Düsseldorf Institute
for Competition Economics

DISCUSSION PAPER

No 241

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December 2016

HEINRICH HEINE
UNIVERSITÄT DÜSSELDORF

d|u|p düsseldorf university press

IMPRINT

DICE DISCUSSION PAPER

Published by

düsseldorf university press (dup) on behalf of
Heinrich-Heine-Universität Düsseldorf, Faculty of Economics,
Düsseldorf Institute for Competition Economics (DICE), Universitätsstraße 1,
40225 Düsseldorf, Germany
www.dice.hhu.de

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DICE DISCUSSION PAPER

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ISSN 2190-9938 (online) – ISBN 978-3-86304-240-0

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The Impact of Trade and Technology on Wage Components *

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December 2016

Abstract

We use a large sample of German workers to analyze the effect of low-wage competition with China and Eastern Europe (the East) on the wage structure within German manufacturing industries. Utilizing the method by Abowd *et al.* (1999), we decompose wages into firm and worker components. We find that the rise of market access and competitiveness of the East has a substantial impact on the dispersion of the worker wage component and in part on positive assortative matching. Trade fails to explain changes in the firm wage premium. The rising dispersion in worker-specific wages can be attributed to increasing skill premia and to changes in the extensive margin of the workforce, leading to a wage polarization for the remaining within-industry workers. We also account for technological change by considering how many routine-intensive jobs are substituted within an industry. The more routine jobs are cut, the higher is the effect on wage inequality, especially on the dispersion of worker-specific wages. Overall, trade explains up to 19% of the recent increase in wage inequality and slightly exceeds the technology effect that accounts for approximately 17%.

Keywords: Wage decomposition, wage inequality, globalization, gravity

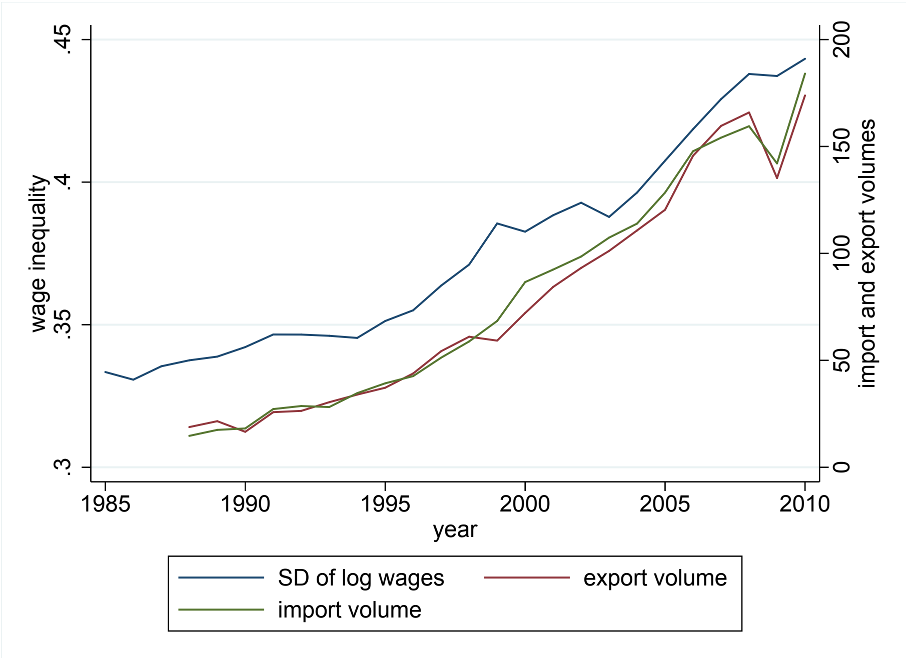
JEL Codes: F16, J31, O33, F14

*The authors thank the conference participants at the Annual Research Meeting on Economic Geography and International Trade (EGIT) 2016 in Frankfurt, the Internal Workshop of the DFG-priority program 1764 2016 in Mannheim, the Annual Conference of the European Trade Study Group (ETSG) 2016 in Helsinki, and the seminar participants at the Universities of Düsseldorf and Regensburg. We also benefited from fruitful discussions with Wolfgang Dauth, Gabriel Felbermayr, Sebastian Findeisen, Johannes Ludsteck, and Jens Südekum. All errors are our responsibility. We gratefully acknowledge financial support from the DFG-priority program 1764 "The German Labour Market in a Globalised World - Challenges through Trade, Technology, and Demographics". Email: linda.borrs2@iab.de, knauth@dice.hhu.de.

1 Introduction

In the public perception, there is a strong connection between globalization and rising income inequality. Indeed, Germany has experienced a large increase in income inequality during the last 30 years (see, e.g., Dustmann *et al.*, 2009; Card *et al.*, 2013). Whereas the rise in wage dispersion has been relatively modest until the mid-1990s, a strong increase has started in the 2000s. Over the course of these years China joined the World Trade Organization (WTO) in 2001 and the Eastern Enlargement of the European Union (EU) took place in 2004. Figure 1 depicts the parallel rise in wage dispersion and in import and export volumes of Germany with China and Eastern Europe[1] (the East). In this paper we use these trade shocks to analyze the impact of increased import competition from the East on the distributional changes in wage components within manufacturing industries in Germany.

Figure 1: Wage Inequality and Trade Volumes in Germany, 1985–2010



Notes: The left axis depicts the standard deviation of log wages of full-time working men between 20 to 60 in West Germany between 1985 and 2010. The right axis depicts import and export volumes in billion Euros between Germany and China as well as Germany and Eastern Europe between 1988 and 2010.
Source: Own calculations, IEB and Comtrade.

We are interested in *how* trade leads to rising wage inequality. The theoretical literature gives possible explanations such as rent-sharing, increased sorting, changes in the skill premium, or positive assortative matching. To analyze these channels separately, we apply the method introduced by Abowd *et al.* (1999, henceforth AKM) and decompose wages to see how much of the income is firm- and how much of it is worker-specific.[2] For Germany, Card *et al.* (2013) find that growing heterogeneity of workers and increasing differences in firm-specific pay

[1]The Eastern European countries in our analysis include Bulgaria, the Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

[2]For readability purposes we use firm, establishment and plant synonymously in this paper, although we do not have information to match multiple establishments in to firms.

premiums explain large parts of rising wage inequality. In addition, they find that assortative matching of high(low)-wage workers to high(low)-wage firms also contributes to the rise of income inequality in Germany to a large extent. In a first step, we follow Card *et al.* (2013) and apply the decomposition method introduced by AKM to separate the effects econometrically. We then use the results of the wage decomposition and regress changes in trade exposure on changes in the distribution of the wage components separately to see through which of these channels trade impacts wages in Germany. Since unobserved shocks can simultaneously affect imports and wages, we apply the gravity residuals approach that has its foundation in general equilibrium theory (see, e.g., Anderson & Van Wincoop, 2003) and measures the relative change in competitiveness of the East compared with German industries through changes in productivity and transport costs. Gravity residuals were previously used by Autor *et al.* (2013, henceforth ADH) and Dauth *et al.* (2014, henceforth DFS).

We find strong evidence that rising competitiveness of the East led to (i) an increase in the dispersion of the skill premium, measured by the deviation of individual fixed effects, and (ii) no effect on the dispersion of the firm component of wages. Furthermore, we find some evidence that import pressure leads to increased assortative matching between "better" firms and workers. Looking at the within skill-group distribution, we show that trade affects the wage dispersion of medium-skilled workers – again, only through the individual wage component. Our sample period is marked by a general decline in terms of the manufacturing workforce. The largest share of jobs is lost in the low-skilled category and there are substantial relative gains in high-skilled jobs. Within these two skill groups we see large increases in wage dispersion, which are not connected to trade as we measure it. As a reference point, we compare our results for the wage components with raw wage inequality. For the latter we find similar results to those from previous studies (see Dustmann *et al.*, 2009; Card *et al.*, 2013).

Generally, our findings favor models of heterogeneous workers with assortative matching (e.g., Helpman *et al.*, 2010; Sampson, 2014; Grossman *et al.*, 2015) and models that are able to explain the positive skill premium, e.g., for cognitive versus manual work, by higher returns to scale in larger markets (e.g., Epifani & Gancia, 2008; Monte, 2011)[3] over models emphasizing the role of firm-wage premia in determining wage inequality (e.g., Egger & Kreickemeier, 2009).

For our empirical analysis, we use a 50% sample of administrative data for all full-time working men in West Germany between 1985 and 2010 and add trade volumes of the United Nations Commodity Trade Statistics Database (Comtrade). By linking the two data sets, we are able to measure the worker and firm contribution to wage inequality within narrowly defined industries, which are heterogeneously exposed to trade.

Our paper contributes to the literature on distributional effects of trade and technological change. ADH find that increased import exposure from China leads to lower manufacturing employment in the United States. They do not find a wage effect in the manufacturing sector. For Germany, DFS show that an increase in export exposure of a region is followed by a small increase in the regional wage level. However, they do not find any impact of the regional import exposure on wages. While ADH and DFS focus on regional effects of trade, we put emphasis on

[3]Theories that assume a monotonic effect on skill cannot explain more complex changes of the wage distribution, e.g., a polarization of wages, mainly driven by a decrease in medium-skilled occupations (see, e.g., Autor *et al.*, 2008; Acemoglu, 2003; Acemoglu & Autor, 2011) or the increase of wage inequality on both ends of the wage distribution.

the industry dimension and on individual and firm components of wages. Ebenstein *et al.* (2014) do not find any effect of increased import exposure on the industry level for the US. However, they find that workers in exposed occupations are pushed out of the manufacturing sector to find themselves in lower-paying sectors and occupations. In addition to trade, technological progress can impact labor demand. Autor *et al.* (2003) describe that new technologies are often substitutes for routine job-tasks. Because a lot of those routine jobs are performed by medium-qualified workers, the task-based approach (see, e.g, Acemoglu & Autor (2011) for the US and Spitz-Oener (2006) for Germany) is able to explain an increase in wage inequality as a consequence of wage polarization due to technological progress. Changes in wage inequality are also attributable to institutional changes and labor market reforms (see, e.g., Dustmann *et al.*, 2009). Felbermayr *et al.* (2014) find an interdependence between unionization and the exporter wage premium for Germany. Therefore, we also consider different effects of trade with regard to changes in the union coverage rate of industries.

