimated specification error is statistically insignificant and the reweighting error is sufficiently small.²⁶

Among the composition effects, depicted in Panel (a) of Figure 4, the ones associated with educational levels (5.56 log points) and the age structure of workers (3.85 log points) have



(a) Composition effect



(b) Wage structure effect

FIGURE 4 Decomposition results of the composition and wage structure effect by percentile wage gaps, 1996–2010. The figure presents the results of the RIF-regressions based OB decomposition approach for the composition and wage structure effect based on log daily wages. The sample is restricted to male full-time workers in the manufacturing sector between 18 and 65 years, who earned more than 10 euros per day and work in West Germany. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 per cent level, respectively. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

played the most important role, which correspond to a relative importance of 41²⁷ and 29 per cent of the composition effect, respectively. These findings are supported by the observed shift towards older and higher educated workers in the underlying data. The contribution of the automation-related composition effect has played a slightly smaller, but non-negligible role and amounts to 1.33 log points, which corresponds to a relative importance of roughly 10 per cent

of the composition effect. As shown in the descriptive analysis, there is an observable trend towards occupations with medium automation threat, accompanied by decreasing shares of occupations with high and low automation threat between 1996 and 2010. Due to the fact that within-group wage inequality is the lowest in the group with the highest automation threat, those compositional changes contribute to an increase in wage inequality. Less pronounced but still significant effects that contribute to wage dispersion are changes in the composition of the sector variable and the nationality variable. A factor that has played a small but highly significant role dampening the effect on wage inequality is provided by changes in the composition of the firm size.

When we consider the detailed results of the wage structure effects, presented in Panel (b) of Figure 4, very different implications become evident. The interpretation of the wage structure effects of the respective factors depends on the choice of the base category. Due to this, the specific contribution of one covariate to a change in the wage structure has to be interpreted relative to its base category. Moreover, the wage structure effects capture both the between group and the within group inequality component. In other words, on the one hand direct changes in the return for individual factors are considered and on the other hand changes in the residual wage inequality within the observed group relative to the base group are observed. Thus, the constant of the wage structure effect can be interpreted as the change in residual wage inequality of the base category.

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

In order to show an appropriate comparison with the results of the 85–15 percentile wage gap, the decomposition results of the Gini coefficient are presented in the second column of Table B4 in Appendix B. In contrast to the previous estimates, the total increase of the Gini coefficient can be divided in equal parts into the composition effect and the wage structure effect.

Among the composition effects, the same covariates like educational levels (1.64) and age (0.7) exhibit the largest statistically significant effects that are associated with an increase in wage inequality. A less pronounced but non-negligible role played collective bargaining (0.37) and automation threat (0.17), which contribute by around 11 and 5 per cent to the composition effect, respectively. Using the Gini coefficient makes it easier to explain the movements behind the contribution of automation threat on wage inequality in the following. The automation-related positive composition effect stems from the observable trend towards occupations with medium automation threat, accompanied by decreasing shares of occupations with high and low automation threat. Due to the fact that within-group wage inequality is the highest in the lowest automation threat group, the estimated RIF coefficients on the middle and high automation threat groups are mainly negative, see Table B11.²⁸ Since the composition effect is defined as the change in the share of employment of the respective groups times the coefficient of the

RIF-regression in 1996, it can be shown why compositional changes regarding the automation threat variable are associated with increasing wage inequality. In other words, in this case the composition effect consists of two negative components, which build together a positive effect that contributes to wage dispersion. As a result, we provide evidence that structural shifts in the workforce composition between occupations with different automation threat contributes to increasing wage inequality. Similar to the 85–15 percentile wage gap, changes in the composition of the firm size has played a small but non-negligible role to dampen wage inequality.

Looking at the wage structure effect, the same covariates like automation threat, age, education, sector and the firm size contribute the rise in wage inequality, where automation threat is the major factor, which amounts to 2.55. Again, a closer look at the results of the RIF-regressions explains this result, see Table B11. As already seen, in 1996 both coefficients of the middle and high automation threat group are negative. This suggests that an increase in the share of the highest automation threat group is associated with a decrease in the estimated Gini coefficient, since this group exhibits a lower within-group wage inequality than the base group of low automation risk. Moreover, regarding the wage structure effect it is important to observe how the coefficients change over time. We see that between 1996 and 2010, the RIF-regressions estimates for the medium and high automation risk group either decrease in absolute terms or even get positive. This means that in 1996 the contribution of the two groups on dampening wage inequality was more pronounced than in 2010, keeping everything else equal. Looking at the equation for the wage structure effect it can be seen that the change in the coefficients becomes positive and is multiplied by the positive employment share of 2010. As a result of this condition, a positive automation-related wage structure effect is estimated.

Among the remaining wage structure effects, the same covariates such as tenure and collective bargaining are associated with a reduction in wage inequality. Other inequality decreasing wage structure effects are either weakly or not statistically significant. In summary, the main results of the two presented inequality measures concerning the whole wage distribution are comparable for most parts. Further, we provide decomposition results of the Variance in Table B13 in Appendix B. Again, the automation-related composition effect has played a small but non-negligible role in rising wage inequality, which amounts to 0.17 log points and corresponds to a relative importance of 4 per cent of the composition effect. The wage structure effect associated with automation threat is the major factor that contributes to wage inequality, amounting to 3.82 log points.

We now turn to the decomposition results of the two inequality measures considering either the lower part or the upper part of the wage distribution. The wage gap between the 50th and 15th percentile increased by 7.11 log points, whereas the 85–50 percentile wage gap increased only by 3.56 log points, see Table B5 in Appendix B. The sum of both increases is again the whole increase of the 85–15 percentile wage gap. Looking at the aggregate composition and wage structure effects we observe different results. Whereas the 50–15 percentile wage gap can be divided roughly into equal positive parts, the 85–50 percentile wage gap exhibits a four times as big positive composition effect compared with the negative wage effect in absolute terms.

In general, the key results of the detailed composition effect are for both measures similar to the overall wage gap, see Panel (a) of Figure 4. Comparing the composition effects on the lower and upper half of the wage distribution, we find that the effects on the upper half of the wage distribution are more pronounced than on the lower part. This holds also true for the automation threat variable. Turning to the wage structure effects on the lower and upper half of the wage distribution different outcomes become apparent, see Panel (b) of Figure 4. Regarding our measure of automation and robotization, we can state that automation threat has a clear

inequality-increasing and highly significant wage structure effect at the lower part of the wage distribution, while it has no statistically significant effect at the upper part of the wage distribution. Thus, the changes in relative wage returns between workers in occupations with high and low automation threat, as predicted by RBTC, are only observable at the lower part of the wage distribution.

5.2 | 2012–2017

5.2.1 | Counterfactual analysis

Figure C5 in Appendix C shows the changes in the wage distribution and the corresponding difference between 2012 and 2017. The shift of the wage distribution to the right is more pronounced. Moreover, no major drop of the peak compared with the development between 1996 and 2010 is observed. In fact, a rather horizontal shift of the distribution where the peak is more located to the right becomes apparent. Furthermore, the counterfactual distribution in 2017, where the composition of the automation threat groups is shifted back to 2012, is illustrated. As seen before, the counterfactual density approaches to the actual distribution in 2012. However, it becomes evident that changes in the composition of automation threat are not responsible for the horizontal shift to the right.

The comparison of the counterfactual difference to the actual difference between 2012 and 2017 is illustrated in Figure C6 in Appendix C. Again, changes in the lower part of the distribution are not affected by a large extent through compositional changes in the automation threat groups, which is represented by a counterfactual difference close to zero. In Figures C7 and C8, we re-estimate the standard inequality measures using counterfactual weights. In this case, we also find supporting results of the above described findings.

5.2.2 | Decomposition results

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

Among the composition effects for the 85–15 percentile wage gap, presented in Table B6 in Appendix B, the one associated with the age structure of workers is no more statistically significant in comparison to the first time period. A still significant although less pronounced composition effect comes from education (1.15 log points), which corresponds to a relative importance of 27 per cent of the composition effect. The most important inequality-increasing composition effect is associated with automation threat (1.72 log points), which corresponds to a relative importance of 41 per cent. Rather small but still significant effects that contribute to wage inequality are driven by changes in the composition of the firm size, sector and nationality variables. Composition effects that are associated with decreasing wage inequality are related to tenure and the bargaining regime, even if their contribution is relatively small.

