Drivers of Wage Inequality in Germany: Trade, Technology, or Institutions?

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Abstract

We quantify the relative contributions of changes in export exposure, new technologies, and collective bargaining regimes to the recent rise in German wage inequality in a unified framework. To this end, we use a linked employer-employee data of the German manufacturing sector and apply a decomposition method based on recentered influence function (RIF) regressions. Our findings suggest that the decline of collective bargaining and changing collective bargaining wage premia have been the most important explanatory factors. Composition effects associated with age and education have also been important, while the contributions of exports and technology have been more modest. When we separately analyse between-plant and within-plant wage dispersion, we find that several explanatory factors have opposing effects on these two subcomponents of wage inequality.

Keywords: Wage inequality; Decomposition; RIF-Regression; Linked employer-employee data

JEL classification: J 31; F 16

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1 Introduction

It is well known that wage inequality has increased considerably over the last two decades in Germany. Dustmann et al. (2009), Card et al. (2013) and Dustmann et al. (2014) have provided rich accounts of the facts. However, the underlying factors that drive this development are still underexplored. What is missing is a unified framework that identifies the most important factors and which quantifies the relative contributions to the rise in wage dispersion. Our paper tries to fill this gap.

Previous research has already pointed to some important factors in the development of German wage inequality. In their seminal contribution Dustmann et al. (2009) stress the role of changes in labor market institutions for the rise in wage dispersion. They argue that the decline in collective bargainng coverage is a key driver of wage inequality, especially at the bottom of the wage distribution. In a different analysis, they also find some indicative evidence for technological change to play a role. Other recent contributions that consider changes in U.S. wage inequality, e.g. Autor et al. (2008) and Firpo et al. (2014), identify technological change as a key driver for recent developments in wage dispersion. Their argument is that technological change can be routine-biased and can affect different workers along the earnings distribution in different ways.[1] Another potential driving factor is related to international trade. Parallel to the increase in inequality, the German economy experienced a rising degree of integration into the world market. Baumgarten (2013) analyzes the role of exports for changes in German wage inequality from 1996 to 2007 and identifies a moderate impact.[2]

In this paper, we aim to give a sound picture of the driving forces for the recent change in German wage inequality. Using German linked employer-employee data over the period from 1996 to 2010 we apply a decomposition approach which was recently developed by Firpo et al. (2009). The method makes use of recentered influence function (RIF) regressions and allows quantifying the impact of different factors on wage inequality in a unified framework. To the best of our knowledge, ours is the first study that tries to quantify the influence of personal characteristics (age, education, occupation), institutional components (collective bargainng coverage) and firm characteristics (technological status, export behaviour) for German wage dispersion in a unified framework.

By applying the RIF-regression approach this paper is closely related to a strand of literature that deals with the decomposition of wage distributions (e.g. DiNardo et al. (1996), Lemieux (2006)). It is a crucial insight of this literature that it is important to distinguish whether changes in inequality can be explained by changes in the workforce composition, or whether they reflect changes in returns to certain characteristics.

Moreover, our work is related to Card et al. (2013) who also analyze German wage dispersion. They argue that especially establishment and match effects between workers and

[1] This idea builds on the so called polarization hypothesis which was pioneered by Autor et al. (2003, 2006). It assumes that technological change - e.g. through the form of automation - may affect workers differently according to their occupation and their related task content. It is assumed that new technologies can act as complements to some and as substitute to other tasks and that this can have an impact on wages.

[2] The central argument in his analysis is related to the empirical fact that exporting plants on average pay higher wages and can therefore have an impact on wage inequality. Related arguments are made by Helpmann et al. (2010).

firms have to be taken into account to explain the recent rise in wage inequality. However, they do not exactly identify which firm characteristics play a role for wage dispersion. We address this point by including firm characteristics into our analysis. Moreover, we build on the insight that firm heterogeneity seems to play an important role and look at between-plant inequality and within-plant inequality separately. We therefore contribute to the literature that stresses the importance of the between-firm component for overall inequality changes (e.g. Davis and Haltiwanger (1991) and Dunne et al. 2004 for the U.S.) and add a new dimension of within-plant inequality to the debate. We separately analyze both inequality components and quantify the contributions of our explanatory factors to their changes.

The main findings of this study are as follows. First, we find that most of the increase in wage dispersion (80%) is due to changes in the compositional structure of the workforce. Second, we can confirm the great importance of the decline in collective bargaining regimes for the rise in wage inequality, thus extending the evidence reported by Dustmann et al. (2009). We find, however, that the compositional shift goes along with a decline in the premium to collective wage bargaining for low wage earners in the first period of our analysis (1996-2003). Thus, our evidence suggests that at least up to 2003 low wage earners are hit by both effects. Third, compositional shifts towards higher education and age groups also play an important role and this effect is especially present at the upper tail of the wage distribution. Furthermore, high wage workers benefit from rising returns to skill. Technology and export status of an establishment seem to play a less important role for developments in overall wage inequality. Fourth, looking at between-plant and within-plant inequality measures yields interesting results. We find that some variables have opposing effects on both components, which explains why it is hard to identify an effect on overall inequality. Moreover, our results suggest an inequality reducing effect of the export status variable on the between-plant component and an inequality increasing effect of technology on within-plant dispersion. Furthermore, we find evidence for positive assortative matching between workers and plants.

