Trade, firm wage premiums, and wage inequality: Worker-level evidence*

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The increase in sorting of high-wage (low-wage) workers into firms that pay high (low) wage premiums explains more than 30% of the rise in wage inequality in the U.S.A and Germany. Despite its relevance for the wage structure, little is known about the causes of the rise in sorting and the underlying mobility pattern of heterogeneous workers. In this paper, I use data on 50% of all West German male employees from 1985 through 2010 and analyze the impact of Germany's trade integration with China and Eastern Europe on the sorting pattern. The effects differ between import-exposed and export-exposed industries. Import exposure triggers increasing displacement rates at high-wage manufacturing firms for all workers. It contributes to the observed increase in sorting because, upon displacement from their original high-wage employer, workers with low formal education performing routine-intensive and codifiable tasks reallocate towards low-wage non-manufacturing firms, whereas more skilled workers more often reallocate towards high-wage non-manufacturing firms. In contrast, workers in export-oriented industries experience a positive job stability effect at high-wage manufacturing firms. This effect is strongest for workers with low observable and unobservable skills and therefore counteracts the observed changes in the sorting pattern.

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1. Introduction

Wage inequality has increased substantially in the U.S.A., Germany, and other countries during the last decades (e.g. Dustmann et al. 2009; Acemoglu and Autor 2011). Recent evidence points to changes in the sorting pattern of workers across firms as an important driver of this phenomenon. Card et al. (2013) and Song et al. (2019) build on the method by Abowd et al. (1999) and decompose log wages into a worker component and a firm component which reflects a proportional wage premium paid by the firm. They provide evidence that increased sorting of high-wage (low-wage) workers into firms paying high (low) wage premiums explains more than 30% of the rise in wage inequality in Germany and the U.S.A., respectively.[1]

Panel (a) of figure 1 illustrates this result for Germany. Following the decomposition in Card et al. (2013), it plots the variance of log daily wages and twice the covariance between estimated worker and firm fixed effects for different 6-year-intervals. The steady increase of the covariance over time reflects the rise in sorting between workers and firms. The increase in the covariance corresponds to about 30% of the rise in wage inequality between the first and the last interval.[2]

In this paper, I address two important questions that follow naturally from the findings in Card et al. (2013) and Song et al. (2019). The first question concerns the causes of the increase in sorting. I use data on 50% of all West German male employees from 1985 through 2010 and analyze how Germany's trade integration with China and Eastern Europe affected the wage structure through its impact on the sorting pattern.

The second question is related to the 'black box' nature of the covariance and the estimated worker effects. The strong changes in the covariance indicate substantial mobility of workers across firms, but little is known about the exact mobility pattern. Did the covariance increase because of downward mobility of low-wage workers towards low-wage firms, because of upward mobility of high-wage workers towards high-wage firms, or both? To what extent did labor mobility from the manufacturing sector to the non-manufacturing sector contribute to the increase in sorting? Does the increase in the covariance reflect an increase in sorting based on observable worker and job characteristics, based on unobservable skill differences, or both? The latter question arises because the worker effects

[1] I use the terms 'establishment' and 'firm' interchangeably. In the empirical analysis, I observe establishments and cannot determine to which firm a given establishment belongs. The same is true for the analysis in Card et al. (2013). Song et al. (2019), in contrast, do observe firms.

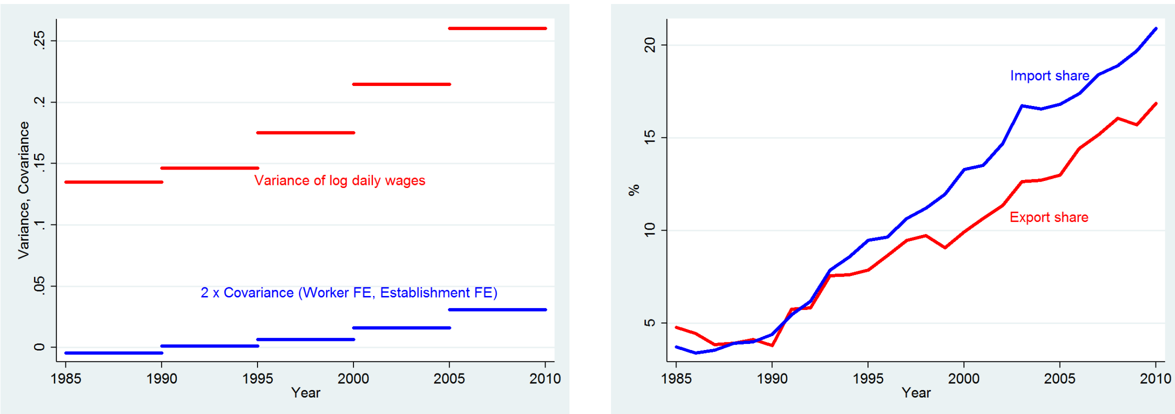
[2] The fixed effects result from a regression of log daily wages of male full-time workers on worker fixed effects, firm fixed effects, and time-varying controls. The worker fixed effect reflects all time-invariant personal characteristics which influence a workers' wage and can be considered as a measure of worker skill. The firm fixed effect reflects a proportional pay premium or discount paid by the firm. One can decompose the variance of log wages and its change over time into several components. Twice the covariance between estimated worker and firm effects reflects the part of the variance which is driven by the sorting pattern. The intervals differ slightly from Card et al. (2013). See section 2 for a more detailed explanation.