When turning to the decomposition results of the wage structure effect for the 85–15 percentile wage gap, there are observable differences compared with the previous period. The wage structure effects related to collective bargaining (2.32 log points) and nationality (0.49 log

points) contribute positively to rising wage dispersion in the more recent time period, while the ones associated with tenure, age, regional differences, education and the plant size dampen it. Again, the most important wage structure effect, which is associated with decreasing wage dispersion is related to tenure, which amounts to -9.63 log points. In comparison to the first time period, automation threat has no more a statistically significant wage structure effect. It seems that in the recent past the change in the composition of automation threat is the prominent channel through which automation contributes to rising wage dispersion.

The decomposition results for the Gini coefficient show a slightly decrease in the overall wage inequality by around 0.31 log points during the considered time period. The aggregate composition effect is positive, while the aggregate wage structure effect is negative, both are rather small (0.77 and 0.81 , respectively). Among the composition effects, the ones associated with education (0.32), automation threat (0.23) and the plant size (0.22) contribute the most to the increase in wage inequality. The relative importance of automation threat belongs to 26 per cent of the composition effect. The positive automation-related composition effect is supported by the observed shift from 2012 to 2017 towards occupations with low and middle automation threat, which are faced with significantly higher wage dispersion. The estimated RIF coefficients on the middle and high automation risk groups are again negative, see Table B11. Thus, we see the same dynamics behind the automation-related composition effect as in the first period. Sectoral differences have played a small but non-negligible role in rising wage dispersion with a relative importance of around 8 per cent of the composition effect. Small but still significant effects that contribute to a decrease in wage inequality are associated with changes in the composition of tenure and the bargaining regime, which is in line with the decomposition results of the 85 – 15 percentile wage gap.

The results of the detailed wage structure effect are more or less equal to the results of the 85 – 15 percentile wage gap, although the automation-related wage structure effect is now the most important factor associated with decreasing wage dispersion, which amounts to -2.22 . A closer look at the results of the RIF-regressions explains this result, see Table B11. In 2012 as well as in 2017 both coefficients of the middle and high automation threat group are negative. This suggests that an increase in the share of the middle and high automation threat group is associated with a decrease in the estimated Gini coefficient. Moreover, we see that between 2012 and 2017, the RIF-regressions estimates for the middle automation threat group increase in absolute terms, while the estimates for the high automation threat group decreases slightly in absolute terms. This means that the contribution of the middle automation threat group on dampening wage inequality was more pronounced in 2017 than in 2012, while the contribution of the high automation threat group on dampening wage inequality was more pronounced in 2012 than in 2017, keeping everything else equal. Due to the fact that the automation-related wage structure effect is negative, the contribution of the middle automation threat group overweigh the contribution of the high automation threat group, thus, the change in the coefficients becomes negative and is multiplied by the positive employment share of 2019 leading to a negative automation-related wage structure effect.

The decomposition results regarding the automation threat variable are comparable to the decomposition results for the Variance, see Table B13 in Appendix B. The automation-related composition effect has played a major role in rising wage inequality, which amounts to 0.33 log points and corresponds to a relative importance of 24 per cent of the composition effect. The wage structure effect associated with automation threat is an important factor, which contributes to a decrease in wage inequality, amounting to -1.96 log points.

We now turn to the decomposition results of the two inequality measures considering the lower and upper part of the wage distribution, see Table B7 in Appendix B. It becomes obvious

that the less pronounced total increase of the 85–15 percentile wage gap is due to the fact that the lower and upper part of the wage distribution are faced with different inequality trends during the last years. While the wage gap at the lower end of the wage distribution increased by 4.66 log points, the wage gap at the upper end of the wage distribution decreased by 2.48 log points.

The aggregate composition effect is for both inequality measures positive. At the lower part of the wage distribution the composition effects related to sectoral differences, automation threat and plant size contribute the most to rising wage inequality, while tenure, collective bargaining and regional fixed effects played a small but significant role to dampen wage dispersion. Those effects are more or less similar to the detailed composition effects at the upper part of the wage distribution. However, it is evident that the automation-related composition effect is more pronounced at the upper part of the wage distribution than at the lower part. This observed difference in the contribution of automation threat along the wage distribution confirms the results from the counterfactual analysis presented in Figure C5 in Appendix C.

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

5.3 | Robustness check

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

5.3.1 | Probability of computerization by Frey and Osborne (2017)

Frey and Osborne (2017) estimate the probability of computerization of different occupations in the United States, which is a commonly used measure of automation risk. Using these

estimated automation probabilities for German occupations creates several problems, which are described in Appendix A.2. Those compatibility and conceptual problems have to be taken into account by interpreting the results.

Frey and Osborne (2017) provide three types of ‘engineering bottlenecks’ to automation, which are (1) perception and manipulation, (2) creative intelligence and (3) social intelligence (Frey & Osborne, 2017, p. 264). The higher the relevance of these bottlenecks for a given occupation, the lower the probability for workers to be substituted by machines. In total, there are estimates for 702 occupations. The data are available at the 6-digit SOC 2010 classification, thus, we have to translate the data into the 3-digit German KldB 2010 classification, see Appendix A.4. The alternative automation threat variable is estimated in a similar way as before, see Equation (5), using the computerization probabilities provided by Frey and Osborne (2017) as θ_j .

The descriptive statistics of this alternative automation threat variable are presented in Table B3 in Appendix B. Similar to the findings in Section 4, the lowest within-group wage inequality is found in the group with the highest automation threat, because workers within the highest automation threat group tend to have similar education and requirement levels. However, the distinct differences in the level of within-group wage inequality are not that much pronounced as in our base variable, which is likely influenced by the different estimation strategies. In the case of Dengler and Matthes (2015), higher automation probabilities are associated with routine tasks, which are often conducted by workers with middle education and similar requirement levels, while lower automation probabilities are associated with non-routine tasks, which could be performed by low and high educated workers with a broader range of requirement levels. This would lead to lower within-group wage inequality in the high automation threat group and higher within-group wage inequality in the middle and low automation threat groups.

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

The decomposition results are presented in Tables B14 and B15 in Appendix B. Turning to the automation-related composition effect, smaller coefficients are now observable for almost all inequality measures during both periods. This underpins our results from the descriptive analysis. For the first time period, the automation-related wage structure effect at the 85–15 percentile wage gap and the Gini coefficient is positive, but no more significant. This is due to the fact that automation threat is now associated with a significant inequality-decreasing wage structure effect at the 85–50 percentile wage gap. This means that wages at the upper part of the wage distribution become more equally distributed between and within the three automation threat groups over the first time period.

In the second time period, the automation-related wage structure effect at the 85–15 percentile wage gap is now positive and significant. Thus, changes in wage dispersion between or within the automation threat groups lead to an increase in the 85–15 percentile wage gap. This is due to the fact that automation threat is now associated with a large positive and highly

significant wage structure effect at the 50–15 percentile wage gap, while the automation-related wage structure effect contributes no more to a decline in the 85–50 percentile wage gap.

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

5.3.2 | Automotive and other vehicles sector

The automotive and other vehicles sector (in the following automotive sector) is by far the most affected sector by automation threat, as already seen in Figure C1. In order to check whether our results are mainly driven by the development in this sector, we exclude the automotive sector in Tables B16 and B17 in Appendix B.

For both periods, the automation-related composition effect at the 85–15 percentile wage gap, the Gini coefficient and the Variance is still positive and significant, but even larger than our basic decomposition results. This can be explained by the fact that most workers within the automotive sector belong to the high automation threat group, see Table B1. In addition, the employment share in the automotive sector increased over the whole period, see Table 1. Due to the fact that wage inequality is the lowest in the group with the highest automation threat, as it is depicted in Figure 2, those structural changes towards the automotive sector lead to a decrease in overall wage inequality. Therefore, this dampening effect on wage inequality is not existent if we exclude the automotive sector, leading to a higher automation-related composition effect. The same pattern becomes apparent if we have a look at the results of the lower and upper part of the wage distribution. As in the basic decomposition, the automation-related composition effect is more pronounced at the upper part of the wage distribution. But again, the contribution to the 50–15 and the 85–50 percentile wage gap is higher than in our basic decomposition analysis.

