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Exporters and the Rise in Wage Inequality

Evidence from German Linked Employer-Employee Data

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Daniel Baumgarten[1]

Exporters and the Rise in Wage Inequality – Evidence from German Linked Employer-Employee Data

Abstract

Using a linked employer-employee data set of the German manufacturing sector, this paper analyses the role of exporting establishments in explaining rising wage dispersion. Over the period of analysis (1996–2007), the raw wage differential between exporters and domestic establishments increased substantially, which can only partly be attributed to corresponding changes in human capital endowments and the returns to them. These findings are consistent with recent heterogeneous-firm trade models that feature an exporter wage premium as well as variability of the premium with respect to increasing trade liberalization. A decomposition analysis shows that the increase in the conditional wage gap indeed contributed to rising wage inequality both within and between skill groups. In contrast, the growing employment share of exporters contributed to a reduction in wage dispersion.

JEL Classification: F16, J31

Keywords: Exports; wages; exporter wage premium; wage inequality; linked employer-employee data; decomposition

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1 Introduction

In recent decades, wage dispersion both within and between demographic groups has increased in most industrialized countries.[1] This rise has occurred against the background of an accelerating globalization, leading to renewed interest in the distributional consequences of international trade within countries despite the fact that earlier research failed to uncover an important contribution of globalization to wage inequality (Katz and Autor, 1999). As pointed out by Krugman (2008), most of this research is based on data that is outdated by now. Moreover, it may not have captured all relevant transmission channels as it hardly made use of firm-level data (Bernard and Jensen, 1997, being the exception) and exclusively focused on skill-wage differentials, neglecting potential effects on wage inequality within skill groups.

Recent theoretical contributions (e.g., Helpman et al., 2010; Egger and Kreickemeier, 2009) suggest that the link between international trade and wage dispersion works through the wage differential between exporters and non-exporters, which can also arise in a setting of ex-ante identical workers. Indeed, the existence of an exporter wage premium is backed up by abundant empirical work that was initiated by Bernard and Jensen (1995) and is summarized in Schank et al. (2007).[2] This wage gap can affect total wage dispersion over time via two channels. First, the share of workers employed at exporters may change, for example due to exporters becoming larger or due to an increasing number of exporting relative to non-exporting plants. Second, the size of the wage differential itself may change. As theory suggests, this may happen due to, e.g., exporters benefiting the most from increasing globalization, leading them to share some of the (additional) gains with their workers.

The present study takes the aforementioned theories to the data. It explores both of the suggested channels and quantifies their respective contributions to the rise in wage dispersion, making use of linked employer-employee data for the German manufacturing sector in the time period 1996 to 2007. For this purpose, a variant of the popular Juhn-Murphy-Pierce decomposition (Juhn et al., 1993) is applied. The latter allows for the decomposition of changes in any distributional metric and, thus, for separate investigations of lower-tail and upper-tail wage inequality. Moreover,

[1] Autor et al. (2008) provide evidence for the US, Goos and Manning (2007) for the UK, and Dustmann et al. (2009) for Germany.

[2] Moreover, an important finding of empirical studies based on linked employer-employee data is that the premium is only partly accounted for by differences in observable and unobservable worker characteristics (Schank et al., 2007; Munch and Skaksen, 2008; Frías et al., 2009).

changes in skill compositions and skill prices can be taken into account, thereby bringing intra-group inequality into focus.

The case of Germany is particularly interesting since it is not only the largest economy in the European Union but also very open to trade, regularly featuring the highest export levels of the world. Furthermore, over the period of analysis, Germany's integration with its European neighbours and the world economy further increased as the following developments illustrate. First, in 1999, the euro was introduced as common currency in initially 11 countries (now 16), arguably leading to reduced transaction costs in cross-border operations, the elimination of exchange rate uncertainties, and greater market transparency. Second, China with its huge market and production potential continued its trade expansion, which was accelerated by its accession to the World Trade Organization in 2001.[3] And third, the enlargement of the European Union from 15 to 27 member states took place, with many of the new members being just at Germany's doorstep.[4]

This paper is related to a small literature analysing the role of exporting plants in driving changes in wage inequality.[5] Using US plant-level data for the period 1973 to 1987, Bernard and Jensen (1997) find that employment shifts between plants and particularly from non-exporters to exporters can account for the largest part of the increase in the wage gap between high- and low-skilled workers.[6] The authors suggest that the exporters' higher demand for skill is responsible for this result. Recently,

[3]Indeed, in recent years, trade flows between Germany and China have been growing at a much faster rate than Germany's total trade. Between 1996 and 2007, the share of exports to China in total exports increased from 1.38 to 3.10 percent, while the share of imports from China in total imports rose from 2.61 to 7.33 percent (Source: German Federal Statistical Office). While the importance of China as an export market may still seem limited, the increasing availability of cheaper imports may well serve as a catalyst for third-country exports.

[4]Ten new member states mostly from Central and Eastern Europe joined in 2004, two (Romania and Bulgaria) did so in 2007. However, it has to be pointed out that the first agreements concerning free merchandise trade between the EU and some of the accession countries were already phasing in at the beginning of the 1990s as part of the accession process, thus already before the period of analysis ("Europe Agreements"). Still, one would expect a further deepening of trade integration to have occurred after 1996 since tariffs were reduced gradually. Furthermore, the enlargement may have led to a reduction in bilateral trade costs through other channels, as well, such as better institutions, more efficient border controls, etc.

[5]Another related strand of the literature investigates the development of between-firm (and within-firm) wage dispersion over time (e.g., Davis and Haltiwanger, 1991; Dunne et al., 2004; Faggio et al., 2010). These studies conclude that it is the between-firm component that is mainly responsible for changes in overall wage dispersion, but they do not explore the role of the firms' trade status in this context.

[6]Due to the lack of more detailed information, the authors have to rely on the frequently used but rather crude distinction between non-production and production workers.

employing the linked employer-employee data set that is also used in this study, Klein et al. (2010) give a thorough account of how the exporter wage premium (or wage discount) differs by skill (as well as by gender and nationality). They find that high-skilled workers enjoy a wage premium, whereas low-skilled workers suffer from a wage discount, implying skill-related wage inequality within exporting plants. They do not explore, however, if and how this translates into changing skill wage differentials over time. Both papers deal with the between-group dimension of wage inequality but abstract from within-group wage inequality. Moreover, they do not relate exports to more general measures of wage dispersion such as the standard deviation or certain interquantile ranges, which are standard in the inequality literature. This paper aims to fill these gaps.

The main findings of this study are as follows. First, in the period from 1996 to 2007, the wage differential between exporters and non-exporters increased by almost eight log points, which is substantial. Second, changes in skill compositions and skill prices can only account for a small fraction of this increase. Third, the rising exporter wage gap indeed contributed to the growth in wage dispersion, whereas the increase in the exporters' share in total employment worked towards a reduction in wage dispersion. The resulting net effect of exporting is positive but moderate. Fourth, these contributions indeed relate predominantly to wage dispersion within skill groups.

The paper is organized as follows. The next section gives a brief account of the theoretical background. Section 3 describes the data set used for the empirical analysis. Section 4 presents trends in the incidence of exporting and the exporter wage gap in German manufacturing. Section 5 explains the methodology for the decomposition of changes in the wage distribution and presents the decomposition results. Section 6 provides the results of two extensions to the baseline decomposition, and Section 7 summarizes and discusses the main findings.

2 Theoretical background

Most theoretical contributions aiming to explain the observed exporter wage gap are elaborated within the influential framework of Melitz (2003), which features monopolistic competition in the product market, fixed and variable costs of exporting, and firms with heterogeneous productivity levels. Only the most productive firms find it worthwhile to export, and they are also the ones that end up with the highest revenues, profits, and employment levels. Note that in the original model of Melitz (2003), there are no wage differences between exporters and domestic firms because labour is assumed to be homogeneous and the labour market to be completely frictionless. However, wage differences can easily arise if the base version of the model is extended.

Frías et al. (2009) give an extensive account of the suggested theoretical mechanisms. The authors classify them into two broad categories: the ones featuring neoclassical labour markets on one side and the ones containing some source of labour market imperfections on the other. In the former class of models, wage differences reflect corresponding differences in worker skill levels, thus not representing true premia. The leading example is the technology-choice model by Yeaple (2005) or Bustos (2010). The same mechanism can also arise in the setting proposed by Verhoogen (2008) where exported products need to be of higher quality than products solely sold on the domestic market. If high-skilled workers are needed to produce high-quality goods and if high-skilled workers have to be paid higher wages than low-skilled workers, the wage differential between exporters and non-exporters again emerges.

Note that one important implication of these models is that any wage differential should disappear once worker heterogeneity is controlled for. As explained before, this prediction has not received a lot of empirical support.[7] In contrast, in the second class of models, ex-ante identical workers earn more at exporters than they would in the outside labour market, which may be induced by search and matching frictions in conjunction with imperfect and costly screening of worker ability (Helpman et al., 2010), efficiency wages (Davis and Harrigan, 2007), or fair-wage effort mechanisms (Amiti and Davis, 2008; Egger and Kreickemeier, 2008, 2009, 2010). In these settings, firm heterogeneity as opposed to worker heterogeneity leads to observed wage differentials.

What are the predictions of the theoretical models regarding the effects of trade

[7]It should be mentioned that Yeaple (2005) prefers a broader interpretation of his skill measure than simply education. According to him, skills could also relate to worker quality that is unobserved by the econometrician but observed by the firm. Under this interpretation, the model is much harder to test empirically. Probably, the work by Frías et al. (2009) comes closest as they allow for time-varying returns to unobserved individual ability. They still find, however, that it is the plant component of average wages and not the worker component that reacts to a positive trade shock.

liberalization on the wage structure? According to Yeaple (2005), there should be an increase in the between-firm wage differential which is equivalent to an increase in the wage differential between skill groups. There is no effect on intra-group inequality because the model does not feature a true exporter wage premium.

In contrast, in Davis and Harrigan (2007) and Egger and Kreickemeier (2009), the wage differential between firms is not affected in the process of globalization. This is because wages paid to workers depend directly (and exclusively) on the monitoring technology and the productivity of the firm, respectively, which are exogenous and constant by construction. Still, there is growing intra-group inequality, which arises through the channel of firm selection and associated worker reallocations.

Finally, in Helpman et al. (2010) and Egger and Kreickemeier (2008, 2010), trade liberalization affects the wage structure through both channels, worker reallocation and the size of the wage differential between firms. In these settings, wages depend (directly or indirectly) on firms' profits or revenues, which are variable. In particular, they are responsive to trade liberalization and rise stronger for more productive firms. Whereas the relationship between trade liberalization and the exporter wage premium is monotonic, this is not the case for aggregate wage inequality. There are two opposing forces. On the one hand, existing and new exporters are able to increase profits and wages the most, thus increasing wage dispersion *ceteris paribus*. On the other hand, the tougher competitive environment leads the least productive and lowest-wage firms to exit, thus reducing wage dispersion *ceteris paribus*. The former effect dominates as long as the initial level of trade openness is not too high. Hence, a move from autarky to trade will always lead to higher inequality but gradual trade liberalization such as a lowering of fixed or variable trade costs not necessarily. Obviously, the latter case is the empirically relevant one in our context.

3 Data

The data set used for the analysis is the German LIAB, the linked employer-employee data set provided by the Institute for Employment Research (IAB).[8] It combines the Employment Statistics with the IAB Establishment Panel. Alda et al. (2005) give a detailed description of the data set.