absorb a combination of the effects of education, occupation, tasks performed on the job as well as purely unobserved factors such as motivation or unobserved ability to the extent that they are time-invariant for a worker.[3]

I address these aspects with the help of a worker-level analysis. I analyze the effects of Germany's trade integration with China and Eastern Europe on worker mobility across firms that differ in terms of their wage premium as in Card et al. (2013) or Song et al. (2019). The rich data I am using allow to follow workers as they move between firms, both within and between industries and sectors, and enable me to differentiate by various observable and unobservable worker and job characteristics. I thereby provide a picture about how changes in the sorting pattern in response to trade integration with China and Eastern Europe affect wage inequality between and within educational and occupational groups and shed light on potential underlying mechanisms. These are the main innovations relative to the previous literature which relies on the industry- or sector-level relationship between trade and sorting as reflected by the covariance between worker and firm effects and therefore is silent about these aspects (Davidson et al. 2014; Borrs and Knauth 2016; Baziki et al. 2016).[4]

Figure 1: Wage Inequality, Sorting, and Trade

(a) Wage Inequality and Sorting (b) Trade with EE and China



Notes: Panel (a) shows the variance of log daily imputed wages for West German male full time workers in different 6-year-intervals. It also depicts twice the covariance of estimated worker and firm fixed effects, separately for each interval. The fixed effects result from a regression of log daily wages on worker and firm fixed effects as well as time-varying controls as in Card et al. (2013). See section 2 for more details. Panel (b) depicts the share of German exports to and imports from Eastern Europe and China in total German export and imports. See section 2 for a list of countries. Data sources: Integrated Employment Biographies (IEB): 50%-sample, Comtrade.

Panel (b) of figure 1 shows that the changes in the sorting pattern coincided with a

[3]Note that education is mostly time-invariant since most workers in the sample have already completed their formal education.

[4]Davidson et al. (2014) for example relate changes in the covariance of estimated worker and firm effects in industries to industry-level changes in tariffs in Sweden.

substantial episode of trade integration with China and Eastern Europe. The share of German exports to and imports from Eastern Europe and China in total German exports and imports increased from below 5% in 1990 to more than 15% in 2010. In absolute terms, exports to and imports from Eastern Europe and China increased by more than 1,000% during that period. The increase in trade with China and Eastern Europe can therefore be called the main globalization shock on the German economy during the last decades.

A large literature documents the effects of this trade shock on labor market outcomes of individual workers. Autor et al. (2014) provide evidence that U.S. manufacturing workers exposed to Chinese import competition experienced substantially lower cumulative earnings than non-exposed workers. Import competition contributed to the rise in earnings inequality because the earnings losses were larger for low-skilled workers who, in contrast to more skilled workers, were less able to move to less exposed industries in the non-manufacturing sector. Dauth et al. (2014) and Dauth et al. (2018) find similar results for import exposure in Germany. In addition, their results suggest that worker employed in export-oriented industries, especially high-skilled workers, benefited from an increase in cumulative earnings.[5]

The paper at hand adds an important new aspect to the understanding of the distributional effects of this trade shock. The previous literature studies the effects on cumulative earnings and employment of workers and thereby to a large extent captures adjustment costs on workers in the form of temporary unemployment during the period of reallocation between firms, industries, and sectors.[6] However, an important question is whether the distributional effects of the trade shock are limited to the unequal distribution of these adjustment costs across workers during the reallocation period. By studying its effects on the sorting pattern over a period of ten years, I provide evidence on a potential channel through which the trade shock can generate earnings inequality that persists even after workers have reallocated. This is the case for example if workers of different skill, in response to import exposure, move into the same sector but to firms that differ in terms of their wage premium.

However, the magnitude and the direction of the impact of the trade shock on the sorting pattern ex ante is unclear and can differ between export-oriented and import-competing industries. Import competition constitutes a negative demand shock on firms

[5] See also Ashournia et al. (2014), Keller and Utar (2015), Nilsson Hakkala and Huttunen (2016), Utar (2018), and Huber and Winkler (2019). See Autor et al. (2013), Dauth et al. (2014), or Balsvik et al. (2015) for evidence on the regional impact of trade with China and Eastern Europe.