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

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

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

5.3.3 | Further affected sectors

As presented in Figure C1 in Appendix C there are further sectors that are outstandingly affected by automation and robotization. Therefore, additional robustness checks are conducted in order to exclude possible misinterpretations. At first the observations of the electronics sector are dropped. The overall estimated results reveal slightly smaller sizes of changes in the used inequality measures. Thus, the effects of the automation threat variable are as well smaller in absolute terms. However, the relative size and statistical significance do not change. Further, since the plastic, chemicals and glass sector is also highly affected by our estimated automation threat, we additionally conduct the robustness check excluding observations of this sector. The results reveal slightly higher sizes of changes in the used inequality measures, however as already seen before the relative effects and information regarding significance do not change. Concluding, it can be seen that the development of these two sectors do not bias the overall estimated results.

6 | CONCLUSION

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

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

We distinguish between two channels through which automation threat contributes to rising wage inequality. First, there is an observable trend towards occupations with medium automation threat, accompanied by decreasing shares of occupations with high and low automation threat. Due to the fact that within-group wage inequality is the lowest in the group with the highest automation threat, those compositional changes contribute to an increase in wage inequality. This automation-related composition effect corresponds to a relative importance of

roughly 10 per cent of the overall composition effect between 1996 and 2010 and actually 41 per cent in the time period until 2017. Second, we find evidence that there is a growing wage dispersion between occupations with low automation threat (containing especially non-routine tasks) and occupations with high automation threat (containing especially routine tasks). This trend contributes to rising wage inequality as predicted by RBTC, where technology increases the relative demand, and consequently the relative wages, for non-routine tasks compared with routine tasks. This automation-related wage structure effect is prevalent in the 1990s and 2000s, while there is no evidence that this effect has played a significant role in the more recent time period.

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

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

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ENDNOTES

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

- ² Due to the fact that the data do not contain any information on the number of working hours, we decide to consider only men working full-time. We are aware of this strong restriction, nevertheless it reduces noise and increases consistency in the analysis.
- ³ In order to circumvent estimations that are driven by the imputation procedure, the analysis provides results including only the uncensored part of the wage distribution represented by the inter-percentile ranges up to the 85th percentile.
- ⁴ We consider only industrial robots in the analysis. Data on service robots is also available since 2002. However, the data is not available at the industry level during the considered time period.
- ⁵ Within the manufacturing sector there is one exception at the 2-digit level. The IFR classification uses the 2-digit code 16-Wood and furniture. This industry contains the ISIC Rev. 4 code 16 and 31.
- ⁶ As Dauth et al. (2021) and Graetz and Michaels (2018), we exclude *All other manufacturing branches*, since it covers only 6.8 per cent of the robot stock in the manufacturing sector in 1996 and the share declines to 1.7 per cent in 2017.
- ⁷ There are already updated versions of the automation probabilities based on the available technology in 2016, see Dengler and Matthes (2018), and 2019, see Dengler and Matthes (2021). Due to the fact that the considered time period in our analysis begins in 1996, we use the automation probabilities calculated on the basis of the available technology in 2013.
- ⁸ For example, if one single occupation contains three different core requirements, and one requirement is assigned to a routine task, then the share would be 1/3.
- ⁹ The requirement levels correspond to the 5th digit KldB 2010 classification: 1-unskilled activities, 2-specialist activities, 3-complex activities, 4-highly complex activities.
- ¹⁰ The occupational information before 2011 was reported using the occupation code KldB 1988. This older classification is less detailed than the occupation code KldB 2010, which leads to inaccuracies.
- ¹¹ Using categorical variables in a detailed decomposition, the estimated wage structure effect depends on the defined base group. Therefore, the effect of changes in the returns have to be interpreted based on this omitted group (Fortin et al., 2011).
- ¹² As discussed by Barsky et al. (2002), if the linearity assumption does not hold, the estimated counterfactual mean wage would not be equal to $\bar{X}_1 \hat{\beta}_0$ in the case of the standard OB decomposition.
- ¹³ (1) 18–25 years; (2) 26–35 years; (3) 36–45 years; (4) 46–55 years; (5) 56–65 years.
- ¹⁴ (1) Low: lower/middle secondary without vocational training; (2) Medium: lower/middle secondary with vocational training or upper secondary with or without vocational training; (3) High: university of applied sciences or traditional university.
- ¹⁵ (1) 0–2 years; (2) 2–4 years; (3) 4–8 years; (4) 8–16 years; (5) >16 years.
- ¹⁶ (1) 1–9 employees; (2) 10–49 employees; (3) 50–199 employees; (4) 200–999 employees; (5) 1000–4999 employees; (6) ≥ 5000 employees.
- ¹⁷ (1) Sector-level agreement; (2) Firm-level agreement; (3) No collective bargaining agreement.
- ¹⁸ The base category is a medium-skilled worker between 26 and 35 years, with 0–2 years of tenure, with German citizenship and is exposed to low automation threat. Further, the worker is employed in an establishment with 200–999 employees, which has no collective bargaining agreement, belongs to the basic metals and fabricated metal products sector and is located in North Rhine-Westphalia.
- ¹⁹ In a familiar way, this approach is used in Anelli et al. (2019) to capture the individual exposure to automation. In a first step, a multinomial logit model is estimated using all available covariates to predict the probability of an individual being in a certain occupation. This probability is multiplied with the corresponding automation probability in that occupation to obtain an individual vulnerability to automation. In a last step, the individual vulnerability is multiplied with the national percentage change in total operational robots in a country. Due to the characteristics of our estimation strategy it is not possible to implement this kind of automation threat variable.
- ²⁰ The data on sectoral employment in 1995 is provided by EU KLEMS database, see Stehrer et al. (2019).

- ²¹ The common support assumption is one of the main conditions proposed by Fortin et al. (2011) that ensures a successful estimation of the decomposition. This assumption imposes the condition of common support on the covariates and makes sure that no observation can serve to identify the assignment into one specific group (Fortin et al., 2011). Due to this condition it is not possible to use a continuous variable measuring automation threat. The considerable increase over time would lead to exclusively present values in points in time $t = 0$ and $t = 1$, which contradicts this assumption.
- ²² For example, if there are in total 300 possible occupation-sector combinations in 1 year, the first group includes the lowest 100 combinations, the second group the 100 combinations in the middle and the third group the 100 highest combinations. There are two cut-off points, namely the values of the 100th and the 200th combination. Of course, the values of these cut-off points increase over time as the values of the automation threat variable increases as well.
- ²³ The group of low automation risk is given if a maximum of 30 per cent of the occupation could be performed by computers. The medium automation risk captures those occupations, which are substitutable by automation between 30 per cent and a maximum of 70 per cent and high automation risk exists if more than 70 per cent of the occupation could be performed by computers.
- ²⁴ Baumgarten et al. (2020) consider similar time periods: 1996–2010 and 2010–2014. Due to a change in the reporting procedure of the social security agency, a considerable increase in the number of missing values occurs in the year 2011. In order to circumvent this possible source of misleading estimation results, we define 2012 as our starting point of the second period of observation. For more information see Schmidlein et al. (2019).
- ²⁵ Comprehensive tables of the decomposition results, which also include specification and reweighting errors, can be found in Tables B4 and B5 in Appendix B.
- ²⁶ In order to show that the main results are not affected by the definition of the used percentiles, the 90th–10th wage gap is estimated as a robustness check. The relative importance of the different explanatory variables in the detailed decomposition analysis does not shift as well as the signs and statistical significance.
- ²⁷ We interpret the specific estimated effect of a covariate as follows: in the observed case we have $5.56/13.42 = 0.41$, where 13.42 is the sum of all detailed composition effects in absolute terms. Thus, we are able to provide percentages that show the respective relative importance in comparison to all other factors and which sum up to 100 per cent.
- ²⁸ All RIF-regressions estimation results of the applied inequality measures and percentiles are presented in Tables B8–B12 in Appendix B.
- ²⁹ Comprehensive tables of the decomposition results, which also include specification and reweighting errors, can be found in Tables B6 and B7 in Appendix B.
- ³⁰ <https://www.bls.gov/soc/soccrosswalks.htm>
- ³¹ <https://www.bls.gov/oes/tables.htm>
- ³² <https://statistik.arbeitsagentur.de/Navigation/Statistik/Grundlagen/Klassifikationen/Klassifikation-der-Berufe/KldB2010/Arbeitshilfen/Umsteigeschluessel/Umsteigeschluessel-Nav.html>
- ³³ Due to the fact that US employment data are only available for SOC 2010 classification, we apply the crosswalk provided by the BLS to map the US employment data from the 6-digit SOC 2010 into the international 4-digit ISCO 2008 classification, using 2014 US employment weights.
- ³⁴ https://statistik.arbeitsagentur.de/Statistikdaten/Detail/201406/iiiia6/beschaeftigung-sozbe-bo-heft/bo-heft-d-0-201406-xlsx.xlsx?__blob=publicationFile&v=1