Similar to our approach, previous papers have already used results of the AKM decomposition to analyze the impact of international trade on wages. For example, Frias *et al.* (2009) and Macis & Schivardi (2016) find evidence for a positive exporter wage premium by examining the relationship between export status of a firm and the establishment fixed effect. A study that is closely related to our approach was conducted by Baziki *et al.* (2016). They provide evidence that increased assortative matching occurs in industries that experience strong Chinese import competition and industries that use information and communication technologies intensively. We extend their focus on the worker-to-firm sorting process by looking at the effects of international trade and technological change on all decomposed wage components separately. Thus, the contribution of our paper is that we examine through which channels, i.e. worker- and firm-specific wages and assortative matching, international trade impacts the wage distribution in developed countries.

The paper is structured as follows. In section 2, we present the data sets used for our empirical analysis and describe the wage decomposition method. In the same section we provide some descriptive results and stylized facts about the inequality of wage components. In section 3 we introduce our estimation strategy and explain the construction of the independent variables. The estimation results on the impact of trade on wage components are presented in section 4. Section 5 concludes.

2 Data and Variable Calculation

2.1 Data Sources

Our main data source are the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB) from which we draw wages and all relevant worker-level information. The IEB are comprehensive administrative data that contain all employees subject to social security in Germany. We use a 50% random sample of the IEB between 1985 and 2010 of all full-time working men aged 20 to 60 in West Germany.[4] All estimations are based on

[4]We restrict our analysis to full-time jobs and exclude trainees. The reason is that non-standard work, like part-time jobs or self-employment, are different sources of wage inequality that we do not want to measure. Thus,

person-year observations that include the highest paid job of a worker in every year. As the data originally is used to calculate social security contributions, it is highly reliable and complete. We correct missing and inconsistent education data by using the routine described in Fitzenberger *et al.* (2005). Apart from that, wages above the threshold level for social security notifications are not recorded and need to be imputed. The imputation procedure follows the method by Card *et al.* (2013). For information on the firm level, e.g., firm size, we use the aggregated data of the Establishment History Panel (BHP).

To calculate an industry's exposure to trade, we use the UN Comtrade database from 1985 to 2010. Following DFS, we look at Germany, China, various Eastern European countries and their bilateral trading partners. We restrict our analysis to manufacturing industries. We match the data along four-digit product codes to the German Classification of Economic Activities 1993 by using correspondence tables of the UN Statistics Division and correct for inflation.

From the BIBB/BAuA Employment Surveys (1979-2012), we draw information on tasks that we need to construct our measure of technological change (see section 3.2). Additionally, we use the IAB Establishment Panel for information on collective wage agreements.

2.2 Estimation of the Dependent Variables

The aim of this paper is to explore how trade and technology influence wages in Germany through changes in either the firm or worker wage component. In a first step we therefore have to decompose wages. We do this by applying the decomposition method introduced by AKM. Their aim was to determine how much of the wage is worker- and how much of it is firm-specific. According to AKM, the individual log wage, y_{it}, can be fully described as an additive separable system of worker and firm fixed effects:

$$y_{it} = \alpha_i + \psi_{\mathbf{J}_{(it)}} + x'_{it}\beta + r_{it} \quad with \quad r_{it} = \eta_{i\mathbf{J}(it)} + \zeta_{it} + \varepsilon_{it}. \tag{1}$$

Here, the worker fixed effect α_i can be interpreted as the worker-specific wage component. It comprises all characteristics of a worker that are equally valuable across firms, i.e. independent of the job a worker holds. The worker fixed effect captures time-invariant observable characteristics, like formal education, as well as unobservable traits, such as motivation and specific (e.g., interpersonal) skills. $\psi_{\mathbf{J}_{(it)}}$ is the establishment component. It comprises the wage that is equally paid by a firm to all of its employees independent of their characteristics. Note that the firm effect also covers region- and industry-specific fixed effects, because only in rare cases firms change the region or industry in our sample.[5] x'_{it} is a vector of observable worker characteristics. Following Card *et al.* (2013), the vector includes year dummies as well as quadratic and cubic terms in age fully interacted with education dummies. By construction, x'_{it} captures education specific tenure. The impact of formal education is mainly included in the worker fixed effect. The reason is that the education information hardly changes over time for most workers in our sample. Typically, people within the age group of our sample (20 to 60) have already completed education when they start full-time regular work. Last, r_{it} is the error term.

we avoid that changes in the use of non-standard work drive our results. Moreover, the data set does not provide exact information on working hours to make full- and part-time daily wages comparable.

[5]Typically, firms would get a new identifier in the IEB if they changed the industry or region.

As described in Card *et al.* (2013), it includes three independent random effects: $\eta_{i\mathbf{J}(it)}$ is the match component, i.e. an individual wage a worker i receives only at firm j. ζ_{it} is a unit root component of the error term. It captures a potential drift in employees' wages, e.g., any form of human capital accumulation or job mobility within the firm. ε_{it} is the transitory error term and includes, e.g., bonuses. We need to assume that all error components are orthogonal to the wage components and have mean zero, conditional on the controls. According to AKM, this requires exogenous mobility. Workers should not sort into firms depending on how good they match with the firm. If workers receive different wages depending on the match quality of their characteristics with the ones of the firm, the firm effect will be estimated with bias. Card *et al.* (2013) show that the exogenous mobility assumption holds for the German labor market. They conclude that match effects are not important by providing evidence that the match-specific wage premium is not considered by workers who switch employers. Moreover, they show that adding a match-specific component in form of a job fixed effect to equation 1 only increases the model fit marginally, implying that endogenous mobility does not play a major role in Germany.

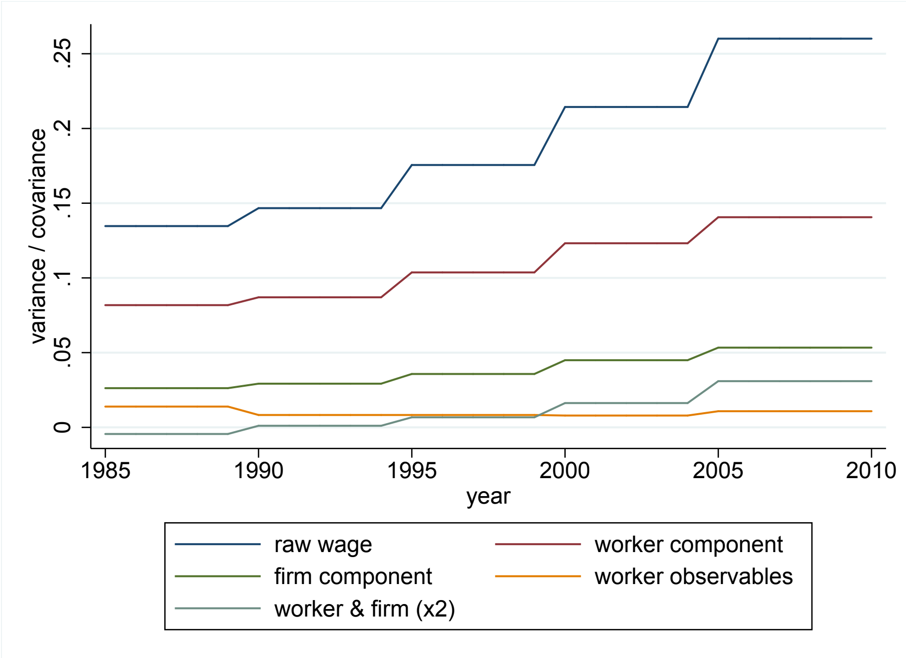
Some work has been done on the relation of endogenous mobility and globalization. According to Helpman *et al.* (2010), more productive firms screen the labor market more successfully and intensively for potential employees because their high productivity is complementary to employees with high abilities. This leads to worker-firm matches of higher quality. Krishna *et al.* (2014) conclude that the matching of employees in more productive exporting firms (in comparison to less productive non-exporters) is not random, and consequently, worker and firm effects are estimated with bias. Ashournia *et al.* (2014) argue that import penetration might change workers' mobility following an unobservable match effect with the firm. Following these arguments, one could assume that the match effect on wages increases in trade exposed sectors in comparison to less export- and import-intensive industries. However, we rely on previous evidence by Card *et al.* (2013), who do not find any evidence for sizeable match effects in Germany.

2.3 Descriptive Results and Stylized Facts about Wage Inequality

In this section, we replicate the results by Card *et al.* (2013), with some adjustments. For computational reasons, we use a 50% sample instead of the complete sample. Moreover, we change the intervals and use more, yet shorter periods (1985-1990, 1990-1995, 1995-2000, 2000-2005 and 2005-2010), which allows us to account for changes in trade more consistently over time. As expected, our results are very similar to those of Card *et al.* (2013) (see also table A1 in the appendix).

In figure 2, we report the results of the AKM model and the variance decomposition. The decomposition of the variance of log raw wages, $Var(y_{it})$, described in equation 2, allows us to assess how much of the increase in overall wage inequality can be explained by changes in the variation of single wage components. Note that the worker and firm component have the form of a fixed effect and consequently do not vary over time. In order to be able to observe changes in the worker and firm component, we estimate equation 1 separately for five overlapping six-year intervals.

Figure 2: Variance Decomposition of Wage Inequality by Interval, 1985–2010



Notes: The graph depicts the results of the decomposition of log wages using the AKM method by intervals. The variance of individual log wages (raw wage) can be described as the sum of the variance of the worker fixed effects (worker component), the variance of the firm fixed effects (firm component), the variance of observable worker characteristics, and their covariances. The sample includes full-time working men between 20 and 60 in the manufacturing sector in West Germany between 1985 and 2010.
Source: Own calculations, IEB.

$$Var(y_{it}) = Var(\alpha_i) + Var(\psi_{J(it)}) + Var(x'_{it}\beta) + 2Cov(\alpha_i, \psi_{J(it)}) + 2Cov(\psi_{J(it)}, x'_{it}\beta) + 2Cov(\alpha_i, x'_{it}\beta) + Var(r_{it}). \tag{2}$$