[6] Autor et al. (2014) motivate their empirical analysis with a specific factors model with two sectors - one trade-exposed sector and one unexposed sector. Workers are perfectly mobile across sectors in the long run but, due to frictions, not necessarily in the short run. Productivity growth abroad in the trade-exposed sector triggers lower cumulative earnings for workers initially employed in this sector relative to workers in the unexposed sector. The earnings differences are entirely due to the short-run frictions that cause a slow reallocation of workers between sectors.

and, as shown in the previous literature, triggers displacement of workers. The effect on the sorting pattern does not only depend on which firms (high versus low wage premium) and which workers (high- versus low-skilled) are most adversely affected. It also depends on the mobility pattern of workers between firms conditional on displacement.[7]

In export-oriented industries, especially firms paying high wage premiums might benefit from a positive demand shock which might translate into a positive job stability effect on workers. To the extent that it differs between worker types, this effect worker either towards an increase or decrease in sorting.[8] In addition, recent contributions modeling worker and firm heterogeneity suggest that exporting firms might adjust their workforce composition in response to trade integration (e.g. Helpman et al. 2010; Caliendo and Rossi-Hansberg 2012; Bombardini et al. 2017).[9] Finally, there might be mobility towards exporting firms and, to the extent that it differs between worker types, this has an effect on the sorting pattern (e.g. Davidson et al. 2008). Importantly, the effects of export and import exposure are mediated by institutional factors such as unions or works councils, which play an important role in Germany and might influence the ability of firms to adjust their workforce composition, especially for incumbent workers. Overall, the effect of trade integration on the sorting pattern is unclear ex ante and this calls for a careful empirical investigation.

The empirical analysis proceeds in two steps. In a first step, I replicate the decomposition in Card et al. (2013) for different time intervals. Based on the estimates, I group workers and firms into three terciles according to their respective estimated fixed effect: High-wage, medium-wage, and low-wage workers and firms. It turns out that high-wage workers on average earn higher wages, have a higher formal education, perform less routine-intensive and less codifiable tasks, and are employed in different types of occupations than medium-wage and low-wage workers.[10] High-wage firms on average pay higher wages, employ more workers and employ a more educated workforce than medium-wage and low-wage firms. In an initial descriptive exercise, I compare workers who move from a

[7]From the perspective of the domestic industry, the increase in imports documented in figure 1 can also partly reflect increased offshoring (to the extent that it comprises imports of inputs used in this industry). Offshoring can affect the sorting pattern for example if its impact differs across workers' characteristics such as the task content of work as suggested by Hummels et al. (2014). I cannot differentiate between imports of final goods and intermediate goods in this paper due to the disaggregated measurement of imports at the 3-digit level.

[8]Models that combine firm heterogeneity with rent sharing predict that high-wage firms select into exporting (e.g. Egger and Kreickemeier 2009; Amiti and Davis 2011; Egger and Kreickemeier 2012). Even though I cannot observe the export status at the firm level, the result that firms paying high wage premiums on average are larger, employ a more educated workforce, and pay higher wages supports this idea.

[9]Other examples that feature firm and worker heterogeneity are Davidson et al. (2008), Sampson (2014), Helpman et al. (2016), Bombardini et al. (2017), Grossman et al. (2017), and Felbermayr et al. (2018). See Harrison et al. (2011), Helpman (2016), or Muendler (2017) for extensive overviews of the theoretical literature featuring firm and worker heterogeneity.

[10]For example, the share of managers and engineers is higher among the group of high-wage workers than among the groups of medium-wage and low-wage workers.

high-wage firm in 1990 (2000) to a low-wage firm in 2000 (2010) to equally skilled workers who remain employed by a high-wage firm. The results point to a mean wage loss of more than 40 log points for movers as compared to stayers and thereby confirm mobility between firm types to be an important metric for the effects of trade on wages and wage inequality.

In a second step, I focus on two ten-year intervals (1990-2000 and 2000-2010) and exploit differences in initial industry affiliation across manufacturing workers. I separately estimate the impact of industry-level export and import exposure on the probability of remaining employed by a given firm type (job stability effect) and on the probability of moving to a different firm type (mobility effect).[11] To provide a picture about how trade affects sorting across firm types, I allow these effects to differ between worker types.[12] To purge the estimates from potential bias, I include a large battery of controls at the worker, firm, industry and regional level and apply the instrumental variable strategy proposed by Autor et al. (2014) and adapted to the German context by Dauth et al. (2014) and Dauth et al. (2018).

The results suggest that import exposure triggers an increase in sorting. It leads to higher separation rates at high-wage manufacturing firms for all workers types. Upon separation from their initial firm, high-wage workers reallocate towards high-wage non-manufacturing firms, whereas low-wage workers mainly reallocate towards low-wage non-manufacturing firms, and this drives the increase in sorting in response to import exposure. A back-of-the-envelope calculation suggests that import exposure explains about 10% of the higher downward mobility of low-wage workers relative to high-wage workers. A closer look shows that this result is driven by the fact that high-wage workers have a higher formal education, perform more complex tasks, and are employed in more skill-intensive occupations than low-wage workers. These results are in line with a higher transferability of skills among high-skilled workers and with eroding labor market prospects of displaced workers performing routine and codifiable tasks, potentially due to technological progress in the non-manufacturing sector (e.g. Autor et al. 2003; Goos et al. 2014). The results suggest that industry-level import exposure has distributional effects that go beyond the unequal distribution of adjustment costs in the short run.