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APPENDIX A

A.1 | Classification of economic activities

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

A.2 | Advantages of the substitution potential provided by Dengler and Matthes (2015)

Frey and Osborne (2017) estimate the probability of computerization of different occupations in the United States. Using these estimated automation probabilities for German occupations creates several problems. First, there are compatibility problems by mapping the occupation classification, used by Frey and Osborne (2017), into the German occupation classification, see Appendix A.4. Second, it is not likely that occupations in the United States 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 United States and Germany are so similar that a direct transformation of the US automation probabilities to Germany is appropriate. Third, Frey and Osborne (2017) estimate the automation probabilities using an occupation-based approach. This underlies the assumption that whole jobs are replaced by automation. As Arntz et al. (2016) argue, it is more realistic to assume that single job-tasks rather than whole occupations are substituted by automation, because high-risk occupations still contain some tasks that are difficult to automate. By applying the occupation-based approach, it is likely that they overestimate the probability of job automatibility, see e.g., Arntz et al. (2016) and Bonin et al. (2015). In order to avoid those problems, it is necessary to investigate the probability of job automatibility directly for occupations in Germany, based on a task-based approach.

A.3 | 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:

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

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

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

A.4 | SOC 2010-KldB 2010 crosswalk

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

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

APPENDIX B

TABLE B1 Comparison between the estimated automation threat and the automation probability provided by Dengler and Matthes (2015), by sector

Economic sector	Automation threat defined by Equation (5)			Automation probability by Dengler and Matthes (2015)		
	Low automation	Medium automation	High automation	Low automation	Medium automation	High automation
1996						
Food and beverages	52.20	4.43	0	10.73	11.37	0.43
Textiles	5.08	13.73	0	3.40	2.32	3.50
Wood, furniture and paper	6.81	13.95	8.62	7.70	5.10	14.31
Plastic and chemical products	13.12	12.92	14.68	22.61	11.29	15.45
Metal products	5.37	6.85	26.88	18.10	14.08	29.23
Electrical products	5.18	8.44	11.81	10.15	12.94	7.91
Industrial machinery	11.37	38.91	17.71	13.38	25.68	16.87
Automotive and other vehicles	0.87	0.77	20.31	13.93	17.22	12.30
2010						
Food and beverages	14.68	20.30	1.11	12.60	11.37	0.45
Textiles	17.19	0	0	1.79	1.01	1.60
Wood, furniture and paper	22.99	25.94	0	9.28	4.26	13.11
Plastic and chemical products	6.85	5.75	18.33	19.69	9.86	18.17
Metal products	14.19	13.01	26.90	14.80	16.42	31.45
Electrical products	14.00	13.12	14.57	16.33	16.79	10.44
Industrial machinery	9.94	21.68	15.22	10.40	20.10	13.58
Automotive and other vehicles	0.16	0.19	23.87	15.11	20.20	11.19

(Continues)

TABLE B1 (Continued)

Economic sector	Automation threat defined by Equation (5)			Automation probability by Dengler and Matthes (2015)		
	Low automation	Medium automation	High automation	Low automation	Medium automation	High automation
2012						
Food and beverages	9.19	21.16	1.42	8.96	11.25	1.12
Textiles	11.86	0	0	1.44	1.05	1.54
Wood, furniture and paper	43.93	10.92	0	7.14	4.40	10.90
Plastic and chemical products	3.49	9.92	17.10	18.73	10.59	16.29
Metal products	7.53	10.84	31.09	14.40	17.47	34.18
Electrical products	11.29	17.16	10.37	17.35	14.00	8.07
Industrial machinery	12.36	29.78	16.89	18.26	22.15	16.58
Automotive and other vehicles	0.35	0.23	23.13	13.72	19.08	11.32
2017						
Food and beverages	13.49	30.40	0.61	13.03	14.47	1.12
Textiles	5.98	0	0	0.64	0.48	1.25
Wood, furniture and paper	54.94	0	0	7.45	3.95	11.50
Plastic and chemical products	2.49	7.33	13.37	13.50	7.69	13.41
Metal products	2.15	10.18	25.82	11.79	12.98	30.88
Electrical products	8.47	22.12	6.63	12.86	11.80	8.28
Industrial machinery	12.04	29.72	16.73	18.17	21.39	16.87
Automotive and other vehicles	0.46	0.24	36.83	22.57	27.25	16.69

Note: The table presents the descriptive statistics for four time points separately for each automation threat group. It is a comparison of our proposed variable measuring automation threat and the automation probabilities provided by Dengler and Matthes (2015). All employment shares are reported in per cent. Sampling weights are employed.

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

TABLE B2 Descriptive statistics of the automation threat variable by groups

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

Note: The table presents the descriptive statistics for four time points separately for each automation threat group. All variables, except the wage are reported in per cent. Sampling weights are employed.

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

TABLE B3 Descriptive statistics of the alternative automation threat variable with automation probabilities provided by Frey and Osborne (2017) by groups

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

Note: The table presents the descriptive statistics for four time points separately for each automation threat group. All variables, except the wage are reported in per cent. Sampling weights are employed.

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Frey and Osborne (2017), own calculations.

TABLE B4 Decomposition of the 85–15 percentile wage gap and the Gini coefficient, 1996–2010

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

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

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

TABLE B5 Decomposition of the 50–15 and the 85–50 percentile wage gap, 1996–2010

Inequality measure	50–15		85–50	
	Coefficient	SE	Coefficient	SE
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)

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

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

TABLE B6 Decomposition of the 85–15 percentile wage gap and the Gini coefficient, 2012–2017

Inequality measure	85–15		Gini coefficient	
	Coefficient	SE	Coefficient	SE
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)

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

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

TABLE B7 Decomposition of the 50–15 and the 85–50 percentile wage gap, 2012–2017

Inequality measure	50–15		85–50	
	Coefficient	SE	Coefficient	SE
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)