The paper is organized as follows. In Section 2 we describe the data and present some stylized facts. Section 3 provides a summary of the decomposition methodology. The main decomposition results are presented in Section 4, where we first present the results of our baseline analysis and then show the results for the between-plant and within-plant inequality decomposition. We briefly conclude in Section 5.

2 Data and stylized facts

2.1 Linked employer-employee data

We build our analysis on the German LIAB data set, which is a linked employer-employee data set provided by the Institute for Employment Research (IAB) in Nuremberg. It combines the IAB Establishment Panel with social security data on all workers who were employed in one of the establishments as of the 30th of June of a given year.

The IAB Establishment Panel is a stratified sample of all establishments that employ at least one worker subject to social security. The strata variables are defined over regions, industries and size classes. Appropriate weights, which are inverse to the sampling probability, are provided to assure the representativeness of the results. The IAB Establishment Panel started in 1993 with West-German establishments, East-German plants are included from 1996 onwards. Although participation in the IAB Establishment Panel is voluntary, the response rate is very high (up to 80 %). The survey covers many different topics. For our analysis, the information regarding the share of exports in total sales, investment in communication technology, and information related to the wage bargaining regime are most important. This information is surveyed every year.[3]

The employee data stem from social security registrations by the employer that are mandated by law. Hence, only workers covered by social security are included in the Employment Statistics. Civil servants and self-employed are not registered. It still covers, however, about 80% of the German workforce. These compulsory social security records contain personal information such as gender, the level of education, the year of birth, detailed information about the occupation (on a three-digit level) and the (top-coded) daily wage.

To make our analysis comparable to previous research (e.g. Dustmann et al. (2009), Card et al. (2013)) we limit our attention to full-time jobs held by men in the age of 18-65. We exclude marginal jobs that are subject to reduced social security contributions as well as workers that undergo training. Workers who hold multiple jobs or draw some form of benefits at the same time are also excluded. The same is true for observations that are reported to have an (implausibly) low daily wage of less than ten euros. Furthermore, we restrict our analysis to the manufacturing sector since information about the establishments' exports are patchy for other sectors.[4] Our period of analysis covers the years from 1996 to 2010, which is the maximum time span for an analysis of the reunified Germany. Taking these restrictions into account we end up with 554 934 (392 907) workers and 1 530 (2 840) establishments in 1996 (2010). It is worth noting, that our sample restrictions may lead to an underestimation of the overall level and growth of wage inequality among German male workers in the manufacturing sector. However, since we cannot control for hours worked, such restrictions are needed to avoid measurement error.

An important limitation of our data is the censoring of wages at the annual social security maximum. In our sample, between nine and 14% of the wage observations are censored every year. To address this problem we follow Dustmann et al. (2009) and impute the missing upper tail of the wage distribution using a series of Tobit regressions.[5] Using the estimated parameters from these models, we replace each censored wage value with a random draw from the upper tail of the appropriate conditional wage distribution. Note that in most cases, we focus on intercentile comparisons of the 85th percentile to the median or the 15th percentile, so that we do not expect that possible biases in the extrapolation

[3]Further establishment variables, such as the industry affiliation on a three-digit level and regional information, are provided from the Establishment History Panel.

[4]Moreover, we do not consider those establishments, where the reporting unit in the Establishment Panel has changed over time. This is due to the fact that such a change in the reporting unit might not be accompanied by a corresponding change in the workforce data, since the establishment id stays the same.

[5]We run a series of Tobit regressions for each year, education-group and region (east/west). The explanatory variables are five age-group dummies, industry and federal-states dummies, occupation dummies as well as indicator variables for export behavior, the investment in technology of plants and the collective bargaining status.

strategy affect the broad findings of our study. All wage information is converted into constant year-2000 euros by deflating them with the Consumer Price Index as provided by the German Federal Statistical Office. Tables A1-A2 in the appendix show summary statistics of our sample.

2.2 Trends in German wage inequality

Panel (a) of Figure 1 displays the evolution of the standard deviation of log real wages in the manufacturing sector as a measure of wage inequality. It can be seen that wage inequality is rising up to the year 2008. It slightly declines in 2009 and remains at this level up to 2010. Panel (b) of Figure 1 shows changes in log real wages over time at different percentiles of the earnings distribution (normalized to the year 1996). Up to the year 2007 workers at the median and at the 85th percentile have realized real wage gains, while workers at the 15th percentile have faced moderate declines in real wages. During the three most recent years of our sample (2007-2010) all workers up to the 85th percentile have realized real wage losses. Considering the 85-50 and 50-15 log wage differential as measures of upper and lower tail inequality, it becomes apparent that most of the overall increase in wage inequality is due to changes in the lower part of the earnings distribution.

[FIGURE 1 HERE]

2.3 Trends in trade, technology and institutions

This increase in German wage dispersion has happened before the background of other important events that hit the German economy at the same time. First, as already discussed by Baumgarten (2013), there has been a considerable increase in trade relations for German establishments. According to the LIAB data the share of exporters increased by 55% from 1996 to 2010 and the share of exports at exporting establishments increased by 63% (see Table 1). Moreover, the employment share of exporting plants rose from 68% to 76% over this time period, thus indicating the importance of exporting plants in the German employment structure.