Previously, domestic outsourcing of certain low-skilled occupations by high-wage firms has been identified as a major driver of increased sorting and wage inequality in Germany (Goldschmidt and Schmieder 2017). With this in-depth analysis, I provide complementary evidence on the impact of import exposure from China and Eastern Europe on sorting and wage inequality. The important role of education as well as occupations and job tasks

[11] Job stability and mobility of course are closely related. For example, an increase in job stability goes along with reduced mobility.

[12] Note that non-random mobility of workers across firms that pay different wage premiums, potentially in response to trade, is in line with the two-way fixed effects specification in Abowd et al. (1999) and Card et al. (2013). See section 2 for a detailed discussion.

documented in this paper suggests that import exposure, through the sorting channel, works towards an increase in both, the skill premium and residual wage inequality. The paper thereby complements previous research which documents that the labor market effects of technological progress and international trade strongly differ by occupations and tasks performed at the workplace (e.g. Autor et al. 2003; Spitz-Oener 2006; Autor et al. 2008; Becker et al. 2013; Baumgarten 2013; Goos et al. 2014; Hummels et al. 2014; Ebenstein et al. 2014; Becker and Muendler 2015).

Increased exports, in contrast, trigger a substantial job stability effect for workers initially employed by high-wage manufacturing firms. This effect is strongest for low-wage and medium-wage workers and therefore works towards a decrease in sorting. Interestingly, not only workers with low observed skills benefit from this effect more than others. In fact, also the least skilled workers within narrowly defined skill groups (i.e. the workers with low unobserved skills) benefit more from the job stability effect than others. A potential explanation for the high job stability effect on low-skilled workers is that these are the workers who are most vulnerable to any kind of negative shock on their employer. Consequently, they are the workers who benefit most from a positive demand shock as compared to a counterfactual scenario without this demand shock. For very high-skilled workers, who generally have a high job stability, the effect of an additional demand shock is much smaller or even non-existent.

With this result, the paper contributes to the understanding of how exports shape the wage structure. By emphasizing the role of firm wage premiums in the context of exports, the paper is related to the literature on the so-called exporter wage premium. The idea that exporting firms pay higher wages than non-exporting firms can be rationalized for example by rent sharing (Egger and Kreickemeier 2009; Amiti and Davis 2011; Egger and Kreickemeier 2012) and receives empirical support (Schank et al. 2007; Amiti and Davis 2011; Baumgarten 2013; Klein et al. 2013; Dauth et al. 2015).[13] Instead of focusing on changes in wage premiums paid by firms, the paper at hand examines how exports change the allocation of heterogeneous workers across firms that differ in terms of their wage setting. With its focus on tasks, the paper is also related to a recent study by Becker et al. (2018) who analyze the effects of trade liberalization on the firm-internal allocation of workers across tasks and thereby address the within-firm component of wage inequality. In contrast, the paper at hand focuses on the role of tasks for mobility of heterogeneous workers between firms that differ in terms of their wage premium.

To the best of my knowledge, this is the first paper which sheds light on the micro-level adjustment of workers which is underlying to the changes in the sorting pattern as documented by Card et al. (2013) and Song et al. (2019) in response to increasing international trade with China and Eastern Europe. Overall, the results give a very

[13] See also Verhoogen (2008), Irrarazabal (2013), and Krishna et al. (2014) for studies on the effect of trade integration on wage inequality in the presence of firm heterogeneity.

nuanced picture about how the trae shock affects different workers through the sorting channel. The effects strongly differ across industries (exporting versus importing) and differences in observed and unobserved worker characteristics matter for the question who benefits and who loses from the changes in sorting that result from changes in the trade environment. These results are robust to a large variety of robustness checks.

The rest of this paper is structured as follows: Section 2 gives an overview of the data, the empirical strategy, and provides some descriptives. Section 3 presents the results, section 4 provides robustness checks, and section 5 concludes.

2. Data, Descriptives, and Empirical Strategy

2.1. Data

The data requirements for the question at hand are demanding as I need longitudinal data on workers, establishments, and trade flows. Especially the replication of the wage decomposition in Card et al. (2013) requires a sufficiently large sample size. To meet these data requirements, I exploit four main datasets: The Integrated Employment Biographies (IEB), the Establishment History Panel (BHP), both provided by the Institute of Employment Research (IAB) in Nuremberg, Germany, the United Nations Commodity Trade Database (Comtrade), and the BIBB/BAuA Employment Surveys.

The IEB contain information on all German workers subject to social security contributions. They are based on employers' notifications to the social security insurance and therefore are highly reliable. The dataset is particularly suited for the question at hand as it contains information on workers' wages, industry-affiliation, location, and a large battery of socio-economic variables on each worker on a daily basis. Crucially for the question at hand, the data allow to follow workers over time as they move between establishments, between and within industries and sectors, occupations, and regions. See Oberschachtsiek et al. (2009) for more information on the IEB. I make use of a 50% random sample of all West German male employees in the IEB.[14] I impute missing and inconsistent education data with the help of Fitzenberger et al. (2005)'s approach. Moreover, since wages are right-censored at the contribution ceiling to social security, I impute censored wages using the procedure described in Card et al. (2013).