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

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

TABLE B8 RIF-regressions 15th quantile, 1996, 2010, 2012 and 2017

	1996	2010	2012	2017
Age: 18–25	-0.0406** (0.0166)	-0.0827*** (0.0171)	-0.0618*** (0.0155)	-0.0347* (0.0208)
Age: 36–45	-0.0442*** (0.0086)	-0.0442*** (0.0104)	-0.0589*** (0.0104)	-0.0582*** (0.0137)
Age: 46–55	-0.0442*** (0.0104)	-0.0887*** (0.0114)	-0.0962*** (0.0117)	-0.0692*** (0.0164)
Age: ≥56	-0.0506*** (0.0115)	-0.0946*** (0.0130)	-0.0983*** (0.0126)	-0.1165*** (0.0172)
Education: low	-0.1148*** (0.0069)	-0.1534*** (0.0084)	-0.1568*** (0.0101)	-0.1383*** (0.0133)
Education: high	0.0779*** (0.0060)	0.1227*** (0.0051)	0.1197*** (0.0051)	0.1277*** (0.0066)
Tenure: 2–4 years	0.0997*** (0.0219)	0.0984*** (0.0232)	0.1237*** (0.0179)	0.0993*** (0.0222)
Tenure: 4–8 years	0.2144*** (0.0189)	0.1975*** (0.0241)	0.1875*** (0.0177)	0.2661*** (0.0231)
Tenure: 8–16 years	0.2721*** (0.0189)	0.3239*** (0.0267)	0.2938*** (0.0187)	0.3606*** (0.0240)
Tenure: ≥16 years	0.3412*** (0.0198)	0.4645*** (0.0286)	0.4519*** (0.0207)	0.4806*** (0.0269)
Nationality	-0.0392*** (0.0084)	-0.0311*** (0.0084)	-0.0455*** (0.0091)	-0.0881*** (0.0127)
Automation threat: middle	0.0021 (0.0099)	-0.0563*** (0.0117)	-0.0042 (0.0097)	-0.0350 (0.0244)
Automation threat: high	-0.0180* (0.0108)	-0.0673*** (0.0109)	-0.0314*** (0.0097)	-0.0191 (0.0221)
Firm level agreement	-0.0097 (0.0198)	0.1666*** (0.0072)	0.1377*** (0.0069)	0.1274*** (0.0090)
Sector level agreement	0.0379** (0.0172)	0.1762*** (0.0071)	0.1781*** (0.0066)	0.1863*** (0.0074)
Plant size: 1–9 employees	-0.3037*** (0.0320)	-0.6222*** (0.0358)	-0.6038*** (0.0365)	-0.5561*** (0.0481)
Plant size: 10–49 employees	-0.1651*** (0.0111)	-0.2516*** (0.0111)	-0.2717*** (0.0109)	-0.2482*** (0.0152)
Plant size: 50–199 employees	-0.0472*** (0.0037)	-0.1045*** (0.0048)	-0.1064*** (0.0048)	-0.1031*** (0.0072)
Plant size: 1000–4999 employees	0.0219*** (0.0021)	0.0404*** (0.0025)	0.0438*** (0.0024)	0.0528*** (0.0045)
Plant size: ≥5000 employees	0.0313*** (0.0029)	0.0386*** (0.0035)	0.0326*** (0.0026)	0.0796*** (0.0066)
Sector: food and beverages	-0.1033*** (0.0179)	-0.2407*** (0.0141)	-0.2665*** (0.0135)	-0.5079*** (0.0226)
Sector: textiles	-0.1922*** (0.0181)	-0.3958*** (0.0282)	-0.3723*** (0.0330)	-0.3915*** (0.0429)
Sector: wood, furniture and paper	0.0229* (0.0132)	-0.1248*** (0.0129)	-0.1117*** (0.0135)	-0.1047*** (0.0270)
Sector: plastic and chemical products	0.0418*** (0.0084)	-0.0183** (0.0076)	0.0056 (0.0078)	-0.0516*** (0.0099)
Sector: electrical products	0.0307*** (0.0093)	0.0217*** (0.0072)	0.0198*** (0.0077)	0.0188* (0.0108)

(Continues)

TABLE B8 (Continued)

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

Note: The table presents the RIF-regressions for the 15th quantile. The observed years are 1996, 2010, 2012 and 2017. SEs are given in parentheses. Sampling weights are employed.

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

TABLE B9 RIF-regressions 50th quantile, 1996, 2010, 2012 and 2017

	1996	2010	2012	2017
Age: 18–25	-0.0720*** (0.0071)	-0.1081*** (0.0076)	-0.0723*** (0.0070)	-0.0496*** (0.0065)
Age: 36–45	0.0049 (0.0052)	0.0033 (0.0051)	-0.0019 (0.0054)	-0.0043 (0.0053)
Age: 46–55	0.0198*** (0.0064)	-0.0141** (0.0055)	-0.0251*** (0.0061)	-0.0077 (0.0066)
Age: ≥56	0.0179** (0.0082)	-0.0187*** (0.0065)	-0.0357*** (0.0068)	-0.0348*** (0.0072)
Education: low	-0.1721*** (0.0038)	-0.1666*** (0.0037)	-0.1567*** (0.0042)	-0.1059*** (0.0047)
Education: high	0.2435*** (0.0050)	0.2769*** (0.0035)	0.2668*** (0.0038)	0.2792*** (0.0043)
Tenure: 2–4 years	0.0313*** (0.0097)	0.0289*** (0.0105)	0.0426*** (0.0079)	0.0394*** (0.0080)
Tenure: 4–8 years	0.0608*** (0.0092)	0.0529*** (0.0125)	0.0763*** (0.0077)	0.0870*** (0.0084)
Tenure: 8–16 years	0.1447*** (0.0100)	0.1239*** (0.0144)	0.1571*** (0.0087)	0.1676*** (0.0089)
Tenure: ≥16 years	0.2259*** (0.0107)	0.2172*** (0.0154)	0.2607*** (0.0100)	0.2489*** (0.0101)
Nationality	-0.0621*** (0.0046)	-0.0660*** (0.0043)	-0.0660*** (0.0045)	-0.0602*** (0.0045)
Automation threat: middle	-0.0074 (0.0075)	-0.0428*** (0.0070)	-0.0613*** (0.0055)	-0.0245*** (0.0090)
Automation threat: high	-0.1009*** (0.0074)	-0.1390*** (0.0068)	-0.2038*** (0.0058)	-0.1649*** (0.0087)
Firm level agreement	0.0026 (0.0119)	0.0477*** (0.0042)	0.0397*** (0.0049)	0.0475*** (0.0047)
Sector level agreement	0.0169* (0.0102)	0.0666*** (0.0037)	0.0799*** (0.0036)	0.1020*** (0.0038)
Plant size: 1–9 employees	-0.1746*** (0.0180)	-0.2226*** (0.0154)	-0.2331*** (0.0143)	-0.2131*** (0.0196)
Plant size: 10–49 employees	-0.1350*** (0.0081)	-0.1495*** (0.0058)	-0.1387*** (0.0060)	-0.1271*** (0.0074)
Plant size: 50–199 employees	-0.0319*** (0.0034)	-0.0719*** (0.0032)	-0.0801*** (0.0036)	-0.0819*** (0.0041)
Plant size: 1000–4999 employees	0.0313*** (0.0018)	0.1098*** (0.0021)	0.1319*** (0.0022)	0.1317*** (0.0028)
Plant size: ≥5000 employees	0.1607*** (0.0024)	0.2317*** (0.0026)	0.2211*** (0.0024)	0.2282*** (0.0038)
Sector: food and beverages	-0.0946*** (0.0106)	-0.1487*** (0.0071)	-0.1886*** (0.0074)	-0.3234*** (0.0086)
Sector: textiles	-0.1808*** (0.0113)	-0.1958*** (0.0147)	-0.2469*** (0.0161)	-0.2124*** (0.0182)
Sector: wood, furniture and paper	0.0129 (0.0087)	-0.1461*** (0.0065)	-0.2175*** (0.0075)	-0.2177*** (0.0111)
Sector: plastic and chemical products	0.0375*** (0.0059)	0.0168*** (0.0042)	0.0117** (0.0048)	-0.0274*** (0.0052)
Sector: electrical products	0.0365*** (0.0072)	0.0858*** (0.0043)	0.0419*** (0.0045)	0.0250*** (0.0065)

(Continues)

TABLE B9 (Continued)

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

Note: The table presents the RIF-regressions for the 50th quantile. The observed years are 1996, 2010, 2012 and 2017. SEs are given in parentheses. Sampling weights are employed.