Second, changes in technology might have influenced the development of wages during the period under study. According to the LIAB data, 34% of plants have invested in information and communication technologies in 1996, while only 29% report to have done such an investment in 2010. This declining share in the technology variable could to some extent mirror the difficulty of measuring technology appropriately (since firms that have invested in one year do not necessarily have to invest in the following year as well to be high-technology-firms). On the other hand it could also represent the "true" development that German establishments have invested more in technology during the 1990s than during recent years.[6]

Finally, the rise in wage inequality happend in the context of a steady decline in the coverage of collective bargaining agreements in Germany. Between 1996 and 2010, the share

[6]The latter explanation seems to be more likely, since an alternative technology measure which refers to the technological status of the establishment also shows a declining share.

of workers covered by an industry-level agreement declined from 77% to 53% and the share of workers belonging to a firm-level agreement only slightly rose by one percentage point. At the plant-level, 36% of firms opted out of industry-level agreements and even 70% opted out of firm-level agreements. Table 1 summarizes the changes in exports, technology and collective bargaining agreements according to the LIAB for the years 1996 and 2010.

[TABLE 1 HERE]

3 Empirical approach and methodology

In order to quanitfy the contributions of different explanatory factors to the rise in German wage inequality, we apply a decomposition method which is based on recentered influence function (RIF) regressions and was introduced by Firpo et al. (2009). For a thorough description of the methodology we refer the reader to the corresponding section in Firpo et al. (2014) and Fortin et al. (2011), where the approach is explained in detail. Before sketching, however, the underlying idea of the decomposition method, we point to the properties that are required for our analysis: First, we want to divide the overall change in wage inequality into a composition effect, which is linked to changes in the distribution of covariates, and a wage structure effect that reflects how the conditional distribution of wages changes over time. Second, we want to quantify the impact of every single factor separately. Therefore, it is not enough to disentangle changes in the composition and changes in the wage structure for the aggregate, but for every single covariate separately. Third, we aim to analyze the effect of each factor at different percentiles of the wage distribution. This allows us to disentangle the impact of each factor on lower tail inequality (50-15 log wage differential) versus its effect on upper tail inequality (85-50 log wage differential). A standard Blinder-Oaxaca decomposition meets the first two requirements, but can only be applied to the mean of a distribution. The RIF-regression method can be thought of as a generalization of the Blinder-Oaxaca decomposition to all quantiles (or other moments) of a distribution.

A RIF-regression is similar to a standard regression with the exception that the dependent variable Y is replaced by the recentered influence function of the statistic of interest. Consider $IF(y;\upsilon)$, the influence function of interest corresponding to an observed wage y for the distributional statistic of interest (e.g., a quantile, the standard deviation, the gini coefficient) $\upsilon(F_Y)$. The recentered influence function is defined as $RIF(y;\upsilon) = \upsilon(F_Y) + IF(y;\upsilon)$ so that it aggregates back to the statistic of interest: $\int RIF(y;\upsilon) \cdot dF(y) = \upsilon(F_Y)$.

Assuming that the conditional expectation of $RIF(y;\upsilon)$ can be modeled as a linear function of the explanatory variables,

$$E[RIF(y;\upsilon)|X] = X\gamma + \epsilon,$$

the corresponding parameters γ can be estimated by OLS. Applying this approach to quantiles, the RIF regression corresponds to an unconditional quantile regression, which allows one to estimate the marginal effect of, say, the share of workers covered by collective bargaining on the τth quantile of the wage distribution. Different from a standard conditional quantile regression, which only captures within-group (or residual) wage effects of the covariates, the unconditional quantile regression captures both within-group and between-group effects. For example, in the case of collective bargaining, the (typically negative) within-group effect on wage inequality stems from the fact that within the covered sector, wages (among comparable workers) tend to be more compressed than in the non-covered sector. On the other hand, the (typically positive) between-group effects results from covered workers usually earning a higher conditional mean wage than non-covered workers. As this example illustrates, the within-group and the between-group effects may go into different directions, and one or the other may dominate at different points of the wage distribution.

Due to the linearization, it is straightforward to apply the standard Blinder-Oaxaca decomposition to the RIF regression. Thus, if one is interested in decomposing changes in the distributional parameter $\upsilon(F_Y)$ between two different time periods ($t = 0$ and $t = 1$), the decomposition reads as

$$\hat{\Delta}_O^{\upsilon} = \overline{X}_1 \left(\hat{\gamma}_1^{\upsilon} - \hat{\gamma}_0^{\upsilon}\right) + \left(\overline{X}_1 - \overline{X}_0\right) \hat{\gamma}_0^{\upsilon} \tag{1}$$

where $\hat{\Delta}_O^{\upsilon}$ denotes the overall change in the statistic υ, the first term on the right-hand side denotes the wage structure effect, $\hat{\Delta}_S^{\upsilon}$, and the second term denotes the composition effect, $\hat{\Delta}_X^{\upsilon}$.