The BHP contains the universe of all establishments that employ at least one worker subject to social security contributions in a given year. The dataset contains information on the establishment's industry affiliation, region, total employment, and detailed information on workforce composition, such as the number of high-skilled workers etc. It can be matched to the worker-level data from IEB based on the unique establishment identifier. See Spengler (2008) for more information on the BHP.

[14] Card et al. (2013) also focus on West German male employees, but use 100% of the workers.

The data on exports and imports stem from the Comtrade database. This database contains annual statistics on commodity trade of more than 170 countries. I convert the trade flows into Euros of 2010 using the exchange rates of the German Bundesbank. With help of the correspondence between the SITC rev.3 product codes and NACE codes provided by the UN Statistics Division, I then aggregate the product-level trade flows to trade flows at the 3-digit industry level. The trade flows can be matched to the IEB and BHP data with the help of the industry identifier.

The data on the tasks that workers perform at their workplace comes from the BIBB/BAuA Employment Surveys. These are surverys that are carried out by the German Federal Institute for Vocational Training and the Research Institute of the Federal Employment Service. They contain a random sample of about one tenth of a percent of the German labor force in a given year. The surveys have been conducted in five waves: 1979, 1985/86, 1991/92, 1998/99, 2005/06. They contain information about workplace characteristics and requirements for about 30,000 individuals in each wave. This datasets have been widely applied to study the role of tasks in the labor market (e.g. Spitz-Oener 2006; Becker and Muendler 2015).

2.2. Estimating worker and firm types

The empirical strategy consists of two main steps. In a first step, explained in the remainder of section 2.2, I replicate the wage decomposition in Card et al. (2013). Based on the estimated fixed effects, I group workers and firms into three terciles: high-wage, medium-wage, and low-wage workers and firms. In a second step, explained in section 2.4, I exploit differences in initial industry-affiliation across manufacturing workers to analyze the impact of trade with China and Eastern Europe on the sorting pattern of worker types across firms types over a period of 10 years (1990-2000, 2000-2010).

To estimate the types of workers and firms, I consider three six-year-intervals: 1985-1990, 1995-2000, and 2005-2010. Following Card et al. (2013), among all full-time worker-firm observations within a given year in the IEB, I select the one with the highest cumulative earnings. For the resulting sample, I estimate the following specification separately for each interval:

$$y_{it} = \alpha_i + \psi_{J(it)} + x'_{it}\beta + r_{it} \tag{1}$$

In this equation, y_{it} denotes the log daily wage of worker i in year t. α_i denotes a worker fixed effect. It captures all time-invariant observable and unobservable factors that influence worker i's wage, and therefore potentially captures effects of for example formal education, occupational effects, ability, and motivation. $\psi_{J(jt)}$ is a firm fixed effect which captures a proportional wage premium or wage discount that it pays to its employees. The existence of these wage premiums can be rationalized for example by rent sharing

(Card et al. 2016).[15] x'_{it} is a vector of control variables that includes year dummies and a quadratic and cubic term in age fully interacted with education dummies as in Card et al. (2013). Finally, the error term r_{it} consists of three different components, for which I assume mean zero and orthogonality to worker and establishment effects conditional on the control variables:

$$r_{it} = \eta_{iJ(it)} + \xi_{it} + \epsilon_{it} \tag{2}$$

A worker-firm match-specific component $\eta_{iJ(it)}$, a unit-root component ξ_{it}, which captures a potential drift in workers' wages, and a transitory error, ϵ_{it}. As pointed out by Card et al. (2013), for the condition of mean zero and orthogonality to hold, mobility of workers between firms must be exogenous to the match-specific component. They provide strong evidence in favor of exogenous mobility and conclude that endogenous mobility based on match-effects is not an issue. Later, in the main empirical analysis, I include a control variable for the residual to make sure that differences in initial match-specific effects do not confound with the effects of trade exposure on worker mobility. To further mitigate concerns that match-specific effects across workers drive the results in the main empirical part of this paper, I perform several robustness checks. See section 4 for the results and a more detailed discussion about this issue in the light of the empirical approach at hand. However, note that non-random mobility with respect to the worker and firm effects, which is at the heart of the main analysis in this paper, is not a problem. This is because the fixed effects estimator conditions on the sequence of firms by which a given worker is employed.

A noteworthy concern is related to the so-called 'limited mobility bias'. Andrews et al. (2008) emphasize that estimation error triggers an overestimation of the variance of worker and firm fixed effects, which translates into a downward bias in the estimated covariance of worker and firm fixed effects. The authors show that this bias is bigger the fewer movers between firms there are in the data. Relative to other studies, the empirical strategy in this paper is more immune against this issue. This is because I do not work directly with the estimated covariance between worker and firm fixed effects. Instead, by grouping workers and firms into three terciles, I allow for a substantial degree of measurement error in the estimated fixed effects (and thereby also the covariance) within these terciles.