[8]The LIAB data are confidential but not exclusive. They are available for non-commercial research by visiting the research data centre of the German Federal Employment Agency at the IAB in Nuremberg, Germany. See http://fdz.iab.de/en.aspx for further information.

The Employment Statistics are administrative social security records, which are based on notifications made by employers on behalf of their employees to the social security authorities at the beginning and end of each employment spell. Moreover, employers send an updating report at the end of each calendar year. Hence, only workers covered by social security are included in the Employment Statistics, whereas civil servants and the self-employed are not. This covers roughly 80 percent of all employees in Germany and even a considerably larger share when it comes to private-sector employment in the manufacturing sector, which is the focus of the subsequent analysis. The information given in the Employment Statistics includes certain demographic characteristics of the individual (year of birth, gender, nationality, level of education/training[9]) and the (top-coded) daily wage.

The employer side of the data set is given by the IAB Establishment Panel, a stratified sample of all the establishments included in the Employment Statistics. Strata are defined over industries and size classes, with larger establishments being oversampled.[10] The IAB Establishment Panel started in 1993 with 4,265 plants in West Germany. East German establishments were included in the Establishment Panel from 1996 onwards. After taking in several waves of additional establishments, the sample size increased to about 16,000 in 2007, which is the last available wave at the time of the analysis. Although participation is voluntary, the response rate of repeatedly interviewed establishments is quite high, amounting to about 80 percent. The survey is very detailed, and although questions concerning labour demand are the main focus, many different areas are covered. Most importantly for the analysis at hand, the share of exports in sales is surveyed in every year.

The IAB establishment Panel and the Employment Statistics can be merged via a common establishment identifier. The worker information refers to the 30th of June of each year, the date of reference for the Establishment Panel. In line with related research (e.g., Dustmann et al., 2009), I restrict attention to full-time

[9]I define four educational categories. 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, which affects about five percent of the sample. To improve the quality of the education variable in the German social security data, Fitzenberger et al. (2006) propose an imputation procedure that relies on extrapolation of past and future information. However, their approach is geared towards the complete employment biographies contained in the IABS and of less use in the (cross-sectional version of the) LIAB data. This is because most workers in the LIAB are only observed at one employer and the recorded educational information does usually not change between different notifications of the same employer.

[10]Sampling weights are given and ensure that the results are representative for the population.

male workers in regular employment. That is, I discard apprentices, trainees, the marginal and part-time employed, individuals younger than 18 or older than 65 as well as workers who are currently on leave due to military service, child-bearing, etc. Workers who hold multiple jobs or draw some form of benefits at the same time are also excluded. Furthermore, I focus on the manufacturing sector because information on establishments' exports is more patchy for other sectors. Finally, the years 1996 to 2007 constitute the sample period since this is the maximum time span covering the whole of (the reunified) Germany.

The dependent variable in the empirical analysis is the real log daily wage, including bonus payments. However, the wage information in the Employment Statistics is rightcensored at the contribution ceiling to the social security system. In the sample at hand, between 10 and 14 percent of the wage observations are top-coded each year. In order not to bias the regression results, I replace censored wages with imputed wages. The imputation procedure works in the following way (cf. Gartner, 2005). In a first step, I run a series of tobit regressions, separately for each year and education group.[11] The explanatory variables are five age-group dummies, industry and federal state dummies, and – because it is of crucial importance for the analysis – a dummy variable for exporting establishments. Rightcensored observations are then replaced by a draw from a truncated normal distribution where the contribution ceiling gives the lower truncation limit and the two moments of the distribution are obtained from the corresponding tobit estimation. Note that similar imputation strategies are generally applied in analyses using this data set (cf. Schank et al., 2007; Dustmann et al., 2009; Guertzgen, 2009). Imputed and non-censored wages are then converted into constant year-2000 euros by deflating them with the Consumer Price Index as provided by the German Federal Statistical Office.

4 Trends in exports and the exporter wage gap

Consistent with prior expectations, Germany's degree of integration with the world economy increased considerably between 1996 and 2007 as can be seen from the summary statistics in Table 1. According to the LIAB data, the share of exporters increased by 34.44 percent, and the share of exports in sales conditional on

[11] The results of these tobit estimations are available upon request.

exporting rose by 57.51 percent. Hence, both the extensive and the intensive margin contributed to the substantial rise in overall export intensity. The employment share of exporters is much higher than their share in the number of establishments, reflecting the well-known fact that exporters are in general much larger than purely domestic establishments. Interestingly, however, even though the employment share of exporters also increased, it did so to a lesser extent.[12] For a comparison, the table also includes information on the exports-to-GDP ratio as given by official statistics. Since the empirical analysis is based on the manufacturing sector, attention is restricted to goods trade, which however (still) accounts for close to 90 percent of all German trade. As can be seen, the globalization trends in the establishment data are not an artefact of the data but mirrored by a strong and quantitatively comparable rise in official trade figures. For the sake of completeness, information on the imports-to-GDP ratio is also listed. The latter made an enormous jump, too, which is not surprising as imports and exports are two sides of the same coin.

Over the same time period, the wage differential between individuals employed by exporters and the ones employed by non-exporters also rose. Figure 1 depicts the mean raw difference and the associated 95-percent confidence interval over time. Note that these mean differences are calculated at the worker level by estimating the following year-specific log wage regressions:

$$\ln w_{ijt} = \beta_{0t} + \beta_{1t} Exp_{jt} + u_{ijt}, \tag{1}$$

where i denotes the individual, j the establishment he is employed at, and t the year of the observation. Exp_{jt} is a binary indicator that equals one if establishment j is an exporter. The standard error of β_1 used to construct the confidence interval is clustered at the level of the establishment.

From 1996 to 2007, the raw log wage gap increased from 0.223 to 0.298 and thus, by 7.5 log points or 34 percent.[13] Apart from a peak in 1997, the gap remained quite stable until 2003 and began to rise thereafter. There is also some indication that wage dispersion increased over time as the widened confidence interval in later

[12] This employment measure refers to total employment as surveyed in the Establishment Panel. When considering only the individuals included in the wage regressions, that is, full-time male workers aged 18 to 65 as given by the administrative Employment Statistics, the respective shares are 63.77 percent (1996) and 70.22 percent (2007), which is equivalent to a growth rate of 10.11 percent.

[13] This difference is statistically significant as a t-test reveals (p-value: 0.0357).

years shows.

In order to interpret the results in light of the theory, it is important to know to what extent the exporter raw wage gap and its change over time can be explained by (changes in) observable characteristics. Therefore, I repeat the previous exercise but now control for several worker characteristics:

$$\ln w_{ijt} = \beta_{0t} + \beta_{1t} Exp_{jt} + \boldsymbol{X'_{it}} \boldsymbol{\beta_{Xt}} + \boldsymbol{I'_{jt}} \boldsymbol{\beta_{It}} + \boldsymbol{R'_{jt}} \boldsymbol{\beta_{Rt}} + u_{ijt}. \tag{2}$$

The vector $\boldsymbol{X_{it}}$ contains dummy variables for age$\times$education groups[14], a quadratic term in tenure, a dummy variable for foreign nationality, and a dummy variable that equals one if the individual has the position of a master craftsman or foreman. Moreover, dummy variable sets for the industry ($\boldsymbol{I_{jt}}$) and for the federal state ($\boldsymbol{R_{jt}}$) are also included.[15] Note that by running year-specific regressions, I allow for both a changing distribution of worker characteristics between exporters and non-exporters as well as changing returns to these characteristics. Figure 2 shows how the conditional wage gap evolved over time. It becomes apparent that the conditional wage difference drops to about half of the raw gap but remains substantial. Moreover, there is again a pronounced upward trend over the period of analysis. The increase in the conditional gap between 1996 and 2007 amounts to 5.4 log points, which is more than 70 percent of the increase in the raw gap.[16] That is, it is indeed the case that exporters pay higher wages to observationally identical workers, and this wage advantage is increasing over time. Hence, simple theories relying on worker sorting cannot account for this pattern.[17]

In a further step, I estimate the conditional wage differential after controlling not only for the variables listed above but also for several additional establishment characteristics:

$$\ln w_{ijt} = \beta_{0t} + \beta_{1t} Exp_{jt} + \boldsymbol{X'_{it}} \boldsymbol{\beta_{Xt}} + \boldsymbol{Z'_{jt}} \boldsymbol{\beta_{Zt}} + \boldsymbol{I'_{jt}} \boldsymbol{\beta_{It}} + \boldsymbol{R'_{jt}} \boldsymbol{\beta_{Rt}} + u_{ijt}. \tag{3}$$

[14] This is the approach chosen by Dustmann et al. (2009). I distinguish five age categories (18–25 years, 26–35 years, 36–45 years, 46–55 years, and 56–65 years) and the four levels of education as described in footnote 9. This leads to twenty groups, one of which is omitted in the regression.

[15] Theoretical models of the exporter wage premium that build on the work of Melitz (2003) predict that wage differences arise between firms within the same industry.

[16] Moreover, this difference is highly significant (p-value: 0.0027).

[17] So far, this refers to sorting on observables. Workers could still differ in their unobservable characteristics, however, and the distribution of the latter may have changed over time. This possibility will be explored below.

The vector $\boldsymbol{Z_{jt}}$ consists of a quadratic term of log total employment in establishment j, a dummy variable that equals one if the self-assessed technology status is state of the art, a dummy variable that equals one if the establishment is not part of a larger group, a dummy variable for the existence of a works council, and two dummy variables that equal one if the establishment follows an industry-level or a firm-level collective agreement, respectively. The estimated coefficients of the export dummy variable are displayed in Figure 3. As can be seen, the latter drops considerably, being 0.013 in 1996, dropping to -0.008 in 1999 and rising to 0.030 in 2007.[18] The correlation is significantly different from zero in the years 2005 to 2007. Hence, other establishment characteristics can explain a good fraction of the gap that remains after controlling for worker characteristics but particularly in more recent years not all of it. At this point, it is worth mentioning that none of the theoretical contributions cited above actually predicts that there should be an exporter wage premium that is not accounted for by returns to other (selected) firm characteristics. This is because the models in the heterogeneous-firm framework are in general able to relate different variables to one "sufficient statistic" (Melitz, 2003, p. 1696), the firm productivity level. For example, according to theory, firms with a higher productivity grow larger and also find it more profitable to export. Hence, in a structural regression, there would be no room for the inclusion of both firm size and the export status among the regressors.[19]

Industry heterogeneity

The trends in the propensity to export and the exporter wage gap discussed so far relate to the manufacturing sector as a whole. Table 2 adopts a narrower perspective and displays these trends by industry. Although there is some heterogeneity in the level values, the upward trend is a general feature and not driven by industry

[18] Note that the difference in coefficients between 1996 and 2007 is not statistically significant (p-value: 0.2776) but the difference between 1999 and 2007 is (p-value: 0.0176).