As Firpo et al. (2014) explain, there may be a bias in the decomposition because the linear specification used in the regression is only a local approximation that does not generally hold for larger changes in the covariates. In particular, the RIF coefficients might change if the distribution of the covariates changes even though the true wage structure remains the same. To circumvent this problem, Firpo et al. (2014) propose to combine the RIF regressions with a reweighting approach, where the counterfactual $\hat{\gamma}_{01}^{\upsilon}$ coefficients are obtained from a RIF regression on the period 0 sample reweighted to mimic the period 1 sample (such that $plim(\overline{X}_{01}) = plim(\overline{X}_1)$). Taken this adjustment into account, the pure wage structure effect amounts to

$$\overline{X}_1 \left(\hat{\gamma}_1^{\upsilon} - \hat{\gamma}_{01}^{\upsilon}\right)$$ [7]

and the pure composition effect to

$$\left(\overline{X}_{01} - \overline{X}_0\right) \hat{\gamma}_0^{\upsilon}.$$ [8]

Just like in the standard Blinder-Oaxaca decomposition, it is possible to obtain the detailed elements of the wage structure and the composition effects which are attributable to different subsets of the vector of explanatory variables, X. However, in case of the wage structure effect, the detailed elements are not unique and, for categorical variables, depend

[7] The estimate of the wage structure effect can be devided into the pure wage structure effect and the reweighting error. See Firpo et al. (2014) for details.

[8] The estimate of the composition effect can be divided into a pure composition effect and a component measuring the specification error. The specification error captures the difference between the composition effect estimated using a non-parametric reweighthing approach and the linear approximation obtained using the RIF-regression.

on the choice of the base category which has to be taken into account when interpreting the results.

We use this decomposition approach to look at the contribution of our explanatory factors to changes in the wage distribution. These factors cover the personal characteristics education (four categories)[9], age (five categories)[10] and dummies for more than 300 different occupations. Moreover, we consider a dummy variable that indicates the export status of an establishment, two dummy variables capturing the bargaining regime of the establishment (sector-level, firm level agreement or no collective bargaining agreement) and a dummy variable that equals one if the plant has invested in communication or information technology. Finally, we include a full set of two-digit industry dummies to capture sectoral shifts during our period under study.[11]

It is worth emphasizing that like many other decomposition methods, RIF regressions assume the invariance of the conditional distribution. That means that the decomposition method ignores general equilibrium effects. For our analysis this implies, e.g., that the union-nonunion wage differential is independent of union coverage.

4 Results

4.1 Baseline decomposition

The results of our baseline decomposition are presented in Table 2. We report changes over time in the 85-15 log wage differential as a measure of overall inequality, and changes in the 50-15 and 85-50 log wage differential as measures of lower tail and upper tail wage inequality, respectively. The numbers represent log percentage point increases between the beginning and the end of the period.[12]

[TABLE 2 HERE]

Considering first the results for overall inequality, it can be seen that almost 80% of the entire increase in wage inequality can be attributed to composition effects. Changes in the wage bargaining regime exhibit the greatest impact and are associated with an increase in wage dispersion of almost six log percentage points. This finding mirrors the impact of the overall decline in collective bargaining coverage over the period of analysis (1996-2010). Comparing the composition effects of collective bargaining coverage across

[9] 1) Low: no vocational training, no high school. 2) Medium: high school and/or vocational training. 3) High: university or technical college. The fourth category consists of observations with missing educational information.

[10] 1) 18-25 years. 2) 26-35 years. 3) 36-45 years. 4) 46-55 years. 5)56-65 years.

[11] We choose our base category to be a worker employed at a non-exporting establishment, which is not covered by a collective bargaining agreement and which has not invested into communication technology. Regarding the categorial variables, we choose the modal categories in 1996 to be our base categories. These are medium skilled workers, in the age of 26 to 35, metalworkers in the manufacture of machinery and equipment industry.

[12] In addition to composition and wage structure effects we also report the specification and reweighting errors for each decomposition. As Firpo et al. (2014) explain, the specification error is the difference between composition effects estimated using RIF regressions and those estimated non-parametrically using the reweighting method. The specification errors are small overall, but clearly not negligible for this period of study. This indicates that there is some discrepancy between the linear approximation used by the RIF regression and the non-parametrical reweighting procedure.

the lower and the upper tail of the distribution shows that the overall effect is amost entirely due to compositional changes at the lower tail. This indicates that the decline in collective bargaining regimes hit especially workers that already earn low wages. Our evidence supports the findings by Dustmann et al. (2009) who document similar effects of deunionization up to the year 2004.

Besides compositional changes related to deunionization, shifts in the education and age profile of workers play an important role for wage dispersion. These compositional shifts are associated with an increase in inequality of 1.3 (education) and 2.8 (age) log percentage points and the largest part of these effects relates to the upper part of the distribution. This captures the fact that over the period of analysis there has been a relative shift towards higher education and age groups, both of which are also associated with higher within-group wage dispersion (Lemieux (2006), Dustmann (2009)).[13]

Regarding our export and technology variable, we do not find any significant impact on wage inequality.[14]

Considering next the effects that can be related to the wage structure, it can be seen that changes in the returns to collective bargaining coverage also work inequality increasing. This is again especially the case for workers at the lower end of the earnings distribution, where the union premium declines. Thus, not only the composition but also the wage structure effect associated with the collective bargaining status contribute to increasing wage dispersion.