The estimation exploits worker mobility across firms during the respective interval to estimate the fixed effects. In the estimation, workers need to be connected by worker mobility and I focus on the largest connected set in each interval which covers about 95% of the initial sample. This corresponds to more than 30 million worker-year observations in each interval. Having estimated equation 1 separately for each interval, I can perform

[15] The descriptive finding that firms pay higher wage premiums on average are larger, pay higher wages, and employ a more educated workforce supports this idea.

the variance decomposition as in Card et al. (2013) for the sake of comparability.[16]

Table A1 provides evidence that the bulk of the increase in wage inequality between the first interval (1985-1990) and the last interval (2005-2010) is driven by an increase in the dispersion of worker effects and firm effects as well as an increase in sorting. The results are qualitatively very similar to those in Card et al. (2013), page 1,000, even though Card et al. (2013) use slightly different time intervals (1985-1991 and 2002-2009). Especially for the first interval, which is similar across both studies (1985-1990 vs. 1985-1991 in Card et al. (2013)), the results of the variance decomposition are almost identical.

In anticipation of the main empirical analysis, I then restrict the sample to manufacturing workers aged 20-50 in 1990 and 2000 and follow these workers over a period of ten years to obtain two ten-year intervals: 1990-2000 and 2000-2010. I end up with 3,084,109 worker-year observations from 174,810 firms for both years together. In what follows, I will refer to the first year of each interval as the base year or t and to the last year of each interval as $t + 10$.

For the base year 1990, I group workers and firms into three terciles (types) based on the estimated fixed effects from the interval 1985-1990: High-wage, medium-wage, and low-wage workers and firms. A high-wage worker is a worker whose fixed effect is within the highest tercile among the sample of full-time employed manufacturing workers in 1990.[17] Analogously, a high-wage firm is a firm whose estimated wage premium is within the top tercile.[18]

Table 1 reports summary statistics of the worker and firm types in the base years. First, and not surprisingly, panel (a) shows a large heterogeneity between workers. The mean worker effect in the group of high-wage workers is 54 log points higher than the mean worker effect in the group of low-wage workers. Panel (a) also suggests that these differences are at least partly driven by differences in formal education, occupations, and tasks performed on the job. The variable 'high education' has the value 1 for workers with at least college or university education. It turns out that high-wage workers on average have a higher formal education than medium-wage and low-wage workers. Table 1 also shows that high-wage workers tend to be employed in more skill-intensive occupations than medium-wage and low-wage workers.[19] Finally, the table shows that high-wage workers on average perform less routine-intensive and less codifiable tasks than medium-wage and low-wage workers.[20]

[16] $var(y_{it}) = var(\alpha_i) + var(\psi_{J(it)}) + var(x'_{it}\beta) + var(r_{it}) + 2cov(\alpha_i, \psi_{J(it)}) + 2cov(\alpha_i, x'_{it}\beta) + 2cov(\psi_{J(it)}, x'_{it}\beta)$.

[17] As a robustness check, I also add the effect of the time-varying controls $x'_{it}\beta$ to the worker fixed effect and rank the workers accordingly. The results remain unchanged. This is not surprising, as the time-varying controls are of minor importance as compared to the worker fixed effects. See also table A1. Educational effects are captured by the worker fixed effect.

[18] As a robustness check, I alternatively rank firms based on their mean log wage. The results remain unchanged. See section 4.

[19] These are combinations of occupational groups according to the definition by Blossfeld (1985).

[20] The variables 'routine job' and 'codifiable' job are based on the BIBB/BAuA data. To construct the

Table 1: Worker and Firm Types (Base Years 1990 and 2000)

	(a) Worker Types		
(Sample means)	High-wage	Medium-wage	Low-wage
Estimated worker effect ($\hat{\alpha}_i$)	4.66	4.34	4.12
Log daily wage (imputed)	4.81	4.42	4.22
High education	0.30	0.07	0.05
Occupational groups:			
Manager/Engineer/Professional	0.23	0.03	0.01
Technician/Qual. services/Admin.	0.41	0.15	0.08
Manual/Simple services	0.36	0.82	0.91
Tasks:			
Routine job	0.10	0.30	0.42
Codifiable job	0.14	0.37	0.48
	(b) Firm Types		
(Sample means)	High-wage	Medium-wage	Low-wage
Estimated firm wage premium ($\hat{\psi}_{J(it)}$)	0.15	-0.02	-0.26
Log daily wage (imputed)	4.45	4.29	4.08
High education	0.12	0.08	0.07
Number of employees	49.66	19.59	5.83
Estimated worker effect ($\hat{\alpha}_i$)	4.29	4.31	4.37

Notes: Each value denotes the sample mean of the respective variable. Workers and firms are grouped into terciles according to the estimated fixed effects in equation 1. See section 2 for a detailed explanation of the data preparation and wage decomposition. Data sources: Integrated Employment Biographies, 50%-sample, Establishment History Panel.