[19] Also see the discussion in Helpman et al. (2010, p. 1256). In empirical work, Verhoogen (2008) and Frías et al. (2009) adopt such a structurally motivated approach and focus on the firm productivity level as the only regressor of interest. Note that both total employment and the propensity to export are among their alternative proxies for productivity. The others are domestic sales, sales per worker, and total factor productivity. The authors state that all proxies lead to similar results. In the present study, I discarded the possibility of focusing on productivity instead of exporting since productivity measures are difficult to construct based on the data at hand. For instance, information on sales is missing for a considerable fraction of the observations. Moreover, as far as production inputs are concerned, information on the capital stock is not available.

outliers. The employment share of exporters increased in 10 out of the 14 industries and the conditional exporter wage gap (estimated using Equation 2) even in 11 out of 14, although the difference in the export coefficient is not always statistically significant. The largest increase in the exporters' employment share occurred in the industry "Shipbuilding and aircraft", while the conditional exporter wage gap rose most strongly in the industry "Precision mechanics" – two technologically rather advanced industries. The largest industry in the manufacturing sector as measured by employment, "Machinery and equipment", is also one of the most internationalized ones with one of the highest employment shares of exporters.

Switchers vs stayers and the role of unobserved heterogeneity

The evolution of the exporter wage gap is measured on repeated cross-sections of the manufacturing sector. Although establishments are in principle repeatedly sampled and interviewed, only a small fraction of individuals can be observed in both of the limiting years 1996 and 2007. This is due to establishments leaving and joining the panel but also due to worker turnover that occurs over such a fairly long time span. Only in rare cases can movers be followed over time since for this to happen, the respective individual has to move from one sampled establishment to another. Notwithstanding, knowing whether the increase in the exporter wage gap is mainly due to a divergent wage growth of the existing workforce at existing exporters and non-exporters or, in contrast, is driven by establishments switching their export status or by workers moving from a non-exporting to an exporting establishment and *vice versa* is certainly of interest. For example, it can help to determine to what extent the (changing) selection of workers into exporters and non-exporters based on unobservable characteristics – that possibly are important determinants of wages in their own right – are able to explain the (changing) correlation of wages with the export status.

Table 3 contains information on the development of wages and wage residuals, respectively, for a balanced sample of individuals, differentiating by their export status in 1996 and 2007. For those individuals that changed their export status between the two years additional information is given on whether this switch involved a change in establishments. Wage residuals are obtained from log wage regressions on the worker characteristics specified above as well as industry dummies and federal state dummies. As can be seen, the unweighted number of observations of this balanced sample is indeed low relative to the unbalanced sample but still reasonably large in absolute terms.

The findings are as follows. Permanent export workers have the highest wages in both years, whereas the opposite is true for permanent non-export workers. The raw gap between these two groups increased by eleven log points, which is more than the increase in the exporter wage gap for the full sample. The same is true for the increase in the wage residuals gap, i.e., that part of wages that is not explained by individual, industry and regional characteristics. Note that this pattern cannot be accounted for by time-constant individual heterogeneity.[20] Looking at the wage residuals of future establishment movers and export switchers also indicates that selection based on time-constant unobservables can only be part of the story. The underlying assumption is that wage residuals represent both unobserved skills and the returns to them (cf. Juhn et al., 1993). It is true that in 1996, unexplained wages of future movers from non-exporters to exporters are, on average, higher than the ones of non-export stayers, whereas future movers from exporters to non-exporters have, on average, lower wage residuals than export stayers. These findings lend some support to the selection-on-unobservables hypothesis. However, unexplained wages of future non-export-to-export movers are lower than the ones of movers into the opposite direction, indicating that the changing composition of unobservable individual-specific skills does not explain the change in the gap. What clearly becomes apparent, however, is that a switch from non-exporting to exporting and, in particular, a move from a non-exporter to an exporter are both associated with the highest increases in unexplained wages.

How do these findings relate to the theoretical explanations discussed in Section 2? Since the wage gap between exporters and non-exporters increased even for the same workers employed at the same firms with the same export status, theories featuring a time-constant between-firm wage differential or none at all are not consistent with the data. In contrast, it seems to be the case that the exporter wage premium rises in a period of increasing trade liberalization as suggested by Helpman et al. (2010) or Egger and Kreickemeier (2008, 2010). In Helpman et al. (2010), an increase in the wage premium is accompanied by a corresponding increase in average (unobserved) worker ability. It is tempting to say that the analysis of the wage residuals of future export switchers and firm movers does not lend support to this

[20]Restricting the sample further to firm stayers gives the same result. Hence, time-constant firm- or match-specific heterogeneity cannot be the reason, either.

proposition. However, there are two caveats to such a statement. First, the balanced sample of workers is a reduced one and does not contain information on hires from non-sampled establishments. Second, and more importantly, Helpman et al. (2010) allow for two interpretations of worker ability. Under the first one, it represents some form of general ability, which would be more difficult to reconcile with the data. Yet under the second one, it is match-specific and independently distributed across worker-firm matches. Hence, wage residuals from 1996 may only partly be informative about unobserved worker ability in 2007. Clearly, a deeper investigation of which of the suggested wage-premium mechanisms is of highest relevance in practice is a promising route for future research.

5 The exporter wage gap and overall wage dispersion

5.1 Trends in wage dispersion

Table 4 documents that wage dispersion in the German manufacturing sector rose considerably between 1996 and 2007, thus only confirming the findings of the existing literature (e.g., Dustmann et al., 2009). When decomposing the standard deviation into a between-establishment and a within-establishment component, it turns out that the former rose much faster. This is in line with the evidence presented, e.g., on the US (Dunne et al., 2004) or the UK (Faggio et al., 2010). It also underscores the need for research on factors influencing between-firm wage differentials in order to understand the recent changes in the German wage structure. Inequality measures based on interquantile ranges also confirm the increase in wage dispersion. Following Dustmann et al. (2009), I measure upper-tail wage inequality by the gap between the 85th and the 50th percentile of log wages and lower-tail wage inequality by the 50-15 log wage gap. Note that both measures are not affected by the wage imputation procedure for top-coded wages since less than 15 percent of the observations are censored. It can be seen that wage dispersion at the bottom increased by more than wage dispersion at the top.[21]

[21] However, the 85-50 log wage differential is a very conservative measure of upper-tail wage inequality. For example, Piketty and Saez (2003) document for the US that (wage) income increased particularly at the very top of the distribution, that is, above the 90th percentile. Unfortunately, due to top-coding, this issue cannot be analysed properly with the data used in this study.

5.2 Methodology: decomposing changes in wage dispersion over time

A first approach to analyse the role of the exporter wage gap in explaining (rising) wage inequality in Germany is to adopt a simple accounting framework as has been done, for example, by Blau and Kahn (1996) in their study on the effect of unionism on wage inequality. That is, the overall variance of log wages in time period t can be decomposed as follows:

$$\sigma_t^2 = \alpha_{dt}\sigma_{dt}^2 + (1-\alpha_{dt})\sigma_{et}^2 + \alpha_{dt}(\bar{w}_{dt} - \bar{w}_t)^2 + (1-\alpha_{dt})(\bar{w}_{et} - \bar{w}_t)^2, \tag{4}$$

where σ_t^2 denotes the overall variance of log wages, α_{dt} the share of individuals employed at purely domestic establishments, σ_{dt}^2 and σ_{et}^2 the variances within the non-exporting and the exporting sector, respectively, $\bar{w}_{dt}$ and $\bar{w}_{et}$ their respective average log wages, and $\bar{w}_t$ the average log wage across all employees. As becomes apparent from the last two terms in Equation (4), in an accounting sense, the exporter wage gap is one factor contributing to overall wage dispersion. This framework can also be used to decompose changes in the variance of log wages over time into four different components, one of which is attributable to changes in the wage gap (cf. Appendix A for details).

In a second step, I apply a variant of the more evolved regression-based decomposition of Juhn et al. (JMP, 1993). In particular, I apply the method proposed by Lemieux (2002), which combines elements of JMP with the reweighting approach suggested by DiNardo et al. (DFL, 1996). The general idea is to decompose changes in the wage distribution into three components: changes in observable characteristics, changes in the prices for these characteristics, and changes in residual inequality. Thus, this decomposition can be thought of as an extension to the techniques pioneered by Blinder (1973) and Oaxaca (1973), which are popular tools for the decomposition of mean differences. Starting point are the year-specific Mincerian wage equations for the years t and s,

$$\ln w_{il} = \boldsymbol{X}_{\boldsymbol{il}}'\boldsymbol{\beta}_{\boldsymbol{l}} + u_{il} \qquad \text{for} \quad l = t, s \tag{5}$$

with $u_{il} = F_l^{-1}(\theta_{il}|\boldsymbol{X}_{\boldsymbol{il}})$. θ_{il} denotes the rank of individual i in the cumulative residual distribution of the corresponding year. It is possible to generate counterfactual log wage distributions by varying prices (coefficients), characteristics and the residual distribution. Holding characteristics and residuals constant but changing the coefficients from their period t to their period s values yields

$$\ln w_{it}^{C1} = \boldsymbol{X'_{it}\beta_s} + F_t^{-1}\left(\theta_{it}|\boldsymbol{X_{it}}\right). \tag{6}$$

Varying both the distribution of covariates and the coefficients gives the second counterfactual wage distribution

$$\ln w_{it}^{C2} = \boldsymbol{X'_{is}\beta_s} + F_t^{-1}\left(\theta_{it}|\boldsymbol{X_{is}}\right). \tag{7}$$

The third counterfactual is generated by changing all three elements, coefficients, characteristics, and residuals:

$$\ln w_{it}^{C3} = \boldsymbol{X'_{is}\beta_s} + F_s^{-1}\left(\theta_{it}|\boldsymbol{X_{is}}\right). \tag{8}$$

Assuming an exact correspondence between the individual ranks in the residual distributions of the two time periods, it holds that[22]

$$\ln w_{it}^{C3} = \ln w_{is}. \tag{9}$$

Comparing distributional measures such as the variance or the interdecile range for $\ln w_{it}$ and $\ln w_{it}^{C1}$ gives the contribution of changing coefficients. The difference between $\ln w_{it}^{C1}$ and $\ln w_{it}^{C2}$ is due to changes in the distribution of covariates (characteristics), and finally, the comparison between $\ln w_{it}^{C2}$ and $\ln w_{is}$ yields the contribution of changes in residual inequality.

A change in the coefficients is easily implemented by using the OLS estimates of Equation (5). However, it is more difficult to account for changes in the distribution of the covariates. As suggested by Lemieux (2002), the DFL reweighting approach may be used for this purpose. The idea is to give more (less) weight to observations that are more (less) likely to be observed in period s as compared to period t. Specifically, DFL propose to pool the data for the two time periods and estimate the probability of being observed in period s conditional on the set of characteristics $\boldsymbol{X_i}$. Denote this probability as $P_{is} = Pr(\text{period} = s|\boldsymbol{X_i})$. The DFL reweighting

[22] Admittedly, this single-index interpretation of the wage residual is a strong one as it ignores issues such as (changes in) measurement error (Lemieux, 2006).

factor then is

$$\psi_i = (P_{is}/(1 - P_{is})) * ((1 - P_s)/P_s)\,, \tag{10}$$

with P_s denoting the unconditional mean, that is, the fraction of individuals observed in period s. Applying this weighting factor to the observations in period t simulates the change in the distribution of covariates that occurred between periods t and s. If the observations cannot be divided in a limited number of cells, the predicted probabilities $\hat{P}_{is}$ can be easily estimated parametrically using a logit (alternatively, a probit) model. One explicit advantage of the method proposed by Lemieux (2002) is that the reweighting takes into account that changes in the distribution of the covariates may also affect the residual distribution. This is the case if heteroskedasticity is present and the dispersion of the residuals increases in, e.g., the level of educational attainment. In contrast, several other implementations of JMP, such as the one by Blau and Kahn (1996), only consider changes in the unconditional residual distribution.