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

TABLE B10 RIF-regressions 85th quantile, 1996, 2010, 2012 and 2017

	1996	2010	2012	2017
Age: 18–25	0.1309 (0.0106)	0.1533*** (0.0089)	0.1564*** (0.0107)	0.1391*** (0.0099)
Age: 36–45	0.1239 (0.0085)	0.1355*** (0.0075)	0.1406*** (0.0083)	0.0914*** (0.0105)
Age: 46–55	0.2275 (0.0101)	0.1785*** (0.0081)	0.1940*** (0.0095)	0.1518*** (0.0121)
Age: ≥56	0.2649 (0.0127)	0.1902*** (0.0095)	0.1939*** (0.0107)	0.1332*** (0.0130)
Education: low	-0.1830*** (0.0046)	-0.1191 (0.0038)	-0.1187*** (0.0049)	-0.0882*** (0.0055)
Education: high	0.9562*** (0.0146)	1.0164 (0.0095)	1.0184*** (0.0109)	0.9216*** (0.0115)
Tenure: 3–4 years	0.0530*** (0.0155)	-0.0044*** (0.0106)	-0.0022 (0.0118)	-0.0059 (0.0138)
Tenure: 5–8 years	0.1376*** (0.0139)	0.0658*** (0.0111)	0.0755*** (0.0130)	0.0684*** (0.0133)
Tenure: 9–16 years	0.2469*** (0.0148)	0.1902*** (0.0126)	0.1943*** (0.0145)	0.1734*** (0.0150)
Tenure: ≥17 years	0.2671*** (0.0155)	0.2219*** (0.0139)	0.2505*** (0.0158)	0.2529*** (0.0174)
Nationality	-0.0759*** (0.0058)	-0.0885*** (0.0049)	-0.0863*** (0.0066)	-0.0679*** (0.0065)
Automation threat: middle	-0.0706*** (0.0166)	-0.0209 (0.0124)	-0.1377*** (0.0112)	-0.1402*** (0.0188)
Automation threat: high	-0.3492*** (0.0160)	-0.2708*** (0.0126)	-0.5368*** (0.0120)	-0.4575*** (0.0179)
Firm level agreement	0.0060*** (0.0179)	0.0045*** (0.0066)	0.0194 (0.0087)	0.0902*** (0.0077)
Sector level agreement	0.0079*** (0.0161)	0.0454*** (0.0057)	0.0673*** (0.0061)	0.0912*** (0.0065)
Plant size: 1–9 employees	-0.1042*** (0.0264)	-0.1108*** (0.0220)	-0.1295*** (0.0210)	-0.1115*** (0.0360)
Plant size: 10–49 employees	-0.1133*** (0.0130)	-0.0923*** (0.0086)	-0.1138*** (0.0097)	-0.0643*** (0.0131)
Plant size: 50–199 employees	-0.0168*** (0.0062)	-0.0526*** (0.0051)	-0.0793*** (0.0067)	-0.0725*** (0.0063)
Plant size: 1000–4999 employees	0.0261*** (0.0032)	0.0771*** (0.0039)	0.1119*** (0.0046)	0.11179*** (0.0053)
Plant size: ≥5000 employees	0.1221*** (0.0043)	0.2125*** (0.0047)	0.2626*** (0.0047)	0.1862*** (0.0064)
Sector: food and beverages	-0.2853*** (0.0194)	-0.1827*** (0.0108)	-0.3242*** (0.0123)	-0.3437*** (0.0138)
Sector: textiles	-0.3253*** (0.0189)	-0.2836*** (0.0237)	-0.4845*** (0.0264)	-0.3932*** (0.0307)
Sector: wood, furniture and paper	-0.0649*** (0.0124)	-0.2411*** (0.0106)	-0.4705*** (0.0125)	-0.4698*** (0.0204)
Sector: plastic and chemical products	0.0176* (0.0098)	0.0308*** (0.0064)	0.0500*** (0.0086)	0.0056 (0.0081)
Sector: electrical products	0.0355*** (0.0097)	0.1485*** (0.0075)	0.0398*** (0.0089)	0.0017 (0.0129)

(Continues)

TABLE B10 (Continued)

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

Note: The table presents the RIF-regressions for the 85th quantile. The observed years are 1996, 2010, 2012 and 2017. SEs are given in parentheses. Sampling weights are employed.

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

TABLE B11 RIF-regressions Gini coefficient, 1996, 2010, 2012 and 2017

	1996	2010	2012	2017
Age: 18–25	0.0591*** (0.0010)	0.0779*** (0.0021)	0.0664*** (0.0018)	0.0502*** (0.0020)
Age: 36–45	0.0306*** (0.0007)	0.0368*** (0.0013)	0.0371*** (0.0012)	0.0227*** (0.0013)
Age: 46–55	0.0544*** (0.0008)	0.0589*** (0.0015)	0.0599*** (0.0014)	0.0424*** (0.0015)
Age: ≥56	0.0635*** (0.0010)	0.0628*** (0.0017)	0.0613*** (0.0015)	0.0489*** (0.0016)
Education: low	0.0059*** (0.0007)	0.0248*** (0.0012)	0.0278*** (0.0012)	0.0231*** (0.0014)
Education: high	0.2834*** (0.0008)	0.2996*** (0.0011)	0.2582*** (0.0009)	0.2298*** (0.0010)
Tenure: 3–4 years	−0.0139*** (0.0014)	−0.0326*** (0.0028)	−0.0332*** (0.0023)	−0.0325*** (0.0027)
Tenure: 5–8 years	−0.0134*** (0.0012)	−0.0292*** (0.0027)	−0.0331*** (0.0022)	−0.0538*** (0.0026)
Tenure: 9–16 years	0.0023 (0.0012)	−0.02236*** (0.0028)	−0.0251*** (0.0023)	−0.0535*** (0.0027)
Tenure: ≥17 years	−0.0099*** (0.0013)	−0.0409*** (0.0029)	−0.0442*** (0.0025)	−0.0520*** (0.0029)
Nationality	−0.0051*** (0.0007)	−0.0095*** (0.0012)	0.0004 (0.0011)	0.0074*** (0.0012)
Automation threat: middle	−0.0145*** (0.0010)	0.0153*** (0.0015)	−0.0158*** (0.0012)	−0.0238*** (0.0016)
Automation threat: high	−0.0509*** (0.0009)	−0.0195*** (0.0015)	−0.0648*** (0.0014)	−0.0631*** (0.0017)
Firm level agreement	−0.0056*** (0.0011)	−0.0322*** (0.0012)	−0.0225*** (0.0011)	−0.0092*** (0.0014)
Sector level agreement	−0.0162*** (0.0009)	−0.0211*** (0.0009)	−0.0228*** (0.0007)	−0.0224*** (0.0009)
Plant size: 1–9 employees	0.0616*** (0.0011)	0.1097*** (0.0020)	0.1128*** (0.0018)	0.0950*** (0.0024)
Plant size: 10–49 employees	0.0208*** (0.0007)	0.0348*** (0.0011)	0.0369*** (0.0010)	0.0334*** (0.0012)
Plant size: 50–199 employees	0.0101*** (0.0006)	0.0109*** (0.0009)	0.0087*** (0.0008)	0.0083*** (0.0010)
Plant size: 1000–4999 employees	0.0011 (0.0007)	0.0163*** (0.0010)	0.0205*** (0.0009)	0.0187*** (0.0011)
Plant size: ≥5000 employees	0.0417*** (0.0009)	0.0668*** (0.0014)	0.0639*** (0.0011)	0.0306*** (0.0014)
Sector: food and beverages	−0.0066*** (0.0013)	0.0269*** (0.0016)	0.0125*** (0.0014)	0.0622*** (0.0016)
Sector: textiles	−0.0119*** (0.0015)	0.0303*** (0.0032)	−0.0023 (0.0030)	0.0436*** (0.0043)
Sector: wood, furniture and paper	−0.0153*** (0.0009)	−0.0111*** (0.0015)	−0.0395*** (0.0016)	−0.0464*** (0.0022)
Sector: plastic and chemical products	0.0007 (0.0008)	0.0049*** (0.0011)	0.0102*** (0.0010)	0.0121*** (0.0013)
Sector: electrical products	−0.0020** (0.0009)	0.0311*** (0.0011)	−0.0021* (0.0011)	−0.0031** (0.0014)

(Continues)

TABLE B11 (Continued)