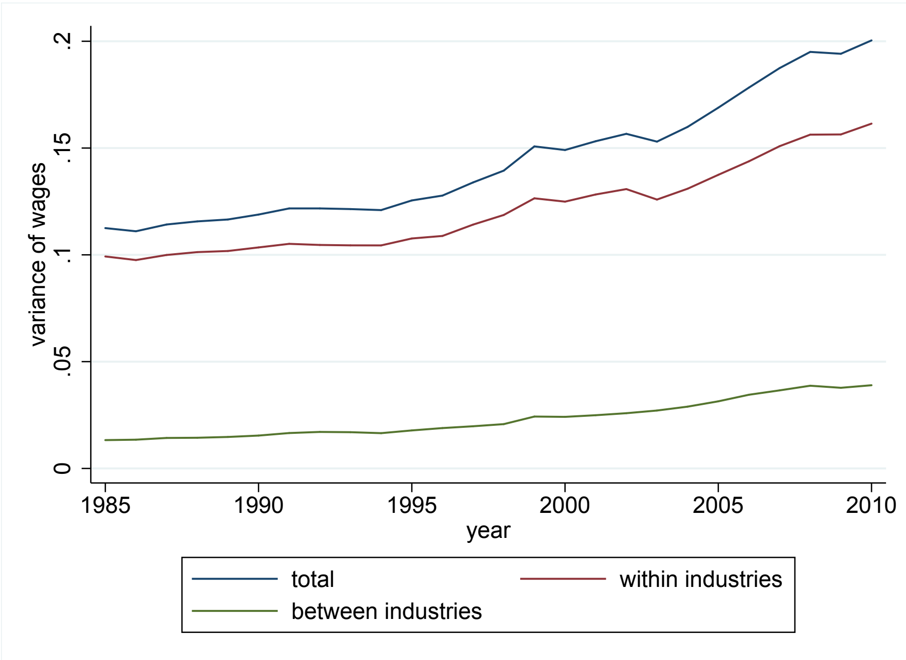
Again, we see that our results are very close to the findings by Card *et al.* (2013), despite our smaller sample and adjusted intervals. Figure 2 illustrates the increasing dispersion of the person and firm component of wages. The variance of the person effect rises from 0.082 to 0.141 over the observation period, representing 47% of the increase in overall wage inequality. The variance of firm effects increases from 0.026 to 0.053, explaining an additional 22%. The variance of time-varying individual characteristics is much lower and has a decreasing pattern. We also see that the correlation of person and firm effects rises from -0.004 to 0.031. This indicates that higher assortativeness in the assignment of workers to firms contributes another 28% to the rising dispersion of wages.[6]

In our empirical model, described in detail in section 3, we analyze whether industry-specific shocks in trade and technology can explain the increase in wage dispersion within

[6] Postel-Vinay & Robin (2006, 2002) argue that as the firm effect is the residual of the person effect (or both are mutual residuals of each other), potential estimation bias in one of the two directly translates into an opposite bias in the other fixed effect. Hence, the correlation between the two is naturally downward biased. This is even more the case as we estimate the AKM model in relatively short intervals, where the average worker only switches the establishment once or twice. Hence, the individual fixed effect is estimated with very high standard errors, but consistently given our very large data set.

sectors. Sectors are differently exposed to import competition from the East and we expect to see different effects on wage inequality within industries. The question arises how much of the overall wage variation in Germany is actually explained by the dispersion within and across sectors. Figure 3 shows that although the between share is on the rise, the within-industry part explains by far the largest share, namely between 81% and 88% of wage inequality in Germany. These figures are in line with other papers, like Helpman (2014) and Baumgarten (2013). Consequently, we are convinced that the major part of wage dispersion can be explained by changes in inequality within three-digit industries.

Figure 3: Within- and Between-Industry Variance of Log Wages, 1985–2010



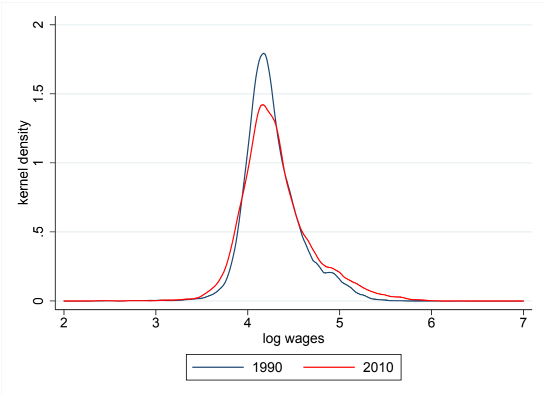
Notes: The graph depicts the variance of log wages (total) and the variance within and between three-digit manufacturing industries. The sample includes full-time working men between 20 and 60 in the manufacturing sector in West Germany between 1985 and 2010.
Source: Own calculations, IEB.

Figure 4 shows that within-industry wage inequality develops differently.[7] The graphs present shifts of the wage distribution for selected industries between the first interval, 1990 to 1995, and the last one, 2005 to 2010, i.e. a while before and after China entered the WTO in 2001 and the 2004 eastern enlargement of the EU. Panel A in figure 4 depicts the textile sector, a typical import sector. The wage distribution widens over time. At the end of our observational period, there are more workers at the lower and the upper end of the distribution, whereas relatively few people are in the middle. Interestingly, the median wage does not change – the median employer earns approximately the same in the first and last interval. Wage inequality also increases within the two-digit sector publishing, printing and reproduction of recorded media (see panel B). This industry is among the sectors with the highest increase in both wage inequality and import exposure (see also table 1). We also find increasing wage inequality in typical export-intensive industries in Germany – the machinery industry, panel C, and the

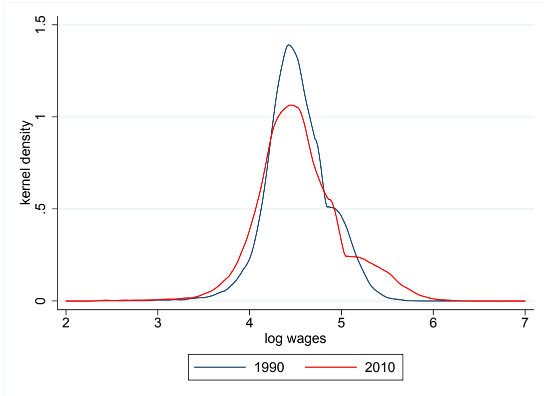
[7] For more information on all manufacturing sectors in our sample see also table 1 in section 3.

automobile sector, panel D. Compared with panels A and B, the distributions of these export-intensive industries shift more to the right, indicating that most of the employees in these sectors experience a wage gain. The automobile industry has the most equal distribution of wages and is also closest to a pattern of first-order stochastic dominance among the four sectors presented here. In general, figure 4 shows an increase in wage inequality with considerably less mass in the middle of the distribution in the later period for all industries.

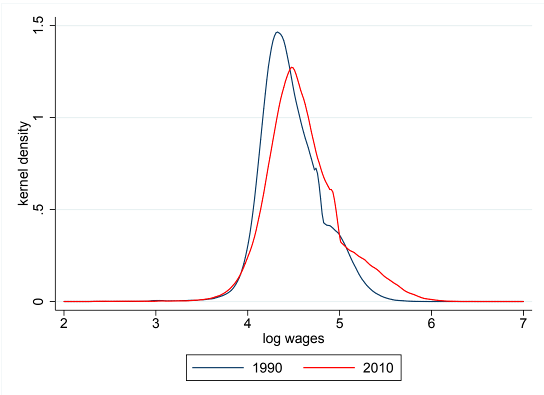
Figure 4: Distributions of Log Wages in Industries of Interest, 1995–2000 and 2005–2010



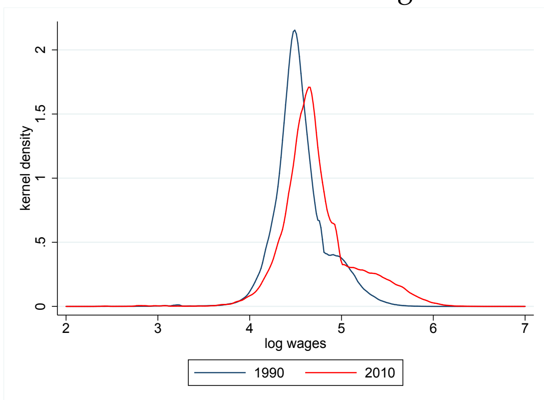
PANEL A: Textiles



PANEL B: Publishing



PANEL C: Machinery



PANEL D: Automobile

Notes: The graphs depict distributions of log wages within four major two-digit industries in Germany in interval 2 (1990-1995) and interval 5 (2005-2010). The sample includes full-time working men between 20 and 60 in the manufacturing sector in West Germany between 1985 and 2010.
Source: Own calculations, IEB.

3 Estimation Strategy

To identify the determinants that impact wage inequality in Germany, we estimate the following empirical model:

$$\Delta INEQM_{jt} = \beta_0 + \beta_1 \Delta NETTRADE_{jt} + \beta_2 \Delta RSH_{jt} + D_t + D_j + \varepsilon_{jt}, \tag{3}$$

where *INEQM* measures the inequality of wages within three-digit industries. The dependent variables are changes in the standard deviation of log wages, in the standard deviation of the firm and the worker component as well as in the covariance of both effects. We run regressions separately for each dependent variable. Although, yearly information on changes in raw wage inequality is available, we prefer to fit the wage data into the same intervals that we have to use when we look at changes in the deviation of the wage components. Since the person and firm effects do not vary within the six-year intervals by construction, all changes are calculated in six-year differences. For example, $\Delta INEQM_{j,2005}$ describes the change in the standard deviation between interval 5 (2005-2010) and interval 4 (2000-2005). $\Delta NETTRADE$ is the change in industries' import exposure, described in detail in subsection 3.1. Furthermore, we add an industry measure for technological progress. The routine share intensity (RSH) is a proxy for labor substituting technologies. It is explained in further detail in subsection 3.2. We also include time dummies (D_t) for each interval to account for general trends in the German economy. As we basically use a first-differenced estimator, we abstain from further industry-level controls in our baseline specification, but add two-digit industry dummies (D_j) as a robustness exercise.

3.1 Trade Exposure across Industries

Equation 3 is subject to endogeneity bias, since the direct import exposure measure, $\Delta NETTRADE$, is correlated with possible demand shocks of industries. Both demand for labor and demand for imports from the East correspond with unobserved demand-side shocks by German industries. The correlation would typically lead the OLS estimate to understate the true effect of rising competitiveness of the East on German labor market outcomes. To avoid estimation bias, we need to isolate the effect of increased competitiveness and openness of the East from other distorting factors. This problem is commonly solved by using an instrumental variable (IV) approach. ADH make use of China's rising trade interactions as a consequence of their increasing competitiveness and the opening of their markets to world trade. Since these events are exogenous to US demand-side shocks and simultaneously affect other trading partners of China, ADH can apply the increase of Chinese exports to other developed countries as an instrument for Chinese exports to the US.The problem of the IV approach is that a correlation between import growth and demand shocks cannot be completely ruled out if product demand shocks between the developed countries are correlated. ADH circumvent this problem by measuring US imports from China as China's comparative advantage and market access to the US by applying a gravity model. Since this approach has a theoretical foundation and rules out parallel demand shocks in the countries used for IV and the country under examination, we use gravity residuals as our main measure of globalization in this paper.