The main virtue of the JMP decomposition is that it explicitly distinguishes observed prices from the residuals. In contrast, a pure DFL decomposition only considers the effect of varying characteristics, while between-group and residual prices are lumped together. Similarly, the decomposition based on regressions of recentered influence functions as recently suggested by Firpo et al. (2009, 2007) only allows for the distinction of a composition (characteristics) and a combined wage structure effect. Thus, both alternatives would not be able to single out the effect of a change in the exporter wage gap as well as in the returns to other characteristics.

Of course, the main interest of this paper is not to determine the contributions of the three components in the aggregate but to isolate the effects of the increasing wage differential between exporters and non-exporters as well as the increasing share of workers employed at exporting establishments. In the case of the coefficient or price effect, this can be done by only changing the coefficient of the export dummy while leaving all other coefficients unaltered. Furthermore – and this is is the second advantage of combining the original JMP decomposition with DFL reweighting as suggested by Lemieux (2002) – DiNardo et al. (1996) show how one can disentangle the contribution of a binary covariate to the characteristics effect. In particular, the authors propose to construct the weight for the binary variable of interest according to changes in the conditional distribution over time, given the other characteristics. In contrast to the alternative of focusing on the marginal distribution, this takes account of the joint distribution of all the covariates.

For example, in the present application, it might be the case that the increase in the share of workers employed at exporters is partly driven by industry shifts, with trade-intensive industries growing over time. One would not like to attribute this hypothetical development to an exporting characteristics effect. In practice, changes in the conditional propensity to export can be calculated by estimating – separately for each of the two years – a logit model with the export status as dependent variable, yielding two sets of coefficients and accordingly, two sets of predicted probabilities, which can be used for the reweighting. To arrive at the weight for the overall characteristics effect in a second step, the conditional weight for the binary variable is multiplied with the unconditional weight for all remaining variables. This leads to a sequential decomposition in the following order: 1) export coefficient effect, 2) coefficient effect attributable to remaining variables, 3) export characteristics effect, 4) characteristics effect attributable to remaining variables, and 5) residual effect. However, one well-known caveat to the whole procedure is its path dependency. That is, the estimated contributions of each element and of the aggregate components depend on the order of the decomposition. Therefore, to check the robustness, I perform the whole decomposition – except for the residual effect, which still comes last – in reverse order, as well (cf. DiNardo et al., 1996).

My preferred regression model for the decomposition is given by Equation (2) and thus includes, apart from the export dummy, standard human capital controls as well as industry and region dummies. As argued in Section 4, this specification has the closest connection to heterogeneous-firm trade models. In an extension, the regression given by Equation (3) is used for the decomposition. The latter specification adds several other firm characteristics and hence, might be able to explain a larger part of the change in wage dispersion. However, the drawback is that it becomes more difficult to disentangle the effect of exporting if – in line with theoretical predictions – different firm characteristics such as size, technology, and the export status are closely interrelated.

Throughout the analysis, statistical inference is based on a bootstrap (200 replications) of the whole decomposition. To account for the correlation of wages within establishments, a block bootstrap procedure is applied where all observations within an establishment are resampled.

Despite the high popularity in many economic applications, there are important caveats to any decomposition analysis of this type, which should not be concealed. In particular, the decomposition abstracts from general equilibrium effects and assumes that changes in quantities do not affect changes in prices. Moreover, exporting (as well as the industry) is treated as an individual characteristic.[23] This implies that a selection into the two groups of exporters and non-exporters based on unobservables is ruled out. Admittedly, this is a strong assumption. However, as discussed earlier, at least the increase in the wage gap does not seem to be caused by changing selection patterns. In fact, the observed increase in the conditional exporter wage gap is even higher if the sample is restricted to workers that never switched their export status. A further assumption behind the decomposition is that there are no spillover effects between exporters and non-exporters.

5.3 Empirical results

Table 5 displays the results of the simple decomposition of the log wage variance outlined in Equation (4) and expanded on in Appendix A. It turns out that by far the largest part of the increase (about 91 percent) occurred within the non-exporting and exporting sectors. As becomes evident from Panel a), wage dispersion among non-exporters rose by more than wage dispersion among exporters. With 10.3 percent of the total, the contribution of the rising wage differential between exporters and non-exporters was moderate but non-negligible. In contrast, the changing employment shares of the two establishment groups worked towards a reduction in wage dispersion, albeit to a very small extent. The reason is that the share of workers in the group whose wages are relatively close to the grand mean (i.e., the ones employed at exporters) further increased. In that sense, workers became more homogeneous over time. This decomposition gives a first indication of the relative magnitudes of different components but is overly simplistic. In particular, it does not take into account simultaneous changes in the workforce composition and in the returns to skill or other observable characteristics, and it does not allow for a distinction between developments at the top and the bottom of the wage distribution, respectively.

Therefore, in a next step, I conduct the regression-based Juhn-Murphy-Pierce type decomposition, applying the method proposed by Lemieux (2002). The latter is applied to the four wage dispersion measures listed above, that is, the standard

[23]This is also the approach adopted in the decomposition studies focusing on the effect of unionization on the wage distribution (e.g., DiNardo et al., 1996; Blau and Kahn, 1996; Dustmann et al., 2009).

deviation of log wages, the 85-15 log wage differential, the 85-50 log wage differential, and the 50-15 log wage differential. The decomposition results are displayed in Table 6.

Focusing first on the aggregate components, changes in coefficients explain the largest part of rising wage inequality, irrespective of the measure used. Their contribution ranges from 53 percent for the standard deviation to 75 percent for the 50-15 log wage differential.[24] Changes in characteristics contribute between 1 (50-15) and 18 (85-50) percent, leaving between one fourth and one third of the total for rising residual inequality.

As already suggested by the variance decomposition above, the coefficient effect of exporting is a source of rising wage dispersion. The former contributes 0.8 log points or 8.9 percent to the increase in the standard deviation of log wages and 11.7 percent to the rise in the 85-15 log wage differential, respectively, which is mainly driven by its contribution to lower-tail wage dispersion. Thus, despite the more evolved decomposition method and the inclusion of human capital, region and industry characteristics in the model, the order of magnitude of the estimated exporter wage gap effect is very similar to the one found using the simple variance decomposition.

On the other hand, the changing employment share at exporting establishments – conditional on the other covariates – tends to work against increasing inequality. This characteristics effect of exporting is negative for the standard deviation of log wages (-5.6 percent), the 85-15 differential (-7.8 percent) and, in particular, the 50-15 differential (-13.1 percent). It is almost negligible (0.7 percent) for the 85-50 differential. These figures are larger (in absolute terms) than the ones obtained by the simple variance decomposition. Recall that the intuitive explanation for the negative impact put forward before was that the high share of workers employed at exporters further increased, leading to rising homogeneity in that respect. Therefore, one cautious interpretation of the larger figures obtained now is that, conditional on covariates, this increase in the employment share of exporters was even more pronounced.

As already explained, the results are not innocuous to the sequence of the de-

[24] These figures are large but not unreasonable. For example, Gernandt and Pfeiffer (2007) apply the (original) JMP decomposition and find that price effects explain about half of the increase in wage dispersion for West German workers in the period 1994 to 2005 – without including any employer-related characteristics among their regressors.

composition. Therefore, I perform the decomposition in reverse order, as well. That is, now the effect of changing human capital, industry, and region characteristics is calculated first, followed in turn by the export characteristics effect, the coefficient effect attributable to the (remaining) control variables, and finally, by the coefficient effect of exporting. The results remain qualitatively the same, although the quantitative importance of the components change to some extent. In particular, the aggregate characteristics effect becomes larger and the aggregate coefficient effect smaller. Recalling the sequence of the decomposition, this indicates that changes in characteristics matter more given 1996 prices than given 2007 prices. Similarly, changes in prices matter more given 1996 characteristics than given 2007 characteristics. This finding largely holds for the marginal contribution of exporting, too. That is, both the positive coefficient effect and the negative characteristics effect of exporting become smaller in absolute terms.[25] In that respect, the change in the characteristics effect is in general more pronounced than the change in the coefficient effect, which is particularly true for the 50-15 differential.

With the coefficient effect and the characteristics effect working in opposite directions, what is the overall contribution of exporting to rising inequality? The answer to this question depends on the sequence of the decomposition. With the exception of the 85-50 differential, the net effect is larger according to the reverse-order decomposition. There, it is highest for the 50-15 log wage differential, amounting to 0.8 log points or 7.8 percent of the overall increase. Interestingly, averaging the net contributions over both sequences, the net exporting effect totals around five percent for all of the four wage dispersion measures.

6 Extensions

6.1 The contribution of additional establishment characteristics to the rise in wage dispersion

The only establishment characteristic controlled for in the decomposition discussed in Section 5.3 was the export status. I now base the decomposition on the regression given by Equation (3), thus accounting for several additional establishment-level variables such as total employment, the technology status, and the existence of firm-

[25] A small exception is the characteristics effect of exporting for the 85-50 differential, which changes from positive to negative but remains insignificant.

or industry-level collective agreements. Doing so is likely to increase the explained part of the rise in wage dispersion but loosens the direct correspondence to the theoretical models outlined in Section 2 and makes it difficult to disentangle the contribution of exporting. The results of this exercise are given in Table 7.

A first inspection reveals that, indeed, the contribution of rising residual inequality substantially decreases. It even becomes negative for the 50-15 and the 85-15 differentials, thus implying that the model partly overexplains the increase in wage dispersion, particularly at the bottom of the distribution. This increase in the explained part is almost exclusively due to a rise in the characteristics effect, while the coefficient effect is in general hardly altered.

As expected, conditional on several other establishment characteristics, the contribution of exporting is diminished. According to the default-order decomposition, the coefficient effect of exporting ranges from 2.2 percent (85-50 differential) to 4.8 percent (50-15 differential), while according to the reverse-order decomposition, the respective contributions are 0.6 percent (85-50) and 3.8 percent (50-15). Thus, rather than increasing the aggregate coefficient effect, the additional covariates absorb some of the export price effect. This can be interpreted as a consequence of having a close connection between different establishment characteristics, which is well in accordance with heterogeneous-firm trade theory. For example, from the summary statistics contained in Tables B1 and B2 in Appendix B, it follows that exporters are not only larger but also make more often use of state-of-the-art technology. Moreover, they are more frequently part of a larger group and more likely to have a works council and to follow a collective bargaining agreement, which can in turn be attributed – at least to some extent – to their size advantage.

Due to these interrelations, I also refrain from interpreting the estimated export characteristics effect in more detail. The implied counterfactual – only changing the export status while keeping all other (establishment) characteristics constant – is not reasonable on these grounds. Instead, I return to the aggregate characteristics effect, which in contrast to the aggregate coefficient effect increased considerably with the inclusion of the additional variables. To obtain an idea of the likely reasons, it is suggestive to identify the main changes in establishment characteristics between 1996 and 2007. Again referring to Tables B1 and B2, establishments became, on average, larger, more technology-intensive, more often part of a larger group, and in particular, less likely to follow a collective agreement. Dustmann et al. (2009) point to this decline in unionization as an important factor behind the growth in wage inequality. Although not the focus of the paper, my results are in line with this claim.