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

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

TABLE B12 RIF-regressions variance, 1996, 2010, 2012 and 2017

	1996	2010	2012	2017
Age: 18–25	0.0567*** (0.0013)	0.0818*** (0.0029)	0.0709*** (0.0025)	0.0488*** (0.0029)
Age: 36–45	0.0306*** (0.0008)	0.0566*** (0.0018)	0.0517*** (0.0017)	0.0349*** (0.0019)
Age: 46–55	0.0573*** (0.0010)	0.0854*** (0.0020)	0.0829*** (0.0019)	0.0617*** (0.0022)
Age: ≥56	0.0684*** (0.0012)	0.0923*** (0.0023)	0.0851*** (0.0021)	0.0699*** (0.0024)
Education: low	0.0134*** (0.0009)	0.0360*** (0.0017)	0.0440*** (0.0017)	0.0354*** (0.0020)
Education: high	0.2951*** (0.0010)	0.3686*** (0.0014)	0.3165*** (0.0013)	0.2890*** (0.0014)
Tenure: 3–4 years	−0.0394*** (0.0017)	−0.0883*** (0.0039)	−0.0877*** (0.0032)	−0.0861*** (0.0038)
Tenure: 5–8 years	−0.0422*** (0.0015)	0.0901*** (0.0039)	−0.0976*** (0.0031)	−0.1346*** (0.0037)
Tenure: 9–16 years	−0.0222*** (0.0015)	−0.1051*** (0.0040)	−0.1015*** (0.0033)	−0.1393*** (0.0038)
Tenure: ≥17 years	−0.0326*** (0.0016)	−0.1319*** (0.0042)	−0.1295*** (0.0035)	−0.1415*** (0.0041)
Nationality	−0.0109*** (0.0009)	−0.0159*** (0.0017)	0.0001 (0.0015)	0.0133*** (0.0017)
Automation threat: middle	−0.0254*** (0.0012)	0.0191*** (0.0020)	−0.0201*** (0.0018)	−0.0254*** (0.0023)
Automation threat: high	−0.0654*** (0.0012)	−0.0360*** (0.0021)	−0.0929*** (0.0019)	−0.0868*** (0.0025)
Firm level agreement	−0.0297*** (0.0013)	−0.0432*** (0.0017)	−0.0346*** (0.0016)	−0.0144*** (0.0019)
Sector level agreement	−0.0428*** (0.0011)	−0.0295*** (0.0012)	−0.0347*** (0.0011)	−0.0318*** (0.0013)
Plant size: 1–9 employees	0.0716*** (0.0013)	0.2133*** (0.0028)	0.1967*** (0.0026)	0.1528*** (0.0034)
Plant size: 10–49 employees	0.0183*** (0.0009)	0.0431*** (0.0016)	0.0477*** (0.0014)	0.0430*** (0.0017)
Plant size: 50–199 employees	0.0037*** (0.0007)	0.0144*** (0.0013)	0.0124*** (0.0012)	0.0098*** (0.0014)
Plant size: 1000–4999 employees	−0.0008 (0.0008)	0.0281*** (0.0014)	0.0339*** (0.0013)	0.0339*** (0.0016)
Plant size: ≥5000 employees	0.0469*** (0.0011)	0.0936*** (0.0020)	0.0977*** (0.0017)	0.0617*** (0.0020)
Sector: food and beverages	0.0090*** (0.0016)	0.0504*** (0.0022)	0.0292*** (0.0020)	0.0797*** (0.0023)
Sector: textiles	−0.0170*** (0.0018)	0.0503*** (0.0046)	0.0140*** (0.0042)	0.0764*** (0.0061)
Sector: wood, furniture and paper	−0.0181*** (0.0011)	−0.0154*** (0.0022)	−0.0573*** (0.0022)	−0.0639*** (0.0032)
Sector: plastic and chemical products	−0.0034*** (0.0009)	0.0134*** (0.0016)	0.0145*** (0.0015)	0.0167*** (0.0019)
Sector: electrical products	−0.0028*** (0.0010)	0.0439*** (0.0016)	0.0045*** (0.0016)	−0.0045*** (0.0020)

(Continues)

TABLE B12 (Continued)

	1996	2010	2012	2017
Sector: industrial machinery	-0.0146*** (0.0009)	-0.0236*** (0.0015)	-0.0300*** (0.0013)	-0.0318*** (0.0016)
Sector: automotive and other vehicles	0.0067*** (0.0010)	0.0006 (0.0017)	0.0198*** (0.0016)	0.0141*** (0.0020)
Schleswig-Holstein	0.0118*** (0.0019)	0.0262*** (0.0031)	0.0203*** (0.0032)	-0.01113*** (0.0039)
Hamburg	-0.0037* (0.0019)	-0.0044 (0.0028)	0.0139*** (0.0024)	-0.0328*** (0.0031)
Lower Saxony	0.0048*** (0.0009)	0.0187*** (0.0017)	0.0182*** (0.0016)	-0.01112*** (0.0019)
Bremen	0.0138*** (0.0026)	0.0102*** (0.0065)	-0.0286*** (0.0043)	0.0037 (0.0057)
Hesse	0.0228*** (0.0010)	0.0171*** (0.0020)	0.0119*** (0.0017)	0.0265*** (0.0020)
Rhineland-Palatinate	-0.0121*** (0.0013)	-0.0103*** (0.0021)	0.0015 (0.0020)	-0.0192*** (0.0022)
Baden-Wuerttemberg	0.0067*** (0.0008)	0.0113*** (0.0013)	0.0151*** (0.0013)	0.0196*** (0.0015)
Bavaria	0.0005 (0.0008)	0.0108*** (0.0013)	0.0021 (0.0012)	0.0256*** (0.0014)
Saarland	-0.0299*** (0.0021)	-0.0059 (0.0036)	0.0218*** (0.0044)	0.0208*** (0.0053)
Constant	0.1681*** (0.0022)	0.1757*** (0.0046)	0.2318*** (0.0039)	0.2696*** (0.0047)
Observations	576,895	389,624	437,336	320,970

Note: The table presents the RIF-regressions for the log Variance. The observed years are 1996, 2010, 2012 and 2017. SEs are given in parentheses. Sampling weights are employed.

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

TABLE B13 Decomposition of the variance, 1996–2010 and 2012–2017

	1996–2010		2012–17	
	Coefficient	SD	Coefficient	SD
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)

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

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

TABLE B14 Decomposition results using the probability of computerization by Frey and Osborne (2017), 1996–2010

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

TABLE B14 (Continued)

Inequality measure	85-15		Gini coefficient		50-15		85-50		Variance	
	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD
Constant	10.09*	(5.92)	3.00**	(1.40)	13.11***	(4.60)	-3.03	(3.53)	4.93	(3.10)
Total	2.19***	(0.64)	2.37***	(0.18)	3.65***	(0.47)	-1.45***	(0.55)	3.09***	(0.29)
Reweighting error	-1.04***	(0.17)	-0.21***	(0.05)	-0.23**	(0.11)	-0.81***	(0.11)	-0.30***	(0.06)

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Frey and Osborne (2017), own calculations.

TABLE B15 Decomposition results using the probability of computerization by Frey and Osborne (2017), 2012–2017

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

TABLE B15 (Continued)

Inequality measure	85-15		Gini coefficient		50-15		85-50		Variance	
	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD
Constant	16.08***	(4.97)	3.21***	(1.04)	2.75	(3.58)	13.33	(3.04)	3.58*	(2.12)
Total	-0.57	(0.51)	-0.69	(0.09)	3.64***	(0.40)	-4.21*	(0.28)	-0.76***	(0.14)
Reweighting error	-0.48***	(0.06)	-0.09***	(0.01)	-0.04**	(0.02)	-0.44***	(0.05)	-0.09***	(0.02)

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

Source: LIAB QM2 9317, International Federation of Robotics (2018) and Frey and Osborne (2017), own calculations.

TABLE B16 Decomposition results without the automotive and other vehicles sector, 1996–2010

Inequality measure	85–15		Gini coefficient		50–15		85–50		Variance	
	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD
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)

TABLE B16 (Continued)

Inequality measure	85-15		Gini coefficient		50-15		85-50		Variance	
	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD
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)

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

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

TABLE B17 Decomposition results without the automotive and other vehicles sector, 2012–2017

Inequality measure	85–15		Gini coefficient		50–15		85–50		Variance	
	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD
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)

TABLE B17 (Continued)

Inequality measure	85-15		Gini coefficient		50-15		85-50		Variance	
	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD	Coefficient	SD
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)

Note: 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 per cent level, respectively. Bootstrapped SEs with 100 replications are presented in parentheses. Sampling weights are employed.