Gravity Approach: Starting with the well-established standard gravity equation, one can assess the relative competitiveness of Germany vis-à-vis the East by the following equation 4:

$$X_{ijk} = \frac{y_{ij} y_{kj}}{Y_{Wj}} \left(\frac{\tau_{ik}}{P_{ij} P_{kj}}\right)^{1-\sigma}. \tag{4}$$

Here, trade of a country i with a partner country k depends on the relative size of the two countries with respect to the world economy (y), the iceberg trade costs τ, and some prize indices P_i and P_k of the two countries. σ is the elasticity of substitution between commodities or industries j.

As shown in equation 5, we exploit the differences between the logs of German and Eastern trade with their respective trading partners. This difference can be interpreted as the relative competitiveness of the East compared to Germany. To control for multilateral trade barriers and distance, country fixed effects are included; and to control for path dependence or industry-specific idiosyncrasies, industry dummies are used. The difference in log trade is then regressed on these dummies. The residuals represent the rise in competitiveness of the East relative to Germany (after taking differences).

$$ln(X_{Ejk}) - ln(X_{Gjk}) = ln(z_{Ej}) - ln(z_{Gj}) - (\sigma_j - 1)[ln(\tau_{Ejk}) - ln(\tau_{Gjk})]. \quad (5)$$

A six-year differenced specification allows us to account for the interval structure of the dependent variables and implicitly allows for lagged effects. Formally, the trade shocks are constructed to affect the last period of an interval. They are defined as the sum of the one-year differences from the last period of the earlier interval to the last period of the latter interval:

$$\Delta GRAVITY^{EAST}_{j,t} = \sum_{t=\tau}^{\tau+5}(GRAVITY^{EAST}_{j,t} - GRAVITY^{EAST}_{j,t-1}), \qquad \forall\tau\epsilon\{1985, 1990, ..., 2005\}. \quad (6)$$

If trade follows the above-mentioned gravity structure, the gravity residuals account for endogeneity in the direct trade measures. In this case the IV approach is not necessary. By exploiting bilateral trade between many countries, the gravity approach uses more information and compares the rise in competitiveness of China and Eastern Europe with Germany, accounting for multilateral resistance.

IV Approach: We also use the conventional IV approach as robustness checks:

$$\Delta ImE^{D\leftarrow EAST}_{j,t} = \sum_{t=\tau}^{\tau+5} \frac{ImE^{D\leftarrow EAST}_{j,t} - ImE^{D\leftarrow EAST}_{j,t-1}}{ImE^{D\leftarrow WORLD}_{j,t-1}}, \qquad \forall\tau\epsilon\{1985, 1990, ..., 2005\}, \quad (7)$$

$$\Delta ExE^{D\rightarrow EAST}_{j,t} = \sum_{t=\tau}^{\tau+5} \frac{ExE^{D\rightarrow EAST}_{j,t} - ExE^{D\leftarrow EAST}_{j,t-1}}{ExE^{D\rightarrow WORLD}_{j,t-1}}, \qquad \forall\tau\epsilon\{1985, 1990, ..., 2005\}. \quad (8)$$

where $ImE^{D\leftarrow EAST}_{j,t}$ are the imports from the East and $ImE^{D\leftarrow WORLD}_{j,t-1}$ are the imports from the rest of the world to Germany of industry j and in year t. An industry's export exposure is derived analogously. The instruments are defined for the same set of countries used in DFS.[8] The regressor we use in the estimations is net imports of German industries with respect to the East:

$$\Delta NetIm^{D\leftarrow EAST}_{j,t} = \Delta ImE^{D\leftarrow EAST}_{j,t} - \Delta ExE^{D\rightarrow EAST}_{j,t} \quad (9)$$

[8]These are Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom.

In the first stage, we regress the instrument countries' import measure on the German import measure.

3.2 Measuring Technological Change within Industries

In order to disentangle the effects of trade from those of technological change, we add the exposure to computerization for each industry as a control variable. Ongoing computerization has an enormous impact on the economy and each sector has different conditions and possibilities to use new technologies as substitutes for labor. According to the task-based approach (Autor *et al.*, 2003), the substitutability of labor by computers and thus labor demand is mainly determined by the degree of routineness. Routine tasks are more easily codifiable and thus more likely be taken over by a machine, robot or computer. Autor *et al.* (2003) provide empirical evidence that indeed the routine-intensive tasks of a job are most easily replaced by automatization. As a result, jobs performing those tasks become obsolete in the production process. In contrast, the demand for nonroutine tasks increases since they complement the work of computers. Inspired by Autor *et al.* (2015), we look at the routineness of industries as a measure of their exposure to computerization. Given the possibility of technological substitution, we assume that there is special pressure on wages in industries with a high share of routine jobs.

In order to measure the routineness of an industry, we first calculate the routine task-intensity of each job l. For this, we apply the operationalization by Matthes (2016). She uses the BIBB/BAuA Employment Surveys (1979-2012) to determine how intensively various task categories (routine-manual [rm], routine-cognitive [rc], analytical [a], interactive [i], nonroutine-manual [nm]) are typically carried out in occupations. Based on this indicator, we calculate the routine task-intensity (RTI) for each job l following Autor & Dorn (2013):

$$RTI_l = ln(T^{rm}_{l,1979}) + ln(T^{rc}_{l,1979}) - ln(T^{a}_{l,1979}) - ln(T^{i}_{l,1979}) - ln(T^{nm}_{l,1979}). \tag{10}$$

Similar to Autor & Dorn (2013), we classify an occupation as routine if it has an RTI above the 66-quantile of the employment-weighted RTI distribution in the initial year 1979. In the next step, we determine the routine employment share (RSH) for each industry:

$$RSH_{jt} = \frac{\sum_{l=1}^{L} emp_{jlt} \cdot m(RTI_l > RTI^{P66})}{\sum_{l=1}^{L} emp_{jlt}}. \tag{11}$$

As in Autor & Dorn (2013), emp_{jlt} is the number of employees in occupation l, industry j and year t. $m(\cdot)$ is an indicator function which is either one if the occupation l is routine-intensive as defined above, or zero if it is not. In this way, RSH reflects the share of employees with routine-intensive jobs in an industry.

3.3 Industry Statistics: Trade, Computerization and Wage Inequality

In table 1 two-digit sectors are listed according to their average import exposure (averages of three-digit industries). In the last interval of our sample, the office machinery and computers sector faces the highest import competition from China and Eastern Europe. It also has a relatively low exposure to computerization. At the end of our sample period, the highest shares of routine-intensive jobs can be found in the paper, rubber and plastic, leather, publishing, and the textile industry. Interestingly, the industries with high average inequality of wages are also among those with a high import exposure (office machinery and computers, as well as radio, tv and other communication equipment). Over the entire sample period from 1990 to 2010, the import exposure rises in all industries. We find by far the highest increase in the office machinery and computers sector, followed by the radio, tv and other communication equipment industry, which is not surprising since China is an exporting nation in these fields. Looking at wage inequality, the highest increase is in the manufacturing of communication equipment. Also the office machinery sector is among those with the highest increase in wage inequality.

Table 1: Trade, Computerization and Wage Inequality by two-digit Industries

	Interval 5				Δ Interval 5 and Interval 2 in %			
Industry (two-digit)	Av. grav.	Av. RSH	Av. SD log wage	Av. # workers	Grav.	RSH	SD log wage	# workers
food	2.373	0.510	0.379	123079	182.7	7.7	13.5	-24.0
basic metals	2.756	0.511	0.329	85425	401.1	-2.9	14.1	-37.6
wood	2.830	0.186	0.331	40605	415.4	6.7	11.6	-26.0
furniture, toys	3.029	0.278	0.378	53465	637.1	-2.2	12.9	-40.5
leather	3.111	0.616	0.426	4332	661.6	-11.8	23.6	-59.6
other transport	3.216	0.265	0.375	4443	654.5	-12.3	23.3	-19.1
machinery	3.305	0.376	0.388	337868	614.5	-10.6	18.8	-25.9
chemicals	3.325	0.512	0.415	124774	559.1	-0.9	19.5	-36.0
textiles	3.330	0.597	0.375	16283	623.7	-3.8	16.3	-61.5
rubber, plastic	3.536	0.658	0.366	114304	915.6	-1.8	21.3	-14.1
wearing apparel	3.629	0.267	0.501	3945	1018.5	-31.9	25.6	-62.2
paper	3.643	0.679	0.337	41795	748.4	2.6	13.1	-25.1
fabricated metals	3.813	0.316	0.385	146289	993.8	-13.6	19.8	-27.5
automobile	3.931	0.275	0.347	263989	893.0	-26.3	22.9	-14.6
medical equipment	4.052	0.226	0.455	94924	1232.1	-18.0	20.6	-23.6
electrical machinery	4.230	0.279	0.434	115123	1418.4	-17.8	22.6	-23.8
publishing	4.404	0.611	0.438	65804	1329.6	-4.1	24.7	-30.6
non-metallic minerals	4.459	0.565	0.340	59360	857.6	-3.7	17.5	-41.4
tobacco	6.409	0.508	0.459	2052	1611.0	-9.4	26.4	-10.0
radio, tv, comun. equipment	7.072	0.191	0.481	48186	3148.8	-12.4	26.7	-14.3
office machinery, computers	8.149	0.266	0.509	13503	5791.4	-2.8	25.4	-48.1

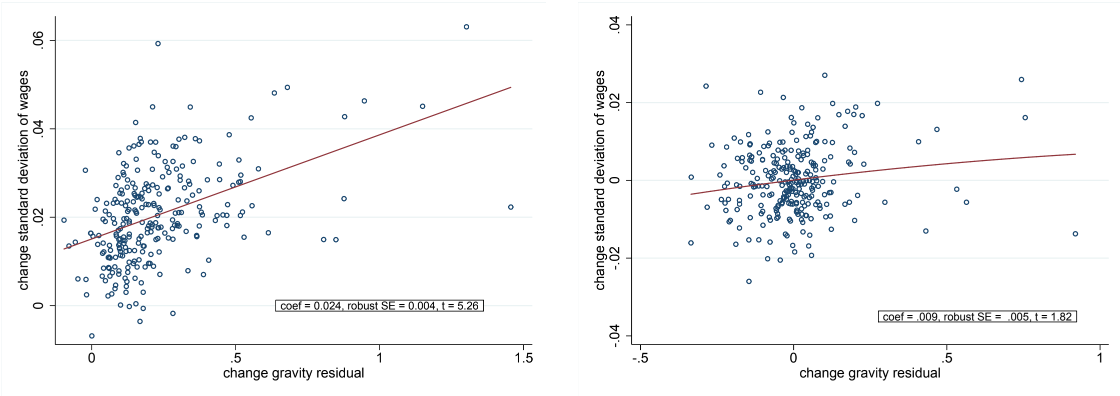
Notes: Grav. describes the gravity residual for each industry. It can be interpreted as the relative competitiveness of the East compared to Germany. RSH describes the routine share intensity, i.e. the share of routine occupations in an industry. The standard deviation of log wages and the number of workers are derived from the 50% random sample of all full-time working men between 20 to 60 in the manufacturing sector in West Germany. Absolute values are averages within the fifth interval (2005-2010) and within two-digit industries. Changes are differences between these averages of the fifth and the second interval (1990-1995) in percent. Source: Own calculations, IEB and Comtrade.