6.2 Between- vs within-group wage dispersion

The analysis focuses on the effect of exporting on inequality while conditioning on changes in the skill composition and changes in the returns to skill. This suggests that within- rather than between-group wage dispersion should be affected. To explore this issue in more detail, I redo the decomposition for the standard deviations of log wages within and between age×education groups, respectively. I focus on the standard deviation since – different from most other measures – the within- and the between-component of the variance add up to the total. For the sake of brevity, I only list the results of the main (parsimonious) model specification as given by Equation (2) (cf. Table 8).

A first result to note is that changes in characteristics and coefficients explain 81 percent of the increase in between-group but only 57 percent of the rise in within-group wage inequality. This is not surprising given that the age×education dummies are part of the model. However, the exporting effect is indeed more pronounced for the within-group standard deviation. The coefficient effect of exporting amounts to 11.1 percent and the characteristics effect to −5.7 percent (reverse order: 10.8 percent and −4.5 percent, respectively). In contrast, according to the default-order decomposition, the coefficient effect contributes only 4.7 percent and the characteristics effect −5.2 percent to the total increase in the between-group standard deviation. While reversing the order of the decomposition hardly affects the export coefficient effect (4.2 percent), the characteristics effect appears to be less stable and turns positive (2.8 percent).

7 Summary and discussion

Using linked employer-employee data for the German manufacturing sector and conducting a variant of the Juhn-Murphy-Pierce decomposition proposed by Lemieux (2002), this paper has explored the role of exporting establishments in explaining the rise in wage dispersion over the years 1996 to 2007. This particular transmission channel between globalization and wage inequality is at the core of recent theoretical contributions based on heterogeneous firms. The period of analysis is of particular interest since during these years, European and global economic integration increased substantially.

The main findings of the analysis are the following. The exporter raw wage gap made an enormous jump and increased by almost eight log points, more than half of which cannot be explained by changes in observable worker, industry and region characteristics, and the returns to them. This increase in the conditional wage differential indeed contributed to growing wage inequality, predominantly within skill groups. In contrast, the growing employment share of exporting establishments worked towards a reduction in wage dispersion. The net contribution to the rise in inequality is positive but moderate, lying in the range of five percent according to the preferred model specification.

These findings are consistent with theories that feature an exporter wage premium which rises with increasing trade liberalization (e.g., Helpman et al., 2010; Egger and Kreickemeier, 2008, 2010). Furthermore, according to these theories, gradual trade liberalization should have a non-monotonic (hump-shaped) effect on wage inequality where the latter increases as long as the initial degree of trade openness is not too high. Taking these predictions seriously, this suggests that the turning point has not yet been reached in Germany. Trade theory, however, is not able to explain all of the increase in wage inequality, particularly not the one occurring within the group of non-exporting firms. In fact, a reduction in fixed or variable trade costs should lower the range of non-exporters (and of their wages), with the most productive ones starting to trade internationally and the weakest ones leaving the market altogether due to a tougher competitive environment. As this paper confirms, changes in general labour market conditions such as the decline in unionization are important explanatory factors in this respect since they are likely to have lowered the implicit wage floor. To the extent that these trends are also driven by global competitive pressures, the direct contribution of exporters addressed in this analysis only partly captures the effect of globalization on the rise in wage inequality.

References

Alda, H., S. Bender, and H. Gartner (2005). The linked employer-employee dataset created from the IAB establishment panel and the process-produced data of the IAB (LIAB). *Schmollers Jahrbuch (Journal of Applied Social Science Studies) 125*(2), 327–336.

Amiti, M. and D. R. Davis (2008). Trade, Firms, and Wages: Theory and Evidence. NBER Working Paper No. 14106.

Autor, D. H., L. F. Katz, and M. S. Kearney (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics 90*(2), 300–323.

Bernard, A. B. and J. B. Jensen (1995). Exporters, Jobs, and Wages in U.S. Manufacturing: 1976–1987. *Brookings Papers on Economic Activity. Microeconomics*, 67–119.

Bernard, A. B. and J. B. Jensen (1997). Exporters, skill upgrading, and the wage gap. *Journal of International Economics 42*(1–2), 3–31.

Blau, F. D. and L. M. Kahn (1994). International Differences in Male Wage Inequality: Institutions versus Market Forces. NBER Working Paper No. 4678.

Blau, F. D. and L. M. Kahn (1996). International Differences in Male Wage Inequality: Institutions versus Market Forces. *Journal of Political Economy 104*(4), 791–837.

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

Bustos, P. (2010). Trade Liberalization, Exports and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinean Firms. *American Economic Review forthcoming.*

Davis, D. R. and J. Harrigan (2007). Good Jobs, Bad Jobs, and Trade Liberalization. NBER Working Paper No. 13139.

Davis, S. J. and J. Haltiwanger (1991). Wage Dispersion between and within U.S. Manufacturing Plants, 1963-86. *Brookings Papers on Economic Activity. Microeconomics*, 115–200.

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

Dunne, T., L. Foster, J. Haltiwanger, and K. R. Troske (2004). Wage and Productivity Dispersion in United States Manufacturing: The Role of Computer Investment. *Journal of Labor Economics 22*(2), 397–429.

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

Egger, H. and U. Kreickemeier (2008). Fairness, Trade, and Inequality. CESifo Working Paper No. 2344.

Egger, H. and U. Kreickemeier (2009). Firm Heterogeneity and the Labor Market Effects of Trade Liberalization. *International Economic Review 50*(1), 187–216.

Egger, H. and U. Kreickemeier (2010). Worker-specific Effects of Globalisation. *World Economy 33*(8), 987–1005.

Faggio, G., K. G. Salvanes, and J. Van Reenen (2010). The Evolution of Inequality in Productivity and Wages: Panel Data Evidence. *Industrial and Corporate Change forthcoming*.

Firpo, S., N. Fortin, and T. Lemieux (2007). Decomposing Wage Distributions using Recentered Influence Function Regressions. Mimeo, University of British Columbia.

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

Fitzenberger, B., A. Osikominu, and R. Völter (2006). Imputation Rules to Improve the Education Variable in the IAB Employment Subsample. *Schmollers Jahrbuch (Journal of Applied Social Science Studies) 126*(3), 405–436.

Frías, J. A., D. S. Kaplan, and E. A. Verhoogen (2009). Exports and Wage Premia: Evidence from Mexican Employer-Employee Data. Mimeo, Columbia University.

Gartner, H. (2005). The imputation of wages above the contribution limit with the German IAB employment sample. FDZ Methodenreport No. 2/2005.

Gernandt, J. and F. Pfeiffer (2007). Rising Wage Inequality in Germany. *Journal of Economics and Statistics (Jahrbuecher fuer Nationaloekonomie und Statistik) 227*(4), 358–380.

Goos, M. and A. Manning (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *Review of Economics and Statistics 89*(1), 118–133.

Guertzgen, N. (2009). Rent-sharing and Collective Bargaining Coverage: Evidence from Linked Employer-Employee Data. *Scandinavian Journal of Economics 111*(2), 323–349.

Helpman, E., O. Itskhoki, and S. Redding (2010). Inequality and Unemployment in a Global Economy. *Econometrica 78*(4), 1239–1283.

Juhn, C., K. M. Murphy, and B. Pierce (1993). Wage Inequality and the Rise in Returns to Skill. *Journal of Political Economy 101*(3), 410–442.

Katz, L. F. and D. H. Autor (1999). Changes in the wage structure and earnings inequality. In J. J. Heckmann and E. E. Leamer (Eds.), *Handbook of Labor Economics*, Volume 3 of *Handbook of Labor Economics*, Chapter 26, pp. 1463–1555. Amsterdam: Elsevier.

Klein, M. W., C. Moser, and D. M. Urban (2010). The Contribution of Trade to Inequality: The Role of Skill, Gender, and Nationality. NBER Working Paper No. 15985.

Krugman, P. (2008). Trade and Wages, Reconsidered. *Brookings Papers on Economic Activity* (1), 103–154.

Lemieux, T. (2002). Decomposing Changes in Wage Distributions: A Unified Approach. *Canadian Journal of Economics 35*(4), 646–688.

Lemieux, T. (2006). Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill? *American Economic Review 96*(3), 461–498.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*(6), 1695–1725.

Munch, J. R. and J. R. Skaksen (2008). Human capital and wages in exporting firms. *Journal of International Economics 75*(2), 363–372.

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

Piketty, T. and E. Saez (2003). Income Inequality in the United States, 1913–1998. *Quarterly Journal of Economics 118*(1).

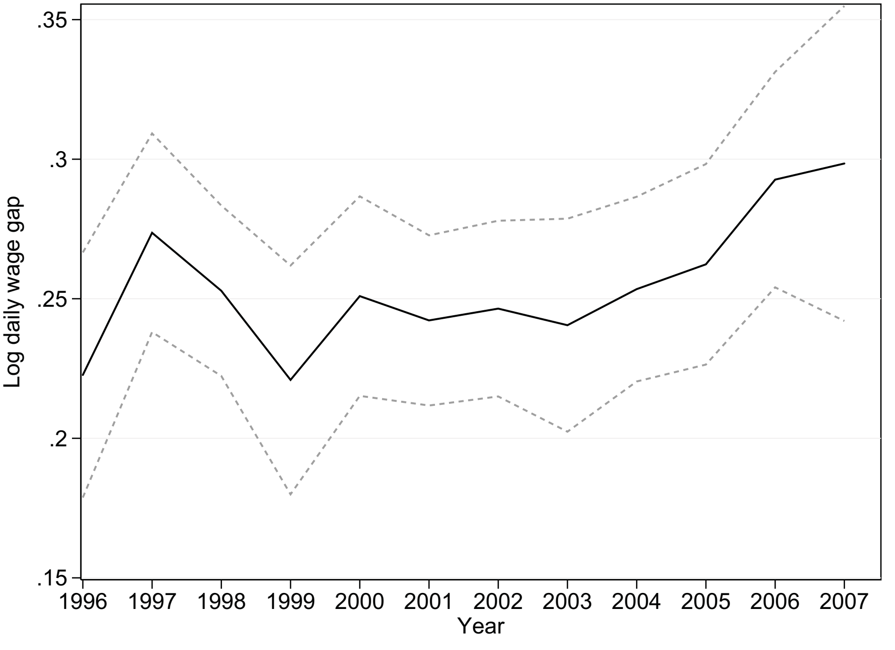
Schank, T., C. Schnabel, and J. Wagner (2007). Do exporters really pay higher wages? First evidence from German linked employer-employee data. *Journal of International Economics 72*(1), 52–74.

Verhoogen, E. A. (2008). Trade, Quality Upgrading and Wage Inequality in the Mexican Manufacturing Sector. *Quarterly Journal of Economics 123*(2), 489–530.

Yeaple, S. R. (2005). A simple model of firm heterogeneity, international trade, and wages. *Journal of International Economics 65*(1), 1–20.