Furthermore, changes in returns to education have an inequality increasing effect, which is concentrated at the upper tail of the distribution. This finding is in line with a rise in the skill premium for workers. The wage structure effect associated with age has an inequality reducing effect. This mirrors the fact that the returns to age (or experience), relative to the base group, have declined over time.

The wage structure effect related to the export variable has a positive sign (thus beeing associated with increasing inequality), but is not significantly different from zero.[15]

So far our analysis has emphasized the importance of classical factors, such as deunionization, education and age for the evolution of German wage dispersion. It is however plausibile, that the rather long time period hides some interesting new dynamics. We therefore split up our sample in two periods, the first ranges from 1996 to 2003 and the second from 2003 to 2010. Table 3 shows the decomposition results for both subperiods.[16] While the composition effects remain qualitatively the same across both periods, we find interesting differences regarding the wage structure effects. Changes in returns to the collective bargaining regime only play a role in the period from 1996 to 2003 and do not play any role in the second subperiod. The wage structure effect related to the export variable, however, shows opposing effects: While changes in the exporter premium do not seem to play a role

[13]The ratio of high to low skilled workers increased from 0.5 to 0.8 and the share of workers that are at least 65 years old increased from 61% to 76% over the period of analysis.

[14]The composition effect related to the export variable has, however, the same positive sign as it was found by Baumgarten (2013). In line with his results, the compositional export channel seems to have a moderate inequality reducing impact. This mirrors the fact that the share of workers employed at exporting firms has increased considerably, leading to an even higher concentration of workers at these establishments.

[15]The sign of the export wage structure effect is again in line with the evidence reported in Baumgarten (2013).

[16]For the sake of clarity we only report results for our overall inequality measure. Decomposition results for the 50-15 and 85-50 log wage differential for both periods are available upon request.

in the first period, they work inequality increasing in the more recent period. These results indicate a growing role of exports for wage inequality in recent years.

[TABLE 3 HERE]

4.2 Intra-plant and between-plant decomposition

In our further analysis we take a different angle and look at other dimensions of wage inequality. More specifically, we build on the results by Card et al. (2013) who stress the role of establishment effects and match effects between workers and plants for the rise in German wage dispersion. To this end we split overall wage inequality into two components: the first component captures between-plant wage dispersion, while the second captures within-plant wage dispersion. We then use our RIF-decomposition approach to identify the contributions of our explanatory variables to each single component.

Looking at between-establishment wage dispersion is well anchored in the recent literature. For example Davis and Haltiwanger (1991) and Dunne et al. (2004) point to the importance of wage dispersion between U.S. manufacturing plants, Faggio et al. (2010) provide evidence for the U.K. and Helpmann et al. (2012) stress the role of firms for changes in wage inequality in Brazil. We contribute to this literature by looking explicitly at separate factors that are behind these between-plant components. At the same time, we investigate within-establishment wage dispersion and therefore add a new dimension to the recent debate. This analysis is driven by the fact that within-plant wage dispersion in Germany still makes up about half of overall wage dispersion and about a third of the change in wage inequality over our period of analysis (see Table 4). Moreover, it is possible that some explanatory factors have opposing effects on between-plant and within-plant inequality, which can explain why the resulting net contribution on overall wage inequality is harder to identify.

Table 4 presents the results of this decomposition analysis. We report the variance of real log wages as our inequality measure at this stage to make use of its additive separability. This ensures that the single components of the between-plant and within-plant decomposition add up to the overall effect.

[TABLE 4 HERE]

First of all it becomes apparent that compositional changes in the collective bargaining status of establishments are the most important driver of between-plant wage inequality. This result is linked to the fact that the share of non-covered establishments has increased and that these plants have a higher between-plant wage dispersion than covered plants. Interestingly, the corresponding effect on within-plant wage dispersion works inequality reducing, which shows that uncovered plants are -on average- associated with a lower within-plant wage dispersion.[17] The wage structure effects related to the wage bargaining regime

[17] At a first glance, this result is puzzling. It can, however, explained by the fact that covered firms are on average larger firms and therefore have a higher within-plant wage dispersion.

point to an overall rise in the union-premium (between-plant effect) and a relative decline in within-plant wage dispersion among covered establishments (within-plant effect).

Moreover, we find divergent effects of the export variable on between-plant and within-plant wage dispersion. The compositional shift towards a higher number of exporting establishments, decreases between-establishment wage dispersion and seem to increase within-plant wage inequality slightly. This mirrors the fact that with exporters, the group with lower between-plant variance and higher within-plant variance is gaining importance. The related wage structure effects indicate that wages within exporting establishments have become more similar (relative to wages within non-exporting plants).

The compositional shifts related to education and age have an inequality increasing effect on both dimensions of plant-inequality. Considering education, the overall effect is almost equally split between the two components. On the one hand these results mirror the increase in within-plant wage dispersion due to a relative shift to high skilled workers (within-plant component) and on the other hand it captures the fact of positive assortative matching between plants and workers: A rising share of high-skilled workers is employed at high wage firms, thus increasing between-plant wage inequality. The same pattern can be observed for age, the size of the sorting pattern, however, is much smaller.