Regarding routine share intensity, we see that most of the sectors experienced a decrease, first and foremost the wearing apparel and automobile industry. However, from the descriptives in table 1 we cannot deduce a clear-cut connection between the decrease in RSH and increasing wage inequality. For a more in-depth analysis of the effect of trade and technological progress on wage inequality and especially on the inequality in the wage components, we apply regression analyses, which will be discussed in the next section.

4 Results

Figure 5 provides a first impression of our subject of interest, the relationship between increasing trade with the East and the dispersion of log wages in Germany. The unconditional relationship depicted in panel A shows that the rise of the East is positively associated with increased wage inequality within industries. It can be seen from the scatter plot in panel B that this relationship holds even if we additionally control for technological change and time, although the size of the coefficient is more than halved.

Figure 5: Changes in Import Exposure and Changes in Wage Inequality, 1995–2010



PANEL A: Unconditional PANEL B: Conditional on Observables

Notes: The graphs plot interval changes in the standard deviation of log wages within three-digit manufacturing industries against changes in West German industries' import exposures from the East. The period covered is six-year intervals from 1995 to 2010. Panel A shows the unconditional correlation, while we include interval dummies and a measure for technological change in panel B.
Sources: Own calculations, IEB and Comtrade.

Table 2 contains the estimation results for equation 3, at first without controlling for technological change. We compare the results for different trade measures. Our main measure is the gravity residual in columns 1 and 2, followed by the IV estimation in models 3 and 4 and a simple OLS estimation with net trade as the independent variable in models 5 and 6.[9] Models in uneven columns include interval dummies and models in even columns additionally control for two-digit industries. The inclusion of these industry dummies reduce the effects of trade to some extent; however, the main effects remain significant.

Panel A of table 2 presents the results for overall wage inequality. In column 1, we find a positive and significant impact of import exposure on the rise of wage inequality within industries. If we consider the average change in the gravity residual of 0.22, the effect of trade accounts for approximately 19% of the increase in the variation in raw wage inequality (100∗[0.2239∗0.0175]/0.0204 = 19.21%). Columns 3 and 4 include the results for the IV estimation instead of gravity residuals. An average increase in trade exposure of 0.0079 explains about 7% of the rise in overall wage inequality ($100 * [0.0079 * 0.174]/0.0204 = 6.74\%$). The increase in eastern competitiveness measured by the structural gravity parameter explains a much larger share of the increase in wage inequality than the instrumented net import measure. The effect size is plausible compared to previous studies (see, e.g., Van Reenen, 2011), indicating that the effect of trade explains less than 20% of the increase in wage inequality. Comparing the OLS to the IV estimates, we see an increase in effect size of factor three to four, pointing to a sizable import endogeneity problem in the OLS results.

[9]Note that models 1 and 2 are also estimated by OLS because the gravity approach eliminates the impacts of possible demand side shocks by construction (see discussion in section 3).

Table 2: Changes in Import Exposure and in Inequality of Wage Components

	Gravity (1)	Gravity (2)	IV (3)	IV (4)	OLS (5)	OLS (6)
PANEL A — Dep. var.: Δ Std. of log wages						
Δ gravity	0.0175***	0.00936**				
	(0.001)	(0.024)				
Δ net imports			0.174**	0.160**	0.0617***	0.0383
			(0.045)	(0.035)	(0.005)	(0.135)
R2	0.266	0.483	0.138	0.433	0.212	0.503
PANEL B — Dep. var.: Δ Std. of worker fixed effects						
Δ gravity	0.0141***	0.00682**				
	(0.000)	(0.045)				
Δ net imports			0.144**	0.138*	0.0283	0.0151
			(0.026)	(0.050)	(0.247)	(0.596)
R2	0.0856	0.230	.	0.153	0.0306	0.236
PANEL C — Dep. var.: Δ Std. of firm fixed effects						
Δ gravity	0.000168	0.00290				
	(0.971)	(0.596)				
Δ net imports			0.0270	0.0255	0.0270	0.0243
			(0.788)	(0.828)	(0.397)	(0.486)
R2	0.166	0.226	0.163	0.214	0.163	0.214
PANEL D — Dep. var.: Δ Cov. of worker and firm fixed effects						
Δ gravity	0.00247*	0.00187				
	(0.067)	(0.153)				
Δ net imports			-0.00801	-0.00292	0.0105	0.0106
			(0.679)	(0.894)	(0.117)	(0.153)
R2	0.0520	0.215	0.0176	0.211	0.0436	0.223
N	263	263	262	262	262	262
Interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes

Notes: Panel A shows the results of a change in trade on changes in the distribution of log raw wages, while panels B to D show the effect of trade on changes in the distribution of individual and firm fixed effects and on changes in the covariance of both components. The independent variables are either trade measured as gravity residuals, instrumented net imports or net imports estimated with OLS. All models include interval dummies and a constant. In addition, columns 2, 4, and 6 include two-digit industry dummies. p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, IEB and Comtrade.

The main contribution of the paper is that we focus on the effect of international trade on changes in the distribution of all wage components. We present the results for changes in the standard deviation of the individual fixed effects in panel B of table 2. Column 1 shows that an increase in the gravity residual by one changes the rise in the standard deviation of the worker wage component by 0.014. Again, considering an average change in the gravity residual of 0.22, trade with the East explains about 18% of the increase of the deviation of the worker fixed effect ($100 * [0.2239 * 0.0141]/0.0179 = 17.64\%$). The effect remains significant even if we control for broader industry effects (model 2) or if we use IV (columns 3 and 4). If we assumes a fixed supply of skills in the economy, this result implies that an increase in the competitiveness of the East leads to an increase of the skill premium (intensive margin) and/or a decrease in the relative demand for medium-skilled workers (extensive margin). This interpretation requires a more in-depth view on changes in the skill-composition of industries. Table A3 shows that the number of low- and medium-skilled workers decreases within all industries, whereas the number of high-skilled workers increases. Thus, considering the extensive margin, low- and medium-skilled workers lose their jobs or downgrade to a low-paying job. Newly hired workers apparently do not replace those workers, but rather fit into the "new" labor market that is more polarized regarding the returns to skill. We observe that the wage distribution is permanently altered and that this can be traced back to the changing demand for skill in the global economy. Workers with a close to average person fixed effect asymmetrically select out of the manufacturing sector and are not replaced, rather the skill distribution is permanently altered under low-wage competition. These results are consistent with the findings by Dauth *et al.* (2016), who show that workers are pushed out of industries that are highly exposed to imports from the East and obtain lower wages in their new jobs.

Figure 6 visualizes the polarization of wages in the manufacturing sector. The wage distribution in 2010 is wider compared with 1990, with more mass at both ends and considerably less mass in the middle. This means that the size reduction of industries is relatively strong in the middle of the wage distribution. Germany has experienced a strong increase in formal education but relatively small changes in (real) average wages. That is, a worker today has a lower position in the wage distribution than workers in the past with similar formal education. Although formally low-skilled workers left manufacturing, we see polarization in the wage distribution.

To sum up, we observe a reduction in formally low- and medium-educated workers (see also figure A1), but at the same time more mass in the low income part of the distribution (compare figure 6). Presumably this process has been ongoing for a longer period already, particularly concerning workers with no training in the manufacturing industry. The increase in formal education is not able to explain recent changes in wage inequality.

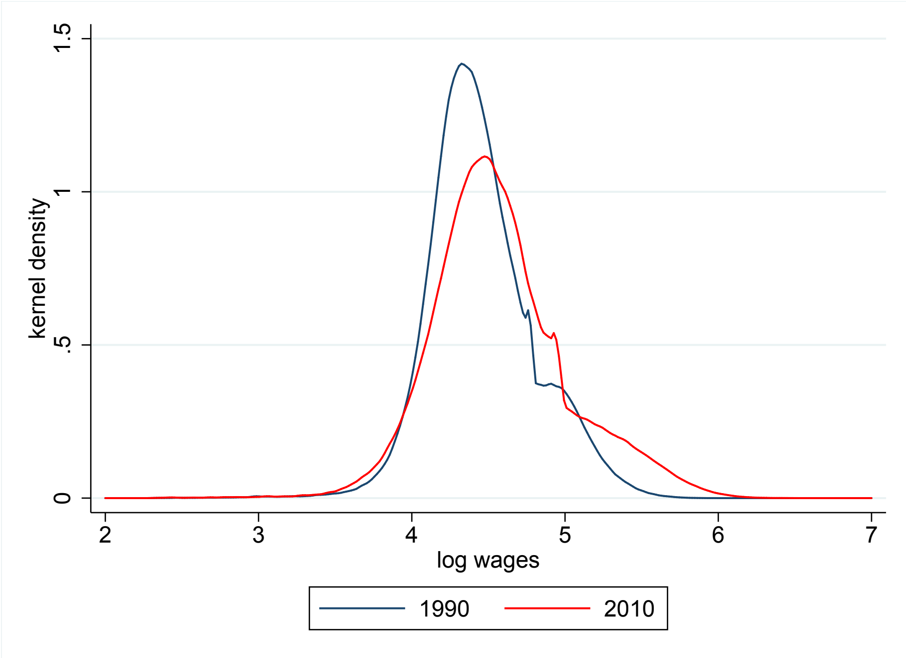
For the firm-specific wage component in panel C of table 2 we do not find any significant effect of trade.[10] This finding contradicts recent contributions in trade theory and empirics, e.g., models of rent-sharing in the trade context (e.g., Egger & Kreickemeier, 2009).[11] Finally, panel D of table 2 depicts the results for the covariance of the person and firm effects. The effect of our structural measure is significant and economically large, indicating that increased import pressure from the East leads to more assortative matching in the manufacturing sector in Germany.[12]

[10]For our analysis on the impact of trade on wage inequality, we measure inequality by the standard deviation of wage components within three-digit industries. In the data we have firm sizes between one and 50,000 workers. In an unweighted measurement both types of firms would count the same and the effect on inequality would be diluted. However, entry and exit of firms may be endogenously determined by trade, leading to a reallocation of workers that would not be visible in the unweighted measurement. This reallocation is again dependent on the firm effect. Hence, we compute the distribution of the firm-specific wage component by weighting it by the number of full-time male workers in the firm.