Panel (b) of table 1 illustrates a striking heterogeneity of estimated firm wage premiums across firm types. The mean firm wage premium among the group of high-wage firms is 41 log points higher than in the group of low-wage firms. Panel (b) additionally shows that high-wage firms on average are larger in terms of number of employees, pay higher wages, and employ workers of higher formal education than medium-wage and low-wage firms. However, the mean estimated worker effect in high-wage and medium-wage firms is slightly lower than in low-wage firms in the base years.

2.3. Mobility between Firm Types

The main empirical analysis focuses on mobility between firm types over a period of ten years (1990-2000 and 2000-2010). As for the base years (1990 and 2000), I group workers and firms into three terciles at $t+10$ (2000 and 2010). Consider the first interval 1990-2000. I follow the workers from the base year 1990 until year 2000 and for this year group them as well as all the firms into terciles based on the wage decomposition for 1995-2000. Analogously, I rank workers and firms into terciles in 2010 based on

variables, I use the 1985/86 survey and focus on these two questions: 1) Are the contents of your job minutely described by the employer? (codifiable) 2) Does the job sequence repeat itself regularly? (routine) I compute the share of workers within 3-digit occupations who report 'almost always' for a given question. Finally, I label the top 25% of occupations with the highest share as routine/codifiable.

the wage decomposition for 2005-2010. Therefore, by separately estimating the wage decomposition for t and $t+10$, I allow worker and firm types to vary over time, which is in line with Card et al. (2013). While each worker in the sample belongs to one of the three firm type categories in t, I have to introduce a fourth category in $t+10$. Workers can be unemployed or self-employed in $t+10$ and I cannot differentiate between these two cases. Additionally, workers can switch to early retirement, part-time work, or the public sector.[21] All of these cases are potential outcomes of trade exposure and I therefore treat them as a fourth separate category called 'out'.[22]

Table 2 provides a look at the mobility pattern of workers between different firm types between year t and $t+10$. The table gives an impression about the mobility pattern of workers which drives the increased sorting documented by Card et al. (2013) and in figure 1. Conditional on starting in a high-wage firm in t, high-wage workers have a 72.57% probability of being employed by a high-wage firm in $t+10$. This value is higher than the corresponding value for medium-wage (69.05%) and low-wage workers (56.83%). Even though employment need not be at the same firm, I will refer to this as a higher job stability effect for high-wage workers at high-wage firms than medium-wage or low-wage workers.[23] The flip side of this coin is that, conditional on starting at a high-wage firm, low-wage and medium-wage workers have a higher probability of downward mobility towards medium-wage and low-wage firms. Table 2 also illustrates that upward mobility of high-wage workers is higher than for medium-wage and low-wage workers. Conditional on starting at a low-wage firm, 22.42% of high-wage workers move to a high-wage firm. In contrast, the corresponding value for low-wage workers is 12.44%.

Figure 2 provides descriptive evidence that a switch between firm types between the base year (1990 or 2000) and ten year later (2000 or 2010) indeed goes along with substantial wage consequences. Panel (a) includes low-wage workers who are employed by a high-wage firm in the base year. It plots median log daily wages as well as the 75th and 25th percentile for two groups of workers: the group of 'stayers' in red includes all workers who are still employed by a high-wage firm ten years later (not necessarily the same firm). The group of 'movers' in blue includes all workers who are employed by a low-wage firm ten years later. While the median stayer experiences a wage increase of 11 log points (4.46-4.35), the median mover experiences a wage loss of 31 log points (4.25-3.94). The same pattern emerges for the 75th and 25th percentile within the groups of movers and stayers. This descriptive exercise therefore suggests that moving from a high-wage to a

[21] The former two cases are not of large importance since I focus on males who are at most 50 years old in the base year. As a robustness check, I run the analysis dropping workers who are older than 40 in the base year.

[22] Few workers belong to the connected set in the wage decomposition for t but not in the wage decomposition for $t+10$. I drop these workers from the analysis. In an alternative estimation, keep them in the analysis and code them as 'out'. The results remain unchanged and are available upon request.

[23] In the empirical analysis, I differentiate between employment in the same firm/industry/sector as in t and employment in a different firm/industry/sector.

Table 2: Worker Mobility between Firm Types

Firm type in t	**Firm type in t+10 (%)**				
	(1) High-wage	(2) Medium-wage	(3) Low-wage	(4) Out	(5) Sum
(a) High-wage workers					
High-wage firm	72.57	8.16	2.27	17.00	100
Medium-wage firm	45.22	29.37	7.32	18.09	100
Low-wage firm	22.42	30.60	22.55	24.44	100
(b) Medium-wage workers					
High-wage firm	69.05	12.17	5.69	18.09	100
Medium-wage firm	43.32	33.91	11.13	11.64	100
Low-wage firm	20.07	34.83	8.75	16.35	100
(c) Low-wage workers					
High-wage firm	56.83	12.25	7.46	23.76	100
Medium-wage firm	30.23	328.67	14.17	26.93	100
Low-wage firm	12.44	24.79	26.78	35.99	100

Notes: The figure shows the share of workers who are employed at a given firm type in year $t + 10$ (2000 or 2010), conditional on the worker type and on the firm type in year t (1990 or 2000). See section 2 for information about data preparation.

low-wage firm on average goes along with a wage loss of 42 log points for movers relative to stayers. To gauge the magnitude of this effect, consider the wage gap between the 25th and the 75th percentile in the base year (table A2), which amounts to 43 log points.