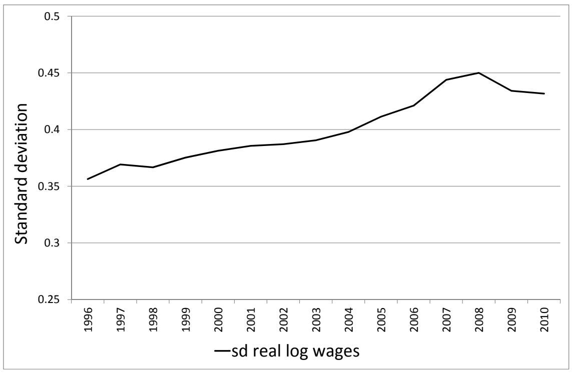
Regarding the impact of technology, we find an inequality reducing wage structure effect on the between-plant component. Thus, technology does not seem to be a driver of the rise in between-establishment dispersion. However, technology works inequality increasing within plants. This captures the fact that technology investments affect workers within a firm differently.

5 Conclusion

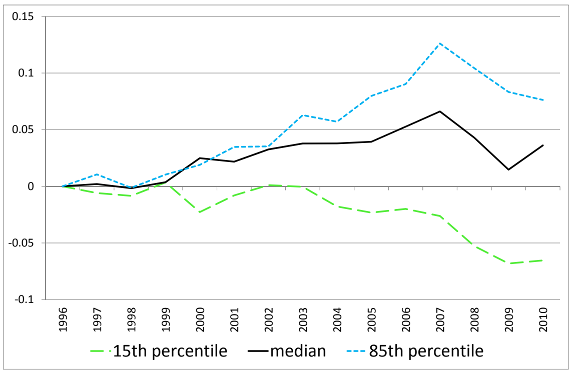
In this paper we analyze the driving forces of the recent rise in German wage inequality. To this end, we apply a decomposition approach, which is based on recentered influence function regressions. Within this framework we are able to quantify the relative contributions of different explanatory factors to inequality. Our results show that most of the increase in wage dispersion (80%) is linked to changes in the compositional structure of the workforce. Moreover, we can confirm the great importance of the decline in collective bargaining regimes for the rise in wage inequality, that hit especially workers at the lower end of the earnings distribution. This compositional shift, however, goes along with a decline in the union premium for low wage earners, so that these workers are hit by both effects. Additionally we find compositional shifts towards higher age and education groups to play an important role. This effect materializes most at the upper tail of the wage distribution. In addition, it is also the high wage workers that benefit from rising returns to skills. Investments in technology as well as the export status of an establishment seem to play a less important role for changes in wage inequality for the whole period of analysis. In more recent years however, changes in the exporter premium are found to have an inequality increasing impact.

In the second part of the paper we focus on two different dimensions of wage inequality: between-plant and within-plant wage dispersion and identify the contributions of our explanatory variables to each single component. We find compositional changes in the wage bargaining status to be the most important factor for between-plant wage inequality, followed by changes in the union-premium and factors that can be linked to positive assortitive matching between high skilled workers and high-wage firms.

With respect to changes in the export status of establishments we identify an inequality descreasing impact on between-plant wage dispersion. Regarding the impact of investments in technology our results suggest that technology affects workers differently within firms and thus has an inequality increasing impact on within-plant wage dispersion.



(a) Evolution of standard deviation of real log wages



(b) Changes at different percentiles

Figure 1. Trends in German wage inequality, 1996-2010

Source: LIAB. Sample includes male full-time workers between 18-65 years in manufacturing sector. Sampling weights are considered. Panel (a) plots the evolution of the standard deviation of real log wages. Panel (b) shows wage developments at the 15th, 50th and 85th percentile, normalized to the year 1996.

Table 1. Trends in exports, technology and collective bargaining coverage

	1996	2010
Share of exporters (in %)	20.04	31.53
Export share in sales of exporters (in %)	19.62	31.94
Employment share of exporters (in %)	67.75	75.78
Share of plants invested in technology (in %)	34.10	28.87
Share of plants covered by industry wage agreement (in %)	50.37	31.70
Share of plants covered by firm wage agreement (in %)	12.84	3.49
Share of workers covered by industry wage agreement (in %)	77.24	53.04
Share of workers covered by firm wage agreement (in %)	10.79	11.92

Source: LIAB. Sample includes male full-time workers between 18-65 years in manufacturing sector. Sampling weights are employed.