[11]As we do not observe export status or export size of individual firms, we cannot rule out that trade affects rent-sharing and efficiency wages at the firm level (see, e.g., Amiti & Davis, 2012; Frias *et al.*, 2009).

[12]We provide another robustness exercise in table A5, where we look at sub-samples of industries manufacturing production and high-tech goods in comparison to consumer goods.

Figure 6: Distribution of Log Wages, 1990–2010



Notes: The graph depicts the distribution of log wages in interval 2 (1990-1995) and interval 5 (2005-2010) of full-time working men between 20 and 60 in the sample of West German manufacturing industries that we use in our analysis.
Sources: Own calculations, IEB.

4.1 Developments within Conventional Skill Groups

To understand the mechanisms behind wage polarization, we look at raw wage inequality and inequality in the wage components within industries and within conventional skill groups in table A2. Here, we group all workers without any formal training (low-skilled), with vocational training (medium-skilled), or with a college or university degree (high-skilled), respectively. For this exercise, we assume that these skill groups are somewhat rigid and, e.g., workers without any training usually do not replace workers with vocational training. Vocational training (in the dual vocational education and training system) is traditionally very important in Germany. A large majority of workers receives this kind of training. While generally there is a strong increase in university enrolment in the last decades, the workforce composition is naturally changing slower and mainly consists of workers with a vocational degree.

We find that import pressure affects within skill-group inequality, but only for the group of medium-skilled workers. That holds for the dispersion of raw wages as well as for the worker wage component. Again, we do not find any significant effect on the firm wages, which is reassuring. There is no effect on the wage dispersion within the groups of high- and low-educated employees.[13] The trade effect on assortative matching is also significant for medium-skill workers, either because manufacturing firms with higher matching better survive competition, or because their job loss is less severe on average. The fact that the effects of trade are only significant within the group of medium-skilled workers speaks in favor of the story

[13]Note that a large fraction of high-skilled workers is subject to top coding. Hence, the effect of the college premium as a driver of inequality is likely larger.

that some jobs in the middle of the wage distribution are cut and not replaced accordingly. Table A3 shows that the employment of vocationally trained individuals decreases heavily in the manufacturing sector, supporting an offshoring story of those jobs. The remaining workers are either specialists whose work cannot be offshored and who are better paid, or workers that have to accept a rather low wage or a lower wage increase because of the import pressure. This argument is in line with Dauth *et al.* (2016) who analyze the individual consequences of trade and find that people working in industries with a high import exposure are more likely to lose their job. Moreover, they find that if workers stay within the same firm or industry, they experience a negative effect on cumulative earnings.[14] Table A3 also shows that there are substantial changes in the workforce for the group of people without vocational training and those with a university degree. However, no effect of trade is found within any of these groups. These results might also indicate that competition from the East does not change the wage policy of firms to a large extent. Import penetration rather leads to a decrease in the demand for certain occupations and also affects between-skill-group redistributions such as the college premium.[15]

To sum up, we find that if an industry faces increasing competition from the East, this will positively affect wage inequality within the industry. A closer look reveals that it is not firm-specific wage premiums that drive wage inequality. In fact, trade drives overall wage inequality mainly through its impact on the inequality of the worker-specific wage component and through increased assortative matching. Our results are in line with findings of other authors, like Schank *et al.* (2007), who find that most of the exporter wage premium is driven by observable and unobservable worker characteristics. Higher assortative matching is in line with the survival of relatively more complex production lines under low-wage competition.

4.2 Trade and Technological Change

Turning to table 3, we replicate the results of table 2 but extend the regression by adding a measure for technological change (ΔRSH). The main results of table 2 remain unchanged. If we control for technological change, the sign of the import competition coefficient is still in line with our expectations, while the size of the coefficient decreases up to 50% compared with the values in table 2. In panel A of table 3 we see that an increase in the share of routine-intensive jobs within an industry reduces raw wage inequality, which conversely means that technological change increases wage inequality. The interpretation is straightforward: If an industry experienced a large decline in routine-intensive occupations in the preceding interval, the industry is assumed "trending" in automation and this pushes the increase in wage inequality. In our sample, the average decrease in an industry's share of routine occupations is -0.0084, explaining about 15% of the increase in wage inequality ($100 * [-0.0084 * (-0.362)]/0.0204 = 14.91\%$) (see panel A and column 3 in table 3).[16] It can be seen from panel B of table 3 that a higher decrease in an industry's RSH leads to a significantly higher increase in the standard deviation of the

[14]Dauth *et al.* (2016) show that high increases in the import exposure lead employees to leave the industry, especially towards the service sector where they earn less. This mobility pattern however is out of the scope of this paper, where we look at within-industry effects.

[15]Note that the AKM model does not control for occupations, heterogeneity between occupations is included in the individual fixed effect (as long as the individual does not change the occupation).

[16]Using the IV approach in model 4 of table 3, we find a comparable effect size for computerization.

Table 3: Changes in Import Exposure, in Technology and in Inequality of Wage Components

	Gravity	IV	Gravity	IV	OLS
	(1)	(2)	(3)	(4)	(5)
PANEL A — Dep. var.: Δ Std. of log raw wages					
Δ gravity	0.0175***		0.00897*		
	(0.001)		(0.069)		
Δ net imports		0.174**		0.0784	0.0459**
		(0.045)		(0.369)	(0.028)
Δ RSH			-0.362***	-0.388***	-0.185***
			(0.000)	(0.000)	(0.000)
R2	0.266	0.138	0.233	0.175	0.323
PANEL B — Dep. var.: Δ Std. of worker fixed effects					
Δ gravity	0.0141***		0.00858**		
	(0.000)		(0.036)		
Δ net imports		0.144**		0.0795	0.0177
		(0.026)		(0.244)	(0.481)
Δ RSH			-0.236**	-0.260**	-0.125***
			(0.011)	(0.010)	(0.001)
R2	0.0856	.	0.0621	.	0.0901
PANEL C — Dep. var.: Δ Std. of firm fixed effects					
Δ gravity	0.000168		-0.00531		
	(0.971)		(0.375)		
Δ net imports		0.0270		-0.0223	0.0218
		(0.788)		(0.843)	(0.501)
Δ RSH			-0.233**	-0.200	-0.0620
			(0.044)	(0.115)	(0.106)
R2	0.166	0.163	0.124	0.124	0.171
PANEL D — Dep. var.: Δ Cov. of worker and firm fixed effects					
Δ gravity	0.00247*		0.00205		
	(0.067)		(0.174)		
Δ net imports		-0.00801		-0.0167	0.00991
		(0.679)		(0.485)	(0.159)
Δ RSH			-0.0176	-0.0351	-0.00700
			(0.516)	(0.297)	(0.585)
R2	0.0520	0.0176	0.0452	.	0.0457
N	263	262	263	262	262

Notes: Panel A shows the results of a change in trade and technology (measured as the change in an industry's routine-share intensity) on changes in the distribution of log raw wages, while panels B to D show the effect of trade on changes in the distribution of individual and firm fixed effects and on the covariance of both effects. Trade is either measured as gravity residuals, instrumented net imports or net imports estimated with OLS. All models include interval dummies and a constant. *p*-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, IEB and Comtrade.

worker wage component, explaining about 11% of the rise in inequality of the worker fixed effect ($100 * [-0.0084 * (-0.236)]/0.0179] = 11.01\%$). Moreover, we find a negative and significant effect of RSH on inequality in the firm pay component and no effect of technological change on assortative matching.

To measure technological progress, we use an industry's decrease in the share of routine occupations. In this way, our measure of technological change might be correlated with the trade variables to some degree. The reason is that routine jobs can typically not only be readily replaced by machines, but are also easily offshorable to labor abundant countries (Blinder, 2009). As the trade coefficients stay significant when we additionally control for RSH, the correlation of the two measures keeps within limits.[17]

Generally, our results are in line with those of other studies looking at the effects of trade on the German labor market. DFS find a negative impact of trade integration with the East in form of job losses in regions that are marked by import-competing sectors. However, given their focus on regional labor markets, they do not find evidence for an effect of rising import exposure on wages within the region. In their recent working paper, Dauth *et al.* (2016) show that import competition leads to lower earnings within job spells and leads employees to leave exposed industries. Also, Dustmann *et al.* (2014) find an increase in wage inequality in tradable manufacturing sectors, where wages of the lower percentile decrease whereas the median and 85-percentile rise.[18]

4.3 Trade and Union Coverage

Another factor that is typically assumed to have an impact on wage inequality is change in labor market institutions. Unions are an important institution because they bargain with employer's federations about wages and non-monetary benefits. Dustmann *et al.* (2014) show that the share of employees covered by a union agreement has strongly declined in Germany. In consequence, the wage-setting process is more decentralized, away from the industry towards the firm level, and thus more heterogenous within industries. Moreover, Dustmann *et al.* (2009) find that 28% of the increase in lower-tail income inequality can be explained by a decline in unionization rates. They explain that in Germany the share of workers covered by union agreements is the decisive measure to estimate the impact of unions. The reason is that in Germany collective bargaining results apply to all workers in a firm that recognizes a union and does not require the individual worker to be a union member.

If we assume that the decline of unions was exogenous, we would observe decreasing unemployment and larger wage inequality (if we abstract from the general decrease of manufacturing jobs). This is because low-paid workers benefit disproportionately from union bargaining, leading to a narrower range especially at the lower end of the wage distribution. In addition to direct effects of union coverage on wage inequality, unions can be seen as a factor determining international competitiveness of an industry or firm. An industry's ability to adjust to trade

[17] If we estimate equation 3 only with RSH but without any variable for trade, technological change explains about 17% of the increase in raw wage inequality and 13% of the increase in worker-specific wage inequality.

[18] Dustmann *et al.* (2014) define the tradable manufacturing sector according to high export volumes. Moreover, they find the strongest increase in wage inequality in the tradable service sector, which we do not consider in this paper.

shocks can be restricted in the intensive (wage) margin through bargaining agreements. Unions can also lower their wage demand if they primarily want to prevent employment losses because of trade.[19] Abstracting from the exogeneity assumption of unions, it is possible that the decline in unionization is a reaction to competitive pressure in the first place, so that firms can easier adjust to trade.