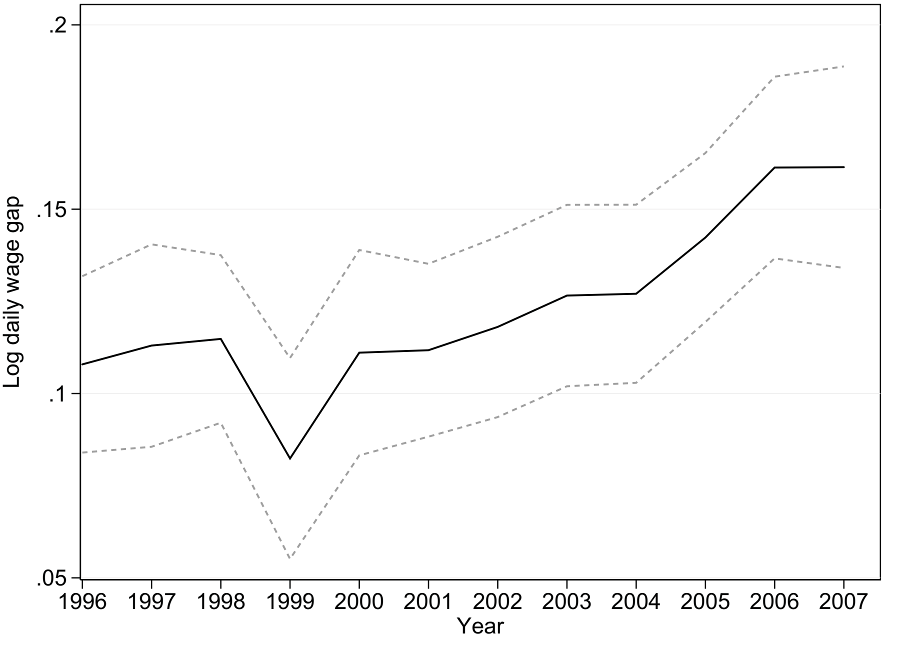
Figures and Tables

Figure 1: Evolution of the Raw Exporter Wage Gap



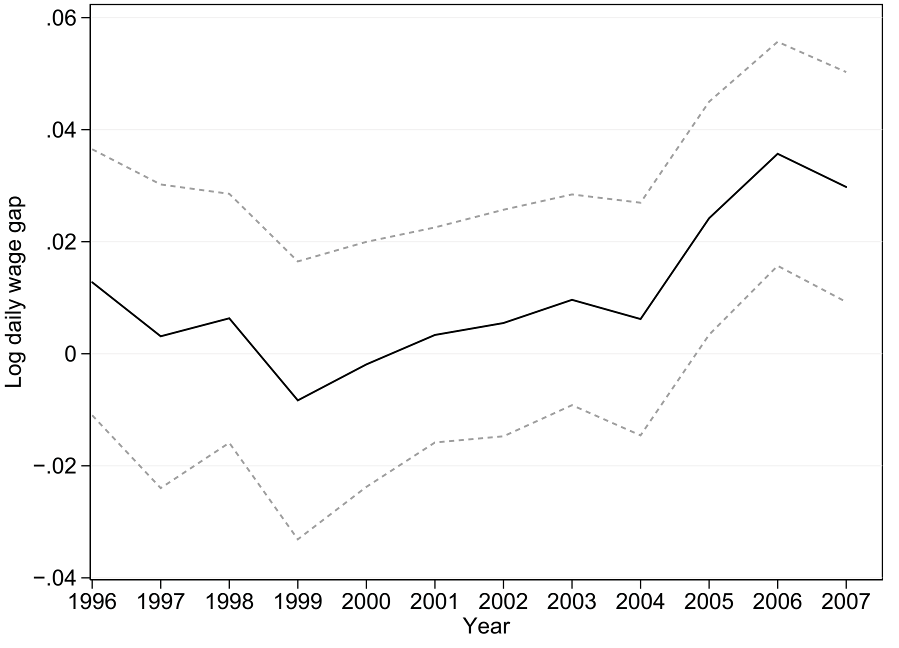
Note: The figure depicts the mean raw log wage gap (solid line) and the associated 95-percent confidence interval (dashed lines) obtained from the year-specific regressions $\ln w_{ijt} = \beta_{0t} + \beta_{1t}Exp_{jt} + u_{ijt}$. Regressions employ sampling weights, and clustering at the establishment level is taken into account.

Figure 2: Evolution of the Conditional Exporter Wage Gap I



Note: The figure depicts the mean conditional log wage gap (solid line) and the associated 95-percent confidence interval (dashed lines) obtained from the year-specific regressions $\ln w_{ijt} = \beta_{0t} + \beta_{1t} Exp_{jt} + \boldsymbol{X'_{it}} \boldsymbol{\beta_{Xt}} + \boldsymbol{I'_{jt}} \boldsymbol{\beta_{It}} + \boldsymbol{R'_{jt}} \boldsymbol{\beta_{Rt}} + u_{ijt}$. The vector $\boldsymbol{X_{it}}$ contains worker characteristics, $\boldsymbol{I_{jt}}$ denotes industry dummies and $\boldsymbol{R_{jt}}$ federal state dummies. Regressions employ sampling weights, and clustering at the establishment level is taken into account.

Figure 3: Evolution of the Conditional Exporter Wage Gap II



Note: The figure depicts the mean conditional log wage gap (solid line) and the associated 95-percent confidence interval (dashed lines) obtained from the year-specific regressions $\ln w_{ijt} = \beta_{0t} + \beta_{1t} Exp_{jt} + \boldsymbol{X'_{it}} \boldsymbol{\beta_{Xt}} + \boldsymbol{Z'_{jt}} \boldsymbol{\beta_{Zt}} + \boldsymbol{I'_{jt}} \boldsymbol{\beta_{It}} + \boldsymbol{R'_{jt}} \boldsymbol{\beta_{Rt}} + u_{ijt}$. The vector $\boldsymbol{X_{it}}$ contains worker characteristics, $\boldsymbol{Z_{jt}}$ establishment characteristics, $\boldsymbol{I_{jt}}$ denotes industry dummies and $\boldsymbol{R_{jt}}$ federal state dummies. Regressions employ sampling weights, and clustering at the establishment level is taken into account.

Table 1: Exporting trends in German manufacturing

	1996	2007	Change (in %)
Share of exporters	18.44	24.79	34.44
Export share in sales of exporters	19.62	30.91	57.51
Export share in sales of all establishments	3.62	7.66	111.74
Employment share of exporters			
- All workers	60.87	64.55	6.05
- Regression sample	63.77	70.22	10.11
Ratio of goods exports to GDP[a]	21.43	40.40	88.50
Ratio of goods imports to GDP[a]	18.53	32.20	73.75

Source: LIAB, establishment-level data and German Federal Statistical Office (items marked with [a]).

Note: Summary statistics of the LIAB data make use of sampling weights.

Table 2: Trends in exporting and the exporter wage gap by industry

Industry	Share in empl. (%)	Empl. share of exporters (%)		Conditional Exporter Wage Gap		
		1996	2007	1996	2007	Change
Chemicals	5.32	87.56	79.22	−0.0362	−0.0117	0.0245
				(0.0376)	(0.0362)	(0.0518)
Rubber and plastics	3.74	81.64	84.06	0.0151	0.0754	0.0604
				(0.0263)	(0.0438)	(0.0511)
Non-metallic mineral products	4.04	51.01	49.42	−0.0210	−0.0299	−0.0090
				(0.0375)	(0.0487)	(0.0625)
Metal production	10.58	67.16	72.85	0.1405*	0.1899*	0.0494
				(0.0261)	(0.0261)	(0.0359)
Structural metal products	7.11	34.49	49.95	0.0826*	0.1775	0.0949
				(0.0263)	(0.1132)	(0.1143)
Machinery and equipment	19.02	87.79	84.14	0.1174*	0.1379*	0.0205
				(0.0412)	(0.0347)	(0.0537)
Vehicle manufacturing	9.99	57.46	51.50	0.2406*	0.2100*	−0.0307
				(0.0386)	(0.0306)	(0.0455)
Shipbuilding and aircraft	1.61	49.50	92.91	0.0761*	0.2319*	0.1559*
				(0.0234)	(0.0749)	(0.0786)
Electrical engineering	12.17	70.01	83.96	0.0850*	0.1001	0.0151
				(0.0383)	(0.0524)	(0.0624)
Precision mechanics	5.34	75.17	76.72	0.1047*	0.3059*	0.2012*
				(0.0329)	(0.0518)	(0.0608)
Wood processing	5.14	44.20	62.17	0.0731	0.0979*	0.0248
				(0.0397)	(0.0285)	(0.0479)
Paper and print	3.82	50.36	63.27	−0.0469	0.0896*	0.1366*
				(0.0304)	(0.0424)	(0.0509)
Textiles and clothing	2.72	65.82	66.97	0.0765	0.2411*	0.1646*
				(0.0589)	(0.0399)	(0.0707)
Food	9.40	28.56	46.16	0.2141*	0.2134*	−0.0007
				(0.0390)	(0.0456)	(0.0594)

Note: Column 2 contains the industry's share in total manufacturing employment, averaged over the two years 1996 and 2007. Columns 3 and 4 display the employment share of exporters within the stated industry. All are based on the (weighted) number of observations in the regression sample. Columns 5 to 7 display the (change in the) conditional exporter wage gap, obtained from separate multivariate regressions (Equation 2) by industry and year. Standard errors of the export coefficients (in parentheses) are clustered at the level of the establishment. * denotes statistical significance at the 5-percent level.

Table 3: Switchers vs stayers and the change in the exporter wage gap

		Obs	Raw Wages			Wage Residuals		
			1996	2007	Change	1996	2007	Change
D - D		2380	4.2765	4.3354	0.0589	−0.0719	−0.1482	−0.0763
			(0.3028)	(0.4265)		(0.2515)	(0.3029)	
D - E	stayer	6007	4.4495	4.5814	0.1319	−0.0787	−0.0374	0.0412
			(0.3330)	(0.4514)		(0.2387)	(0.3168)	
	mover	754	4.2505	4.5963	0.3458	−0.0538	0.0634	0.1173
			(0.3179)	(0.6030)		(0.2276)	(0.4168)	
E - D	stayer	1051	4.5176	4.6040	0.0864	0.0439	−0.0017	−0.0456
			(0.3658)	(0.3696)		(0.2291)	(0.2807)	
	mover	2416	4.4473	4.6297	0.1824	−0.0036	0.0341	0.0377
			(0.2923)	(0.3699)		(0.2019)	(0.2686)	
E - E		74517	4.5581	4.7270	0.1689	0.0557	0.0510	−0.0046
			(0.3237)	(0.3717)		(0.2325)	(0.2842)	

Note: The table displays the evolution of raw log wages and log wage residuals, respectively, for a balanced sample of individuals, differentiating by their export status in 1996 and 2007. The first letter in the first column denotes the export status in 1996 (D: domestic, E: exporter), the second letter the export status in 2007. For export switchers, the second column characterizes whether this switch occurred due to establishments starting to export (stayers) or due to individuals moving from a non-exporting to an exporting plant (mover). The third column displays the unweighted number of observation for each category. Wage residuals have been obtained from year-specific log wage regressions (on the full, unbalanced sample), using as controls a set of age×education dummies, a quadratic term of establishment tenure, a dummy for foreign nationality, a dummy for holding a position as a master craftsman or foreman as well as industry dummies and federal state dummies. Standard errors are given in parentheses. Regressions and summary statistics make use of sampling weights.

Table 4: Trends in log wage inequality in German manufacturing

	1996	2007	Change
Standard deviation:			
- Total	0.367	0.461	0.094
- Between establishments	0.260	0.343	0.083
- Within establishments	0.258	0.307	0.049
85-15	0.712	0.875	0.163
85-50	0.409	0.471	0.062
50-15	0.303	0.405	0.101

Note: Summary statistics make use of sampling weights.