Table 2. Detailed decomposition results, baseline specification
1996-2010

	overall inequality		lower-tail inequality		upper tail inequality	
	85-15		**50-15**		**85-50**	
Observed change	13.49	***	10.15	***	3.34	
	(2.17)		(1.23)		(2.03)	
Composition effects:						
exports	-0.40		-0.36		-0.04	
	(0.26)		(0.23)		(0.31)	
collective bargaining	5.77	***	4.98	***	0.79	
	(1.86)		(1.64)		(0.61)	
technology	-0.04		-0.03		-0.01	
	(0.08)		(0.06)		(0.04)	
occupation	1.26		1.16		0.10	
	(1.24)		(0.71)		(0.88)	
education	1.33	***	0.70	***	0.63	*
	(0.44)		(0.21)		(0.35)	
age	2.75	***	0.83	***	1.92	***
	(0.48)		(0.17)		(0.39)	
industry	-0.08		-0.33		0.25	
	(0.38)		(0.29)		(0.24)	
Total	10.59	***	6.95	***	3.64	***
	(2.85)		(2.05)		(1.29)	
Wage-structure effects:						
exports	1.79		3.87		-2.09	
	(6.07)		(4.89)		(3.07)	
collective bargaining	10.96	**	10.46	**	0.49	
	(3.95)		(3.73)		(1.6)2	
technology	-1.28		-2.10		0.82	
	(2.80)		(2.22)		(1.41)	
occupation	-3.45		-4.93		1.48	
	(14.75)		(14.34)		(4.69)	
education	4.65	***	1.96		2.70	***
	(1.58)		(1.17)		(0.84)	
age	-5.47	*	-5.03	**	-0.44	
	(2.93)		(2.20)		(1.65)	
industry	-1.52		-1.72		0.20	
	(16.84)		(9.36)		(10.60)	
constant	-5.78		-2.20		-3.58	
	(23.18)		(16.35)		(10.82)	
Total	-0.10		0.31		-0.41	
	(2.39)		(2.28)		(0.97)	
Reweighting error	-0.04		-0.12		0.08	
	(0.71)		(0.57)		(0.47)	
Specification error	3.04	*	3.01	**	0.03	
	(1.47)		(1.25)		(0.87)	

Source: LIAB. Sample includes male full-time workers between 18-65 years in manufacturing sector. Sampling weights are employed. Table contains bootstraped standard errors in parenthesis (200 replications of the eintire procedure and clustered at the industry level). Asteriks indicate statistical significance at the 1% (***), 5%(**) or 10%(*) level. To account for the rather low number of of degrees of freedom, statistical inference is based on the Student's t-distribution with 14-1=13 degrees of freedom rather than the standard normal distribution.

Table 3. Detailed decomposition of two subperiods

	1996-2003		2003-2010	
	overall inequality		overall inequality	
	85-15		**85-15**	
Observed change	5.68	***	7.82	***
	(1.72)		(1.66)	
Composition effects:				
exports	-0.24		-0.52	
	(0.17)		(0.35)	
collective bargaining	3.17	***	2.30	***
	(0.82)		(0.67)	
technology	0.16		0.18	
	(0.26)		(0.28)	
occupation	0.61		0.63	
	(0.62)		(0.98)	
education	0.42	**	0.95	***
	(0.19)		(0.31)	
age	1.43	***	1.23	***
	(0.33)		(0.17)	
industry	0.11		-0.41	
	(0.30)		(0.44)	
Total	5.67	***	4.35	***
	(1.66)		(1.34)	
Wage-structure effect:				
exports	-3.96		4.58	**
	(3.80)		(2.06)	
collective bargaining	12.18	**	-1.51	
	(4.65)		(3.20)	
technology	-1.39		-0.84	
	(2.29)		(1.89)	
occupation	-4.87		4.89	
	(12.67)		(7.88)	
education	1.90	**	1.69	**
	(0.78)		(0.80)	
age	-0.84		-3.36	
	(1.46)		(2.43)	
industry	-1.88		- 0.77	
	(15.02)		(16.49)	
constant	-1.83		-0.88	
	(22.01)		(19.87)	
Total	-0.68		3.80	**
	(1.28)		(1.55)	
Reweighting error	-0.29		-0.03	
	(0.34)		(0.20)	
Specification error	0.98		-0.31	
	(0.72)		(0.60)	

Source: LIAB. Sample includes male full-time workers between 18-65 years in manufacturing sector. Sampling weights are employed. Table contains bootstraped standard errors in parenthesis (200 replications of the eintire procedure and clustered at the industry level). Asteriks indicate statistical significance at the 1% (***), 5%(**) or 10%(*) level. To account for the rather low number of of degrees of freedom, statistical inference is based on the Student's t-distribution with 14-1=13 degrees of freedom rather than the standard normal distribution.

Table 4. Decomposition between-plant and within-plant inequality

	1996-2010		1996-2010	
	between-plant variance		**within-plant variance**	
Variance 1996	6.38		6.98	
Variance 2010	10.41		8.85	
Observed change	4.02	***	1.87	***
	(0.63)		(0.20)	
Composition effects:				
exports	-0.27	*	0.14	
	(0.15)		(0.08)	
collective bargaining	2.33	***	-0.24	***
	(0.41)		(0.05)	
technology	-0.02		-0.01	
	(0.03)		(0.01)	
occupation	0.01		-0.01	
	(0.03)		(0.02)	
education	0.31	***	0.43	***
	(0.10)		(0.13)	
age	0.12	**	0.56	***
	(0.05)		(0.03)	
industry	-0.12		-0.04	
	(0.12)		(0.06)	
Total	2.36	***	0.83	***
	(0.38)		(0.18)	
Wage-structure effect:				
exports	0.17		-0.94	**
	(0.75)		(0.36)	
collective bargaining	2.12	**	-0.60	**
	(1.01)		(0.29	
technology	-1.53	**	0.90	**
	(0.59		(0.38)	
occupation	0.19		-0.27	
	(0.29)		(0.17)	
education	0.28		0.33	**
	(0.17)		(0.15)	
age	-1.43	***	0.35	
	(0.49)		(0.22)	
industry	0.99		0.14	
	(9.47)		(2.60)	
constant	1.12		1.19	
	(9.72)		(2.63)	
Total	1.91	***	1.10	***
	(0.57)		(0.13)	
Reweighting error	-0.08		-0.04	
	(0.09)		(0.03)	
Specification error	-0.33		-0.09	
	(0.30)		(0.12)	