In this section we present some evidence on the correlation between changes in international trade, deunionization and the inequality in wage components. The co-movement of these factors hints at a reinforcing character of trade and deunionization. To derive the union coverage rate for two-digit industries, we use information of the IAB Establishment Panel and construct a union coverage share for industry level bargaining.[20] We then check whether the results of our main specification change if we differentiate between industries with a high or low decrease in the union coverage rate. In a way, this procedure gives us the possibility to consider the influence of labor market institutions, too. Column 1 of table 4 shows that the effect of trade on raw wage inequality is strong in industries with a high decrease in the union coverage rate. The interaction effect shows that the impact in industries with a lower decrease in unionization is significantly smaller and roughly halved, at least for the general inequality measure. The effect of increasing import competition on inequality of the worker wage component is significantly positive for the group of industries with a high decline in union coverage (column 3). The effect does not substantially differ for industries with a low decline. The same holds for the impact on changes in assortative matching (column 5). Again, the establishment pay premium remains unaffected within both groups (column 4).

Table 4: Import Exposure, Inequality of Wage Components and Deunionization

	Δ Std. wage	Δ Std. wage	Δ Std. worker FE	Δ Std. firm FE	Δ Cov. FE
	(1)	(2)	(3)	(4)	(5)
Δ gravity	0.0175***	0.0259***	0.0196***	0.000467	0.00242*
low union dec.		0.00132	0.000730	-0.000796	0.000155
(Δ gravity * low union dec.)		-0.0135*	-0.00868	-0.000498	0.0000804
R2	0.266	0.287	0.0963	0.167	0.0528
N	263	263	263	263	263

Notes: In columns 1 and 2, the dependent variable is the change in the standard deviation of log raw wages. In columns 3 to 5, the dependent variables are the change in the standard deviation of the worker fixed effect, the firm fixed effect and the change in the covariance of both effects, respectively. The baseline gravity results are included in column 1. In columns 2 to 5, we interact the changes in gravity measure of trade with a dummy that is one if the decrease in the union coverage rate in a two-digit industry is below the median. All models include dummies for intervals and a constant. *p*-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, IEB, Comtrade and IAB Establishment Panel.

[19] For more information on the relationship between trade and unions see Egger & Etzel (2012) and Felbermayr *et al.* (2014).

[20] Firms can also implement firm-wide contracts. We do not include such house agreements in our measure of deunionization, because the effect would be part of the establishment-specific pay premium. It would certainly coincide with the firm effect.

5 Conclusion

This paper provides evidence *how* international trade influences the wage distribution within industries. We pay particular attention to the impact of import competition with low-wage countries on changes in the wage components, i.e. worker- and firm-specific pay premiums and assortative matching. In this way, our paper contributes to a better understanding of how labor markets adjust to globalization processes.

Our main finding is that the reinforcing effect of trade on overall wage inequality mainly works through increased inequality in the worker wage component. The rise in competitiveness of China and Eastern Europe has a significant impact on the increase in the deviation of the individual wage component. We find this effect to be significant both within the group of vocationally trained workers, and between them and university educated workers. Both the group of low- and medium-skilled manufacturing workers is declining, while the high-skilled workforce increases in almost all industries. Thus, our results provide evidence that international trade increases the inequality of the worker wage component through both a rising skill premium of qualified workers and by changing the composition of the workforce in a way that wages are more polarized. We do not find any evidence that international trade affects the firm component of wages. Moreover, we find a relationship between rising assortative matching and increased competitiveness of the East. This is in line with the interpretation that more complex production lines or plants (as in the O-ring production technology in Kremer, 1993) are more likely to survive low-wage competition. Note that Postel-Vinay & Robin (2002, 2006) argue that assortative matching is likely underestimated by the decomposition method of AKM, as errors go in opposite directions by construction. Consequently, the effect we found should be interpreted as a lower bound. Generally, the German data seem to meet the relatively strong exogenous mobility assumption of the AKM approach quite well (see Card *et al.*, 2013). They are therefore particular suitable for our analysis.

Our findings are in line with other studies which use German linked employer-employee data and control for many worker characteristics (e.g., Schank *et al.*, 2007). Our results favor theoretical models of heterogeneous workers with assortative matching (e.g., Helpman *et al.*, 2010; Sampson, 2014; Grossman *et al.*, 2015) over models emphasizing the importance of firm wage premia for inequality (e.g., Egger & Kreickemeier, 2009).

A limitation of this study is that we are restricted to industry-level trade data. Other papers, like the work by Frias *et al.* (2009), focus on the export status of firms and thus use detailed firm-level information. Having no firm-level information on trade exposure, we cannot rule out an effect of trade in this respect.

We emphasize the channel of import competition as an important driver of wage inequality, while competitiveness in exporting has an offsetting effect. Additionally, we find the effect of technological change, measured by the decline in routine-intensive jobs in a given industry, to be almost equally important. In total, we are able to explain about a quarter of the recent increase in wage inequality in the German manufacturing sector.

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Appendix A: Results of the AKM Model

Table A1 reports the results of the AKM model. The high R^2, increasing from 87% to 92%, and low residual wage components indicate a high explanatory power of the AKM model. Our results are very close to the findings by Card *et al.* (2013), although we use a smaller sample and different time intervals.

Table A1: Summary Statistics of the AKM Effects

Interval 1: 1985-1990			
Observations	33,632,369	Corr. pers.& firm effect	-0.048
Std. log (daily wage)	0.367	Corr. pers. effect & Xb	0.066
Std. person effects	0.286	Corr. firm effect & Xb	0.068
Std. firm effects	0.162	RMSE of AKM residual	0.139
Std. Xb	0.118	Adjusted R-squared	0.873
Interval 2: 1990-1995			
Observations	35,845,173	Corr. pers. & firm effect	0.011
Std. log (daily wage)	0.383	Corr. pers. effect & Xb	0.140
Std. person effects	0.295	Corr. firm effect & Xb	0.087
Std. firm effects	0.171	RMSE of AKM residual	0.141
Std. Xb	0.091	Adjusted R-squared	0.878
Interval 3: 1995-2000			
Observations	33,813,314	Corr. pers. & firm effect	0.055
Std. log (daily wage)	0.419	Corr. pers. effect & Xb	0.109
Std. person effects	0.322	Corr. firm effect & Xb	0.097
Std. firm effects	0.189	RMSE of AKM residual	0.147
Std. Xb	0.091	Adjusted R-squared	0.892
Interval 4: 2000-2005			
Observations	32,605,834	Corr. pers. & firm effect	0.109
Std. log (daily wage)	0.463	Corr. pers. effect & Xb	0.094
Std. person effects	0.351	Corr. firm effect & Xb	0.122
Std. firm effects	0.212	RMSE of AKM residual	0.152
Std. Xb	0.089	Adjusted R-squared	0.909
Interval 5: 2005-2010			
Observations	31,291,419	Corr. pers. & firm effect	0.178
Std. log (daily wage)	0.510	Corr. pers. effect & Xb	0.073
Std. person effects	0.375	Corr. firm effect & Xb	0.132
Std. firm effects	0.231	RMSE of AKM residual	0.157
Std. Xb	0.104	Adjusted R-squared	0.921

Notes: The table follows Table III in Card *et al.* (2013) for slightly different intervals and for a 50% sample of the IEB including full-time working men between 20 and 60 in the manufacturing sector in West Germany between 1985 and 2010. Xb includes interaction terms of year dummies with education dummies as well as a the interaction of quadratic and cubic terms in age with education dummies.
Source: Own calculations, IEB.

Appendix B: Within Skill Groups

Table A2 summarizes the results if we estimate our regression model within conventional skill groups. We group all workers with no training, with vocational training and those with a college or university degree.

Table A2: Changes in Import Exposure and in Inequality of Wage Components within Education Groups

	No vocational training				Vocational training				College/university degree			
	Gravity	Gravity	IV	IV	Gravity	Gravity	IV	IV	Gravity	Gravity	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PANEL A — Dep. var.: Δ Std. of log wages												
Δ gravity	0.0174	0.00139			0.0285**	0.0285**			0.00117	0.0191		
	(0.333)	(0.939)			(0.026)	(0.028)			(0.956)	(0.406)		
Δ net imports			-0.254	-0.361			0.364	0.116			0.0612	0.347
			(0.444)	(0.287)			(0.132)	(0.665)			(0.783)	(0.182)
R2	0.201	0.304	0.168	0.276	0.146	0.238	0.0680	0.220	0.0602	0.167	0.0497	0.115
PANEL B — Dep. var.: Δ Std. of worker fixed effects												
Δ gravity	0.0157	-0.00595			0.0267**	0.0208*			0.000799	0.0236		
	(0.336)	(0.738)			(0.026)	(0.086)			(0.968)	(0.246)		
Δ net imports			-0.311	-0.434			0.414*	0.0815			-0.117	-0.106
			(0.318)	(0.175)			(0.089)	(0.777)			(0.609)	(0.731)
R2	0.232	0.332	0.202	0.302	0.318	0.394	0.242	0.385	0.0128	0.174	0.0191	0.172
PANEL C — Dep. var.: Δ Std. of firm fixed effects												
Δ gravity	0.000168	0.00290			0.000168	0.00290			0.00195	0.00593		
	(0.971)	(0.596)			(0.971)	(0.596)			(0.747)	(0.373)		
Δ net imports			0.0270	0.0255			0.0270	0.0255			0.0184	0.170
			(0.788)	(0.828)			(0.788)	(0.828)			(0.867)	(0.258)
R2	0.166	0.226	0.163	0.214	0.166	0.226	0.163	0.214	0.0817	0.211	0.0788	0.169
PANEL D — Dep. var.: Δ Cov. of worker and firm fixed effects												
Δ gravity	0.00265	0.00195			0.00359**	0.00275*			-0.0000943	0.000404		
	(0.227)	(0.411)			(0.013)	(0.063)			(0.974)	(0.909)		
Δ net imports			-0.00876	-0.000338			0.00998	0.00694			0.0378	0.0535
			(0.809)	(0.993)			(0.615)	(0.766)			(0.415)	(0.375)
R2	0.00949	0.114	.	0.113	0.0861	0.187	0.0676	0.194	0.00559	0.0423	.	.
N	263	263	262	262	263	263	262	262	263	263	262	262
Interval FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Panel A shows the results of a change in trade on the change in the distribution of log raw wages. In panels B to D the dependent variables are the change in the standard deviation of the worker fixed effect, the firm fixed effect and the change in the covariance of both effects, respectively. The independent variables for trade are either measured as gravity results or instrumented net trade. All models include interval dummies and a constant. In addition even columns include two-digit industry dummies. *p*-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, IEB and Comtrade.