Table 5: Decomposition of the changes in the log wage variance by export status

a) Evolution of components

	1996	2007	Change
σ^2	0.1344	0.2122	0.0778
σ_d^2	0.1257	0.2143	0.0886
σ_e^2	0.1214	0.1848	0.0634
α_d	0.3623	0.2978	-0.0645
$\bar{w}$	4.4667	4.5315	0.0648
$\bar{w}_d$	4.3247	4.3219	-0.0028
$\bar{w}_e$	4.5474	4.6203	0.0730

b) Decomposition results

		[%]
Within-group variance effect	0.0709	[91.14]
Within-group composition effect	-0.0003	[-0.35]
Between-group wage differential effect	0.0081	[10.35]
Between-group composition effect	-0.0009	[-1.13]
Total change: $\sigma^2_{2007} - \sigma^2_{1996}$	0.0778	[100]

Note: The table displays the results of the simple decomposition outlined in Section 5.2 and Appendix A. σ^2: overall variance; σ^d_2: variance within the group of non-exporters; σ^2_e: variance within the group of exporters; α_d: share of individuals employed at non-exporters; $\bar{w}$: average log wage; $\bar{w}_d$: average log wage at non-exporters; $\bar{w}_e$: average log wage at exporters. Contribution of each component to the overall increase in wage dispersion given in square brackets (Panel b, column headed '[%]'). Decomposition makes use of sampling weights.

Table 6: Results of the Juhn-Murphy-Pierce type decomposition: short model

		sd		85-15		85-50		50-15	
		logs	[%]	logs	[%]	logs	[%]	logs	[%]
Default order									
Coefficients	Export	0.0083	[8.85]	0.0192	[11.73]	0.0041	[6.53]	0.0151	[14.93]
		(0.0027)		(0.0062)		(0.0023)		(0.0052)	
	Other	0.0417	[44.31]	0.0914	[55.88]	0.0302	[48.43]	0.0612	[60.47]
		(0.0089)		(0.0289)		(0.0094)		(0.0222)	
	Total	0.0500	[53.16]	0.1105	[67.60]	0.0343	[54.96]	0.0763	[75.39]
		(0.0094)		(0.0297)		(0.0103)		(0.0221)	
Characteristics	Export	−0.0052	[−5.55]	−0.0128	[−7.84]	0.0004	[0.70]	−0.0133	[−13.10]
		(0.0023)		(0.0077)		(0.0040)		(0.0061)	
	Other	0.0171	[18.19]	0.0249	[15.26]	0.0105	[16.91]	0.0144	[14.24]
		(0.0065)		(0.0201)		(0.0113)		(0.0154)	
	Total	0.0119	[12.63]	0.0121	[7.42]	0.0110	[17.61]	0.0012	[1.14]
		(0.0070)		(0.0228)		(0.0122)		(0.0175)	
Residual		0.0322	[34.21]	0.0408	[24.98]	0.0171	[27.44]	0.0237	[23.47]
		(0.0068)		(0.0195)		(0.0167)		(0.0121)	
Total		0.0940	[100]	0.1635	[100]	0.0623	[100]	0.1012	[100]
		(0.0123)		(0.0296)		(0.0229)		(0.0122)	
Reverse order									
Characteristics	Other	0.0197	[20.91]	0.0522	[31.92]	0.0258	[41.46]	0.0264	[26.05]
		(0.0057)		(0.0153)		(0.0112)		(0.0087)	
	Export	−0.0017	[−1.77]	−0.0064	[−3.93]	−0.0005	[−0.81]	−0.0059	[−5.85]
		(0.0011)		(0.0046)		(0.0023)		(0.0042)	
	Total	0.0180	[19.13]	0.0458	[27.99]	0.0253	[40.65]	0.0204	[20.19]
		(0.0055)		(0.0147)		(0.0108)		(0.0087)	
Coefficients	Other	0.0361	[38.39]	0.0608	[37.16]	0.0175	[28.14]	0.0432	[42.72]
		(0.0055)		(0.0117)		(0.0057)		(0.0099)	
	Export	0.0078	[8.27]	0.0161	[9.87]	0.0024	[3.78]	0.0138	[13.62]
		(0.0026)		(0.0065)		(0.0023)		(0.0061)	
	Total	0.0439	[46.66]	0.0769	[47.03]	0.0199	[31.91]	0.0570	[56.34]
		(0.0060)		(0.0134)		(0.0058)		(0.0116)	
Residual		0.0322	[34.21]	0.0408	[24.98]	0.0171	[27.44]	0.0237	[23.47]
		(0.0068)		(0.0195)		(0.0167)		(0.0121)	
Total		0.0940	[100]	0.1635	[100]	0.0623	[100]	0.1012	[100]
		(0.0123)		(0.0296)		(0.0229)		(0.0122)	

Note: sd: Increase in standard deviation of log wages between 1996 and 2007; 85-15/85-50/50-15: increase in 85-15/85-50/50-15 log wage differential between 1996 and 2007. Decomposition as described in Section 5.2, taking the year 1996 as reference. Variables contained in the vector 'Other': worker characteristics (age×education dummies, quadratic term of establishment tenure, dummy for foreign nationality, dummy for holding position as master craftsman or foreman), industry dummies and federal state dummies. Order of elements from top to bottom gives order of sequential decomposition. Bootstrap standard errors based on 200 repetitions given in parentheses. Contribution of each element to the overall increase in wage dispersion given in square brackets (column headed '[%]'). Estimation makes use of sampling weights.

Table 7: Results of the Juhn-Murphy-Pierce type decomposition: extended model

		sd		85-15		85-50		50-15	
		logs	[%]	logs	[%]	logs	[%]	logs	[%]
Default order									
Coefficients	Export	0.0024	[2.55]	0.0063	[3.78]	0.0014	[2.22]	0.0049	[4.78]
		(0.0023)		(0.0057)		(0.0019)		(0.0043)	
	Other	0.0466	[48.69]	0.1019	[60.87]	0.0341	[52.36]	0.0678	[66.31]
		(0.0066)		(0.0199)		(0.0097)		(0.0137)	
	Total	0.0490	[51.23]	0.1082	[64.66]	0.0356	[54.58]	0.0727	[71.09]
		(0.0066)		(0.0196)		(0.0102)		(0.0128)	
Characteristics	Export	−0.0005	[−0.55]	−0.0010	[−0.60]	0.0008	[1.18]	−0.0018	[−1.73]
		(0.0030)		(0.0083)		(0.0046)		(0.0064)	
	Other	0.0344	[35.98]	0.0791	[47.29]	0.0090	[13.81]	0.0702	[68.63]
		(0.0094)		(0.0237)		(0.0146)		(0.0182)	
	Total	0.0339	[35.43]	0.0781	[46.69]	0.0098	[14.99]	0.0684	[66.90]
		(0.0101)		(0.0259)		(0.0158)		(0.0193)	
Residual		0.0128	[13.34]	−0.0190	[−11.35]	0.0198	[30.43]	−0.0388	[−37.99]
		(0.0103)		(0.0249)		(0.0221)		(0.0173)	
Total		0.0957	[100]	0.1674	[100]	0.0652	[100]	0.1022	[100]
		(0.0125)		(0.0286)		(0.0229)		(0.0119)	
Reverse order									
Characteristics	Other	0.0374	[39.03]	0.1022	[61.08]	0.0394	[60.49]	0.0628	[61.46]
		(0.0086)		(0.0223)		(0.0130)		(0.0163)	
	Export	−0.0025	[−2.57]	−0.0096	[−5.72]	−0.0044	[−6.77]	−0.0052	[−5.05]
		(0.0016)		(0.0071)		(0.0031)		(0.0057)	
	Total	0.0349	[36.46]	0.0927	[55.36]	0.0350	[53.72]	0.0577	[56.40]
		(0.0084)		(0.0210)		(0.0123)		(0.0160)	
Coefficients	Other	0.0455	[47.52]	0.0894	[53.41]	0.0099	[15.22]	0.0795	[77.75]
		(0.0056)		(0.0169)		(0.0095)		(0.0138)	
	Export	0.0026	[2.68]	0.0043	[2.58]	0.0004	[0.62]	0.0039	[3.83]
		(0.0023)		(0.0062)		(0.0017)		(0.0055)	
	Total	0.0480	[50.20]	0.0937	[55.99]	0.0103	[15.85]	0.0834	[81.58]
		(0.0054)		(0.0165)		(0.0098)		(0.0133)	
Residual		0.0128	[13.34]	−0.0190	[−11.35]	0.0198	[30.43]	−0.0388	[−37.99]
		(0.0103)		(0.0249)		(0.0221)		(0.0173)	
Total		0.0957	[100]	0.1674	[100]	0.0652	[100]	0.1022	[100]
		(0.0125)		(0.0286)		(0.0229)		(0.0119)	

Note: Variables contained in the vector 'Other': worker characteristics (age×education dummies, quadratic term of establishment tenure, dummy for foreign nationality, dummy for holding position as master craftsman or foreman), **establishment characteristics** (quadratic term of log total employment, dummy for state-of-the-art technology status, dummy for not being part of a larger group, dummy for the existence of a works council, two dummy variables for following an industry-level or a firm-level collective agreement, respectively), industry dummies, and federal state dummies. See Table 6 for further explanatory notes.

Table 8: Results of the Juhn-Murphy-Pierce type decomposition: between- vs within-group wage dispersion, short model

		sd between		sd within	
		logs	[%]	logs	[%]
Default order					
Coefficients	Export	0.0030	[4.66]	0.0079	[11.14]
		(0.0010)		(0.0026)	
	Other	0.0275	[42.94]	0.0321	[45.26]
		(0.0037)		(0.0096)	
	Total	0.0305	[47.59]	0.0400	[56.41]
		(0.0039)		(0.0096)	
Characteristics	Export	−0.0033	[−5.22]	−0.0041	[−5.75]
		(0.0027)		(0.0022)	
	Other	0.0309	[48.30]	0.0003	[0.38]
		(0.0077)		(0.0059)	
	Total	0.0276	[43.08]	−0.0038	[−5.37]
		(0.0083)		(0.0067)	
Residual		0.0060	[9.33]	0.0347	[48.97]
		(0.0076)		(0.0052)	
Total		0.0640	[100]	0.0709	[100]
		(0.0122)		(0.0081)	
Reverse order					
Characteristics	Other	0.0240	[37.48]	0.0082	[11.62]
		(0.0072)		(0.0043)	
	Export	0.0018	[2.82]	−0.0032	[−4.49]
		(0.0014)		(0.0015)	
	Total	0.0258	[40.30]	0.0051	[7.14]
		(0.0072)		(0.0040)	
Coefficients	Other	0.0296	[46.21]	0.0235	[33.14]
		(0.0046)		(0.0050)	
	Export	0.0027	[4.16]	0.0076	[10.76]
		(0.0010)		(0.0025)	
	Total	0.0322	[50.37]	0.0311	[43.90]
		(0.0047)		(0.0055)	
Residual		0.0060	[9.33]	0.0347	[48.97]
		(0.0076)		(0.0052)	
Total		0.0640	[100]	0.0709	[100]
		(0.0122)		(0.0081)	

Note: sd between/sd within: increase in standard deviation of log wages between and within 20 age×education groups, respectively, between 1996 and 2007. See Table 6 for further explanatory notes.