See notes to previous tables. We obtain between-plant variance by running yearly OLS regressions of imputed log real wages on plant-dummies and taking the variance of the explained part of the wage. Accordingly, we obtain within-plant variance by taking the variance of the residual wages.

A1: Summary statistics 1996

year: 1996					
worker-level					
	N	mean	sd	min	max
log daily real wage	554934	4.489	0.366	2.347	6.471
exporter	554934	0.677	0.467	0	1
investment in ICT	554934	0.619	0.486	0	1
collective bargaining coverage	554934	0.880	0.325	0	1
education: missing	554934	0.036	0.185	0	1
education: low	554934	0.159	0.366	0	1
education: medium	554934	0.726	0.446	0	1
education: high	554934	0.080	0.271	0	1
age: 18-25	554934	0.074	0.261	0	1
age: 26-35	554934	0.320	0.467	0	1
age: 36-45	554934	0.287	0.453	0	1
age: 46-55	554934	0.225	0.417	0	1
age: 56-65	554934	0.094	0.292	0	1
establishment-level					
	N	mean	sd	min	max
exporter	1530	0.200	0.400	0	1
investment in ICT	1530	0.341	0.474	0	1
collective bargainng coverage	1530	0.632	0.482	0	1
wage-level					
	N	mean	sd	min	max
exporter	491898	4.554	0.349	2.347	6.471
non-exporter	63036	4.352	0.362	2.435	6.238
covered	538914	4.518	0.348	2.347	6.471
non-covered	16020	4.276	0.416	2.550	6.135
investment in ICT	434420	4.531	0.369	2.347	6.471
no investment in ICT	120514	4.422	0.349	2.405	6.431
education: missing	14366	4.301	0.385	2.405	6.431
education: low	91485	4.345	0.237	2.382	5.728
education: medium	380194	4.475	0.337	2.347	6.204
education: high	68889	4.996	0.387	2.646	6.471
age: 18-25	32735	4.211	0.266	2.347	5.201
age: 26-35	165756	4.424	0.302	2.382	6.258
age: 36-45	167745	4.528	0.366	2.405	6.459
age: 46-55	141187	4.581	0.393	2.512	6.471
age: 56-65	47511	4.589	0.408	2.387	6.431

Source: LIAB. Sample includes male full-time workers between 18-65 years in manufacturing sector. Sampling weights are employed.

A2: Summary statistics 2010

year: 2010

worker-level

	N	mean	sd	min	max
log daily real wage	392907	4.514	0.439	2.149	7.151
exporter	392907	0.758	0.428	0	1
investment in ICT	392907	0.595	0.491	0	1
collective bargaining coverage	392907	0.650	0.477	0	1
education: missing	392907	0.084	0.277	0	1
education: low	392907	0.120	0.326	0	1
education: medium	392907	0.696	0.460	0	1
education: high	392907	0.099	0.299	0	1
age: 18-25	392907	0.061	0.238	0	1
age: 26-35	392907	0.178	0.383	0	1
age: 36-45	392907	0.298	0.457	0	1
age: 46-55	392907	0.329	0.470	0	1
age: 56-65	392907	0.134	0.341	0	1

establishment-level

	N	mean	sd	min	max
exporter	2840	0.315	0.465	0	1
investment in ICT	2840	0.289	0.453	0	1
collective bargainng coverage	2840	0.352	0.478	0	1

wage-level

	N	mean	sd	min	max
exporter	353386	4.579	0.419	2.149	7.151
non-exporter	39521	4.307	0.437	2.151	6.625
covered	324088	4.628	0.402	2.149	7.151
non-covered	68819	4.302	0.425	2.149	6.393
investment in ICT	282853	4.594	0.429	2.149	7.151
no investment in ICT	110054	4.395	0.426	2.149	6.760
education: missing	21512	4.256	0.444	2.151	6.554
education: low	39006	4.358	0.291	2.196	6.292
education: medium	280728	4.486	0.381	2.149	6.332
education: high	51661	5.110	0.452	2.149	7.151
age: 18-25	22036	4.172	0.344	2.149	5.441
age: 26-35	68713	4.404	0.381	2.149	6.440
age: 36-45	119138	4.564	0.431	2.172	7.151
age: 46-55	135562	4.580	0.447	2.151	6.804
age: 56-65	47458	4.538	0.448	2.149	6.771

Source: LIAB. Sample includes male full-time workers between 18-65 years in manufacturing sector. Sampling weights are employed.

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