Appendix C: Workforce Changes

Table A3 shows the workforce changes during our observational period. The manufacturing industry lost a substantial part of its workforce in the 1990s and 2000s. While the textile industry lost more than two thirds of its workforce, the automobile industry only lost about 20%. Besides the general decline in the manufacturing workforce, we find an increase of college educated workers in almost all industries. Hence, we see the general trend of tertiarization (the general workforce of Germany increased during that period) as well as the rise in the education level of the German workforce.

Table A3: Workforce Changes by Industries and between Skill Groups in %, 1990–2010

Industry (two-digit)	All (1)	No voc. training (2)	Voc. training (3)	College / Univ. (4)
wearing apparel	-69.1	-77.4	-70.9	36.6
textiles	-69.8	-82.5	-64.3	-18.1
leather	-60.8	-78.5	-56.5	54.5
office machinery, comp.	-54.5	-68.1	-61.5	-38.2
non-metallic minerals	-44.6	-72.0	-33.8	11.5
basic metals	-40.7	-65.5	-28.5	10.7
furniture, toys	-45.7	-66.1	-43.8	57.1
publishing	-40.3	-55.9	-45.4	70.9
chemicals	-39.1	-71.2	-36.4	5.4
tobacco	-10.0	-63.0	-6.5	131.7
food	-27.7	-42.7	-26.9	45.2
wood	-32.4	-61.4	-22.9	85.1
paper	-29.6	-61.6	-16.1	23.4
medical equipment	-24.4	-53.2	-31.9	28.3
electrical machinery	-25.2	-61.0	-27.7	21.1
machinery	-24.8	-62.3	-25.8	55.0
other transport	-16.7	-59.7	-20.8	35.1
automobile	-20.2	-74.6	-11.0	116.9
radio, tv, comun. equip.	-21.1	-61.5	-32.4	53.1
fabricated metals	-22.5	-51.7	-17.4	73.7
rubber, plastic	-21.2	-52.5	-11.1	59.5
Mean	-35.3	-63.9	-32.9	43.7

Notes: The table depicts changes in the number of workers (full-time men between 20 and 60 in West Germany) between the years 1990 and 2010 in two-digit manufacturing industries. E.g., the wearing apparel industry lost 69.1% of its workforce. Columns 2 to 4 depict the workforce changes by different skill groups.
Source: Own calculations, IEB.

Looking at table A3 one could assume that the increasing dispersion is solely driven by between-education-group effects of the workforce. In addition to table A3, table A4 shows the within-industry changes in the worker fixed effect distribution. The dispersion of the individual wage component increases for all workers within their education group in all industries. Thus, the between-education-group effects of wages cannot explain all of the dispersion in overall wages and in the worker fixed effect.

We also see the changes of the employment shares of different skill groups in figure A1. We

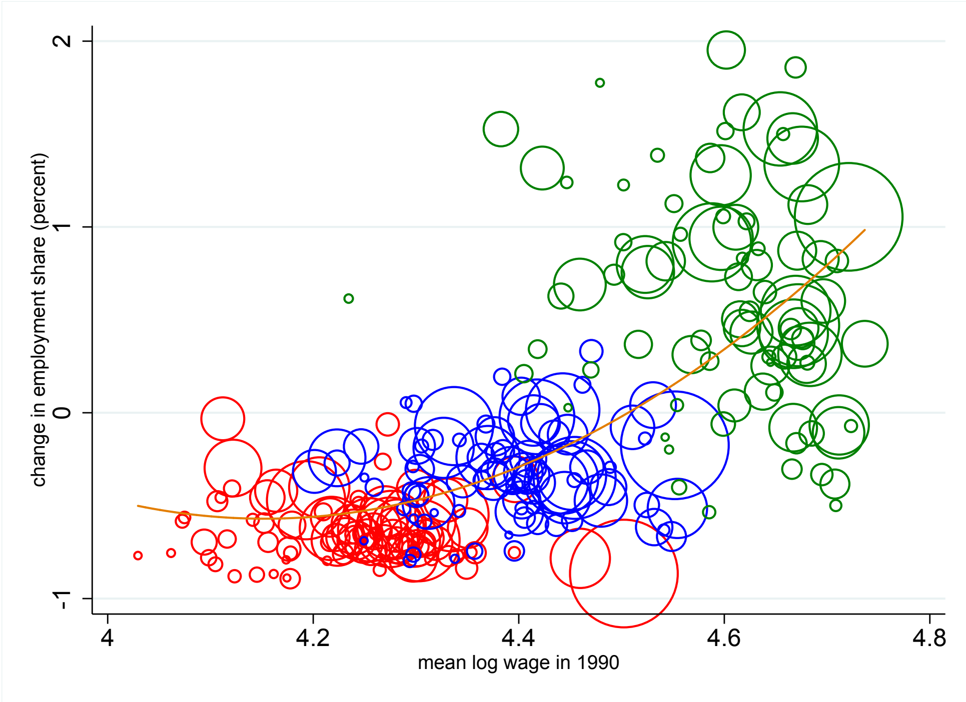
Table A4: Within Skill-Group Changes in the Worker Wage Component in %, 1990–2010

Industry (two-digit)	No voc. training (1)	Voc. training (2)	College / Univ. (3)
wearing apparel	21.97	18.85	11.42
textiles	9.38	5.86	14.35
leather	25.99	17.92	25.78
office machinery, comp.	33.99	34.58	73.62
non-metallic minerals	12.26	9.30	27.13
basic metals	12.64	1.09	30.99
furniture, toys	14.84	12.08	20.63
publishing	40.80	25.44	33.69
chemicals	23.00	9.13	48.63
tobacco	46.64	19.11	55.88
food	8.23	9.61	32.38
wood	12.98	7.39	20.80
paper	3.03	1.89	36.38
medical equipment	31.90	12.44	40.43
electrical machinery	35.67	8.49	42.04
machinery	30.36	6.13	26.37
other transport	89.34	17.12	38.54
automobile	86.63	21.32	79.93
radio, tv, comun. equip.	66.83	18.03	39.09
fabricated metals	19.03	6.62	24.40
rubber, plastic	20.13	5.87	31.44
Mean	30.75	12.77	35.90

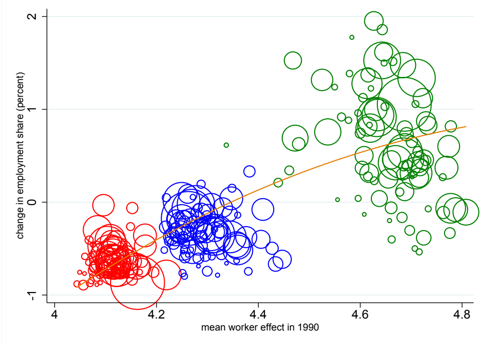
Notes: This table shows changes in the dispersion of the worker fixed effct within skill groups and industries, e.g., the variance of the worker wage component in wearing apparel has increase by 21.97% in the period between 1990 and 2010.
Source: Own calculations, IEB.

find a general increase in college-educated workers and moderate to strong declines in non-college-educated workers. This pattern alone cannot explain the polarization of wages found in figure 6, although the increase in wages at the right of the distribution is partly attributable to the rise in high-skilled workers. These findings, emphasize the necessity to look at wage inequality within skill groups. Note that around 80% of workers are in the medium-skilled category.

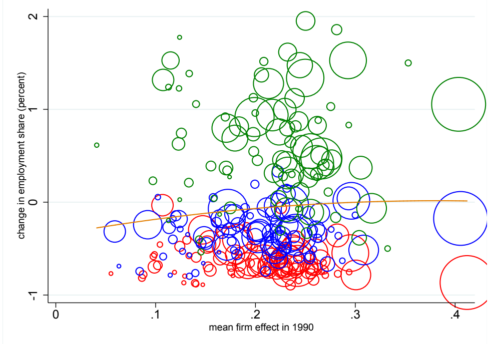
Figure A1: Changes in Industry-Skill Group Employment



PANEL A: Raw Wages



PANEL B: Person Fixed Effect



PANEL C: Firm Fixed Effect

Notes: The y-axis depicts changes in employment shares of industry-skill-groups from 1990 to 2010. On the x-axis these industry-skill-groups are ranked according to their position in the distribution of mean log wages (panel A), mean worker fixed effects (panel B) and mean firm fixed effects (panel C) in 1990. The skill groups are no training (red), vocational training (blue), and college or university degree (green). Circle sizes represent overall industry sizes.
Sources: Own calculations, IEB.

Appendix D: Product Classes

In table A5 our main trade variable, the gravity residual, is interacted with three different product classes. The product classes are consumer, intermediate and high-tech products. According to those categories, the industries are classified as follows: Consumer industries are industries, which, according to the German input-output table of the Federal Statistical Office of Germany, sell most of their products to final consumers. Intermediate industries sell their products to other industries, e.g., materials. High-tech industries have high shares of R&D without a clear profile of producing intermediate or final products. With the results presented in table A5, we want to check the plausibility of our previous results. We expect that industries producing low-tech consumer goods are very prone to low-wage competition, as the tasks required in their production processes are more likely to be done overseas. The results are in line with our expectations, the effects for consumer products are the largest and those for intermediate products are significantly smaller in size. Interestingly, the assortative matching effect, though insignificant, is largest for high-tech industries and completely irrelevant and even negative for intermediate industries.

Table A5: Product Classes

	Δ Std. log wages	Δ Std. worker FE	Δ Std. firm FE	Δ Cov. worker and firm FE
	(1)	(2)	(3)	(4)
Δ gravity	0.0250***	0.0203***	-0.00643	0.00153
	(0.000)	(0.000)	(0.226)	(0.226)
Δ gravity	-0.0177**	-0.0103*	0.00612	-0.00166
* production	(0.017)	(0.085)	(0.377)	(0.274)
Δ gravity	-0.00997	-0.00897	0.0166*	0.00318
* high-tech	(0.171)	(0.201)	(0.066)	(0.141)
R2	0.348	0.113	0.178	0.114
N	263	263	263	263

Notes: The table shows the baseline gravity measure for trade interacted with three different industry groups: Consumption goods (reference category), production goods and high-tech goods. The dependent variables are changes in the distribution of log wage inequality, in the individual and firm fixed effects and in the covariance of both effects, respectively. All models include a constant and dummies for intervals. p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, IEB and Comtrade.

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ISSN 2190-9938 (online)
ISBN 978-3-86304-240-0