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

APPENDIX C

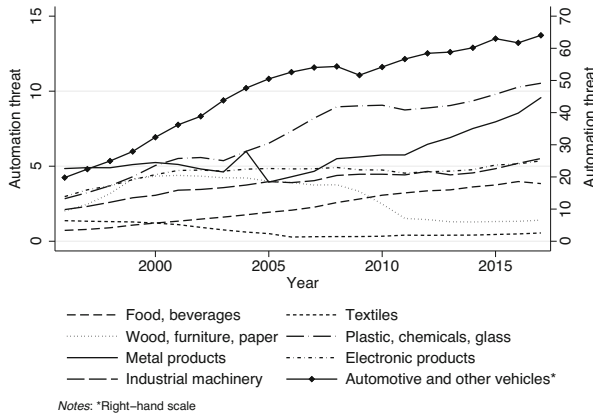


FIGURE C1 Automation threat in Germany across sectors in the manufacturing industry from 1996 to 2017. The figure presents the evolution of the automation threat variable across sectors in the German manufacturing industry. In the case of the automotive and other vehicles sector the development is right-hand scaled. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

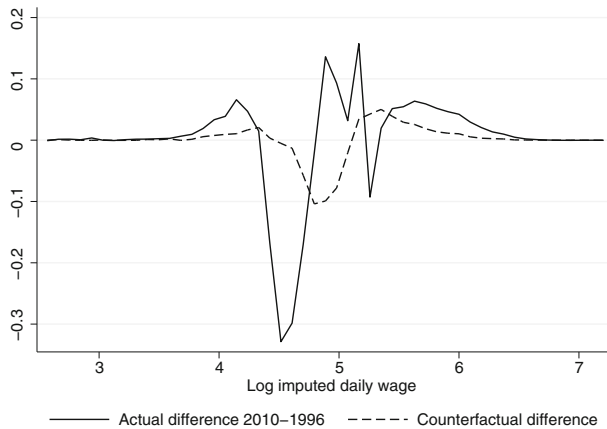


FIGURE C2 Actual and counterfactual differences, 1996–2010. The figure presents the comparison between the actual and counterfactual differences between 1996 and 2010. Counterfactual weights are estimated using multinomial logit estimations, see Appendix A.3. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

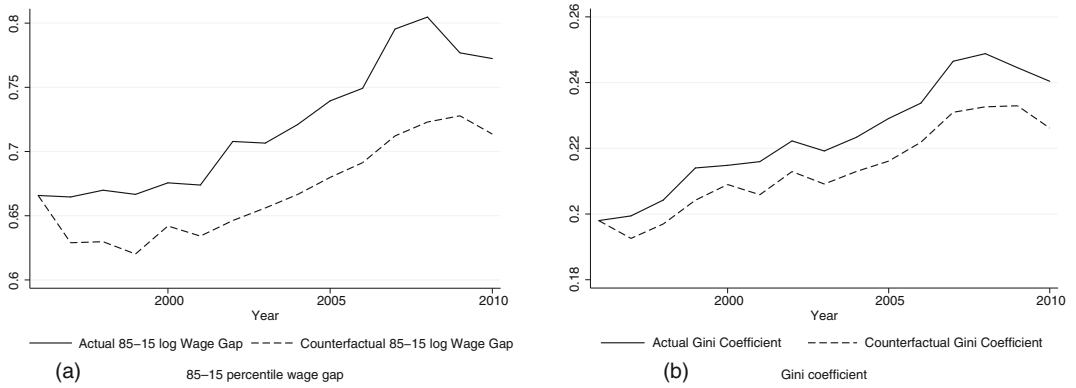


FIGURE C3 Actual and counterfactual 85–15 percentile wage gap and Gini coefficient from 1996 to 2010. Panel (a) (Panel (b)) of the figure presents the evolution of the actual 85–15 percentile wage gap (Gini coefficient estimations) as well as the counterfactual 85–15 percentile wage gap (Gini coefficient estimations) that would have prevailed if automation and robotization had remained at the level of 1996. Counterfactual weights are estimated using multinomial logit estimations, see Appendix A.3. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

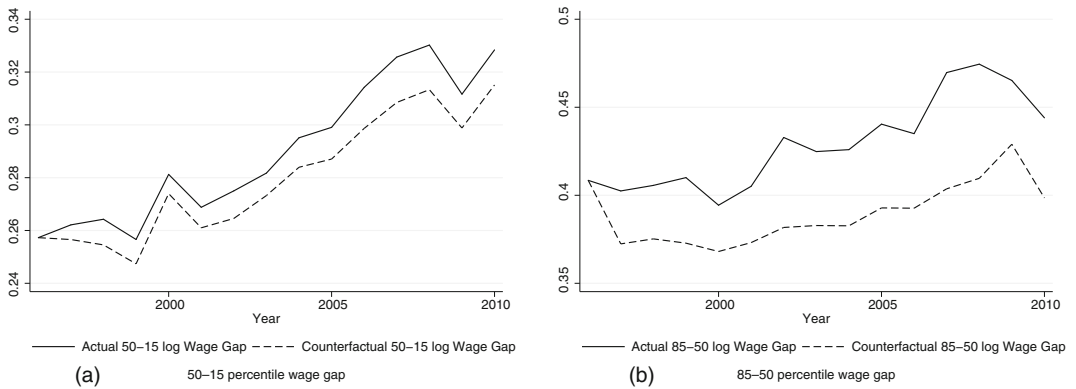


FIGURE C4 Actual and counterfactual 50–15 and 85–50 percentile wage gap from 1996 to 2010. Panel (a) (Panel (b)) of the figure presents the evolution of the actual 50–15 (85–50) percentile wage gap as well as the counterfactual 50–15 (85–50) percentile wage gap that would have prevailed if automation and robotization had remained at the level of 1996. Counterfactual weights are estimated using multinomial logit estimations, see Appendix A.3. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

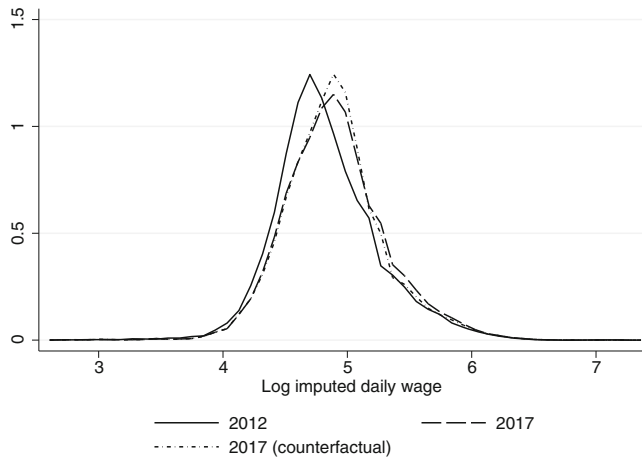


FIGURE C5 Actual and counterfactual wage distributions, 2012–2017. The figure presents the actual wage distributions in 2012 and 2017 as well as the counterfactual wage distribution that would have prevailed if automation and robotization had remained at the level of 2012. Counterfactual weights are estimated using multinomial logit estimations, see Appendix A.3. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.

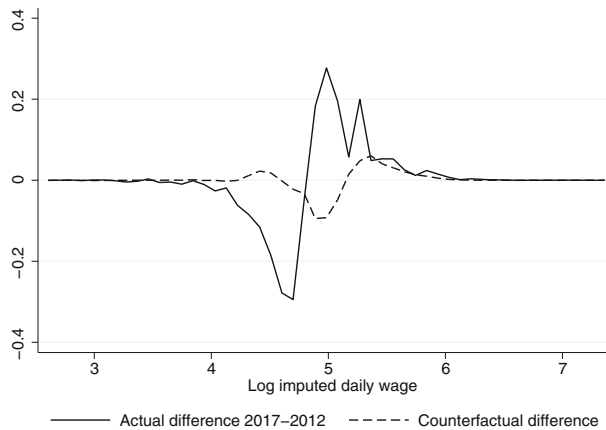


FIGURE C6 Actual and counterfactual differences, 2012–2017. The figure presents the comparison between the actual and counterfactual differences between 2012 and 2017. Counterfactual weights are estimated using multinomial logit estimations, see Appendix A.3. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.



FIGURE C7 Actual and counterfactual 85–15 percentile wage gap and Gini coefficient from 2012 to 2017. Panel (a) (Panel (b)) of the figure presents the evolution of the actual 85–15 percentile wage gap (Gini coefficient estimations) as well as the counterfactual 85–15 percentile wage gap (Gini coefficient estimations) that would have prevailed if automation and robotization had remained at the level of 2012. Counterfactual weights are estimated using multinomial logit estimations, see Appendix A.3. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations.



FIGURE C8 Actual and counterfactual 50–15 and 85–50 percentile wage gap from 2012 to 2017. Panel (a) (Panel (b)) of the figure presents the evolution of the actual 50–15 (85–50) percentile wage gap as well as the counterfactual 50–15 (85–50) percentile wage gap that would have prevailed if automation and robotization had remained at the level of 2012. Counterfactual weights are estimated using multinomial logit estimations, see Appendix A.3. Sampling weights are employed. *Source:* LIAB QM2 9317, International Federation of Robotics (2018) and Dengler and Matthes (2015), own calculations