Appendix

A Decomposing changes in the variance of log wages

Starting from Equation (4), the change in the variance of log wages between two periods t and s can be decomposed as follows (cf. Blau and Kahn, 1994):

$$\begin{aligned}
\sigma_s^2 - \sigma_t^2 &= \left\{\alpha_{ds}\left(\sigma_{ds}^2 - \sigma_{dt}^2\right) + (1-\alpha_{ds})\left(\sigma_{es}^2 - \sigma_{et}^2\right)\right\} \\
&+ \left\{\sigma_{dt}^2\left(\alpha_{ds} - \alpha_{dt}\right) + \sigma_{et}^2\left[(1-\alpha_{ds}) - (1-\alpha_{dt})\right]\right\} \\
&+ \left\{\alpha_{ds}\left[\left(\bar{w}_{ds} - \bar{w}_s\right)^2 - \left(\bar{w}_{dt} - \bar{w}_t\right)^2\right] + (1-\alpha_{ds})\left[\left(\bar{w}_{es} - \bar{w}_s\right)^2 - \left(\bar{w}_{et} - \bar{w}_t\right)^2\right]\right\} \\
&+ \left\{\left(\bar{w}_{dt} - \bar{w}_t\right)^2\left(\alpha_{ds} - \alpha_{dt}\right) + \left(\bar{w}_{et} - \bar{w}_t\right)^2\left[(1-\alpha_{ds}) - (1-\alpha_{dt})\right]\right\}
\end{aligned}$$

The term in the first curly bracket captures changes in wage dispersion within the two sectors ("within-group variance effect"). The component in the second curly bracket measures the contribution of changing employment shares in the high-variance and low-variance sectors, respectively ("within-group composition effect"). The third component measures the effect of changes in the wage gap between the two sectors ("between-group wage differential effect"). Finally, the component in the fourth curly bracket measures the effect of changing employment shares in the sector whose wages are relatively far from the average ("between-group composition effect").

B Additional tables

Table B1: Summary statistics: 1996

	All		Non-Exporters		Exporters	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Log daily real wage	4.467	0.367	4.325	0.354	4.547	0.348
Educ: missing	0.040	0.195	0.053	0.224	0.032	0.176
Educ: low	0.153	0.360	0.121	0.327	0.170	0.376
Educ: medium	0.730	0.444	0.785	0.411	0.698	0.459
Educ: high	0.078	0.268	0.041	0.198	0.099	0.299
Age: 18–25	0.077	0.266	0.097	0.296	0.066	0.248
Age: 26–35	0.326	0.469	0.355	0.479	0.309	0.462
Age: 36–45	0.286	0.452	0.273	0.445	0.293	0.455
Age: 46–55	0.220	0.415	0.198	0.399	0.233	0.423
Age: 56–65	0.091	0.287	0.077	0.266	0.099	0.298
Tenure (days)	2,976.596	2,529.430	2,242.922	2,225.117	3,393.379	2,596.246
Master craftsman, foreman	0.044	0.205	0.054	0.227	0.038	0.191
Foreign nationality	0.099	0.299	0.083	0.276	0.108	0.311
Est: Export	0.638	0.481	0.000	0.000	1.000	0.000
Est: Log total employment*	5.059	2.016	3.575	1.591	5.911	1.718
Est: High technology*	0.207	0.405	0.196	0.397	0.213	0.410
Est: Not part of larger group*	0.584	0.493	0.724	0.447	0.504	0.500
Est: Works council*	0.694	0.461	0.431	0.495	0.845	0.362
Est: Collective agreement at industry level*	0.767	0.423	0.716	0.451	0.796	0.403
Est: Collective agreement at firm level*	0.114	0.318	0.092	0.290	0.127	0.333
Ind: Manuf. of chemical products	0.053	0.224	0.018	0.134	0.073	0.260
Ind: Manuf. of rubber and plastic products	0.037	0.190	0.019	0.136	0.048	0.214
Ind: Manuf. of non-metallic mineral products	0.040	0.197	0.055	0.227	0.032	0.177
Ind: Manuf. of iron and steel products	0.106	0.308	0.096	0.294	0.111	0.315
Ind: Manuf. of structural metal products	0.071	0.257	0.129	0.335	0.038	0.192
Ind: Manuf. of machinery and equipment	0.190	0.392	0.064	0.245	0.262	0.440
Ind: Manuf. of motor vehicles	0.100	0.300	0.117	0.322	0.090	0.286
Ind: Manuf. of ships and aircraft	0.016	0.126	0.022	0.148	0.012	0.111
Ind: Manuf. of electrical equipment	0.122	0.327	0.101	0.301	0.134	0.340
Ind: Manuf. of fine mechanical products	0.053	0.225	0.037	0.188	0.063	0.243
Ind: Manuf. of wood and wood products	0.051	0.221	0.079	0.270	0.036	0.185
Ind: Manuf. of paper products; printing	0.038	0.192	0.052	0.223	0.030	0.171
Ind: Manuf. of textiles and textile products	0.027	0.163	0.026	0.158	0.028	0.165
Ind: Manuf. of food products	0.094	0.292	0.185	0.389	0.042	0.201
Reg: Schleswig-Holstein	0.018	0.132	0.014	0.118	0.020	0.139
Reg: Hamburg	0.018	0.133	0.026	0.159	0.013	0.115
Reg: Lower Saxony	0.104	0.306	0.119	0.324	0.096	0.295
Reg: Bremen	0.011	0.105	0.008	0.089	0.013	0.114
Reg: North Rhine-Westphalia	0.251	0.434	0.174	0.379	0.295	0.456
Reg: Hesse	0.070	0.256	0.057	0.231	0.078	0.268
Reg: Baden-Württemberg	0.152	0.359	0.123	0.328	0.169	0.374
Reg: Bavaria	0.146	0.353	0.119	0.323	0.161	0.367
Reg: Berlin	0.049	0.215	0.106	0.307	0.016	0.126
Reg: Brandenburg	0.018	0.132	0.032	0.177	0.009	0.096
Reg: Mecklenburg-Vorpommern	0.011	0.106	0.022	0.148	0.005	0.072
Reg: Saxony	0.040	0.197	0.069	0.253	0.024	0.153
Reg: Saxony-Anhalt	0.023	0.148	0.040	0.196	0.013	0.112
Reg: Thuringia	0.024	0.154	0.037	0.189	0.017	0.129
Reg: Rhineland-Palatinate, Saarland	0.065	0.246	0.055	0.228	0.071	0.256
Observations (unweighted)	565,163		68,245		496,918	

Variables preceded by *Est* denote establishment characteristics. Establishment characteristics marked with * are included in the extended regression model. Due to missing values they are based on 538,382 observations for the whole sample (67,884 at non-exporters and 470,498 at exporters). Summary statistics are calculated using sampling weights. The table displays separate summary statistics for five age groups and four education categories. Note that in the regression, dummies for age×education groups are used instead.

Table B2: Summary statistics: 2007

	All		Non-Exporters		Exporters	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Log daily real wage	4.531	0.461	4.322	0.463	4.620	0.430
Educ: missing	0.073	0.259	0.111	0.315	0.056	0.230
Educ: low	0.114	0.318	0.090	0.286	0.124	0.330
Educ: medium	0.711	0.453	0.745	0.436	0.697	0.460
Educ: high	0.102	0.303	0.054	0.225	0.123	0.329
Age: 18–25	0.072	0.259	0.090	0.286	0.065	0.246
Age: 26–35	0.193	0.395	0.215	0.411	0.184	0.387
Age: 36–45	0.333	0.471	0.316	0.465	0.341	0.474
Age: 46–55	0.288	0.453	0.267	0.442	0.297	0.457
Age: 56–65	0.113	0.316	0.112	0.316	0.113	0.317
Tenure (days)	4,059.487	3,168.611	3,481.807	2,927.754	4,304.480	3,234.397
Master craftsman, foreman	0.034	0.182	0.048	0.213	0.028	0.166
Foreign nationality	0.072	0.259	0.058	0.233	0.078	0.269
Est: Export	0.702	0.457	0.000	0.000	1.000	0.000
Est: Log total employment*	5.445	2.072	3.891	1.687	6.099	1.860
Est: High technology*	0.224	0.417	0.182	0.386	0.241	0.428
Est: Not part of larger group*	0.525	0.499	0.719	0.449	0.443	0.497
Est: Works council*	0.682	0.466	0.389	0.487	0.806	0.395
Est: Collective agreement at industry level*	0.603	0.489	0.515	0.500	0.641	0.480
Est: Collective agreement at firm level*	0.093	0.290	0.080	0.271	0.098	0.297
Ind: Manufacture of chemical products	0.055	0.229	0.039	0.193	0.063	0.242
Ind: Manufacture of rubber and plastic products	0.042	0.201	0.023	0.149	0.051	0.219
Ind: Manufacture of non-metallic mineral products	0.023	0.150	0.039	0.194	0.016	0.126
Ind: Manufacture of iron and steel products	0.164	0.371	0.150	0.357	0.171	0.376
Ind: Manufacture of structural metal products	0.012	0.109	0.020	0.141	0.009	0.092
Ind: Manufacture of machinery and equipment	0.171	0.376	0.091	0.287	0.204	0.403
Ind: Manufacture of motor vehicles	0.187	0.390	0.304	0.460	0.137	0.344
Ind: Manufacture of ships and aircraft	0.026	0.159	0.006	0.079	0.035	0.183
Ind: Manufacture of electrical equipment	0.119	0.323	0.064	0.245	0.142	0.349
Ind: Manufacture of fine mechanical products	0.036	0.187	0.029	0.166	0.040	0.196
Ind: Manufacture of wood and wood products	0.040	0.196	0.051	0.220	0.035	0.185
Ind: Manufacture of paper products; printing	0.047	0.212	0.058	0.234	0.042	0.202
Ind: Manufacture of textiles and textile products	0.018	0.133	0.020	0.140	0.017	0.130
Ind: Manufacture of food products	0.059	0.236	0.107	0.309	0.039	0.194
Reg: Schleswig-Holstein	0.015	0.122	0.021	0.142	0.013	0.112
Reg: Hamburg	0.039	0.194	0.038	0.190	0.040	0.195
Reg: Lower Saxony	0.079	0.270	0.077	0.266	0.080	0.271
Reg: Bremen	0.006	0.078	0.010	0.098	0.005	0.068
Reg: North Rhine-Westphalia	0.212	0.409	0.229	0.420	0.205	0.403
Reg: Hesse	0.081	0.272	0.079	0.269	0.081	0.273
Reg: Baden-Württemberg	0.166	0.372	0.145	0.352	0.176	0.380
Reg: Bavaria	0.193	0.395	0.125	0.331	0.222	0.415
Reg: Berlin	0.015	0.122	0.023	0.148	0.012	0.109
Reg: Brandenburg	0.017	0.130	0.030	0.170	0.012	0.108
Reg: Mecklenburg-Vorpommern	0.012	0.109	0.026	0.159	0.006	0.077
Reg: Saxony	0.044	0.206	0.061	0.239	0.037	0.190
Reg: Saxony-Anhalt	0.019	0.137	0.033	0.179	0.013	0.114
Reg: Thuringia	0.029	0.167	0.038	0.191	0.025	0.155
Reg: Rhineland-Palatinate, Saarland	0.073	0.259	0.067	0.250	0.075	0.263
Observations (unweighted)	486,990		62,130		424,860	

Note: Variables preceded by *Est* denote establishment characteristics. Establishment characteristics marked with * are included in the extended regression model. Due to missing values they are based on 485,596 observations for the whole sample (61,810 at non-exporters and 423,786 at exporters). Summary statistics are calculated using sampling weights. The table displays separate summary statistics for five age groups and four education categories. Note that in the regression, dummies for age×education groups are used instead.