Panel (b) of figure 2 performs the same exercise for high-wage workers employed by a high-wage firm in the base years. The median stayer experiences a wage increase of 15 log points (5.01-4.86). Wages for the median mover decrease by 30 log points (4.72-4.42). This implies that moving from a high-wage to a low-wage firm on average goes along with a wage loss of 45 log points for movers relative to stayers. This is strikingly close to the corresponding value for low-wage workers (42 log points). One can view this as evidence in favor of the additive structure of the underlying wage decomposition. This result is consistent with the result in Bonhomme et al. (2018) who, using a different method, provide convincing evidence that log earnings are approximately additive in worker and firm heterogeneity in Sweden.[24]

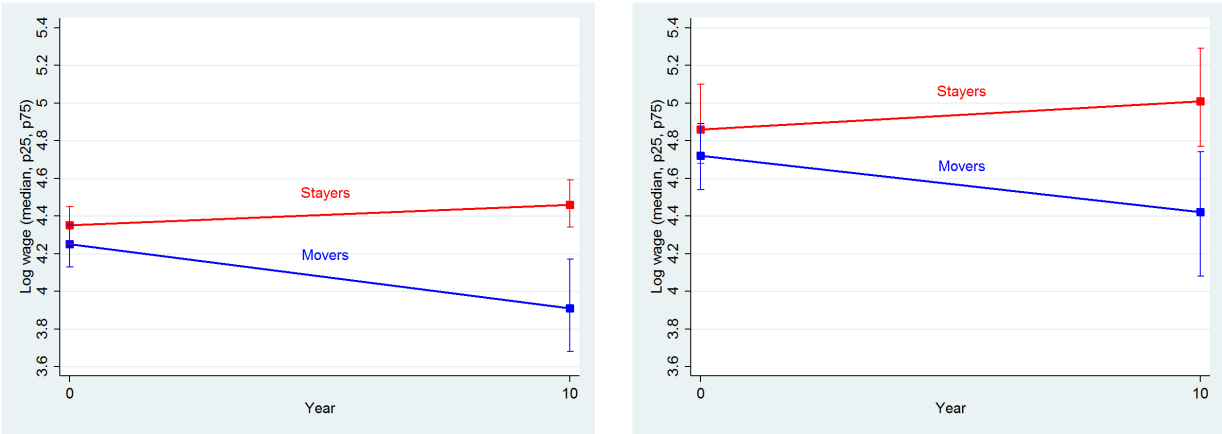
2.4. Estimating the effect on sorting across firm types

To what extent is Germany's trade integration with Eastern Europe and China related to the mobility pattern that table 2 documents? To provide evidence on this question, I

[24]Figure A1 in the appendix compares stayers to movers to a medium-wage establishment. The latter on average experience a very small decrease in wages which is in stark contrast to the increase in wages for stayers. Figure A2 performs the same exercise for workers moving from low-wage towards high-wage establishments. This case, however, is of little relevance for the analysis at hand because the results point towards no effect of trade on mobility out of low-wage and medium-wage workers.

Figure 2: Wage effects of moving from a high- to a low-wage firm: a descriptive look

(a) Low-wage workers (b) High-wage workers



Notes: Panel (a) includes low-wage workers employed by a high-wage firm in year 0 (the base year 1990 or 2000). It plots median wages as well as the 75th and 25th percentile of wages in the base year and ten years later (2000 or 2010). The group of 'stayers' in red includes all workers who are still employed at a high-wage firm ten years later (not necessarily the same firm). The group of 'movers' in blue includes all workers who are employed at a low-wage firm ten years later. Note that in 1990 firms are partitioned into terciles based on the wage decomposition for the interval 1985-1990. The partitioning of firms in 2000 (2010) is based on the wage decomposition for interval 1995-2000 (2005-2010). Panel (b) shows the same results for high-wage workers employed by a high-wage firms in year 0. See section 2 for a more detailed description.

estimate the following specification separately for workers initially employed by high-wage, medium-wage, or low-wage firms:

$$\mathrm{Y}_{ijt} = \beta Trade_{jt} + \gamma_1 Trade_{jt} D_{it}^{MW} + \gamma_2 Trade_{jt} D_{it}^{HW} + \delta_1 D_{it}^{MW} + \delta_2 D_{it}^{MW} + \kappa X_{ijt} + \epsilon_{ijt} \quad (3)$$

Y_{ijt} is a binary variable that equals 1 if individual i who works in industry j in the base year t (1990 or 2000) is employed by a given firm type (high-wage, medium-wage, low-wage firm, or out) in year $t+10$ (2000 or 2010), and zero otherwise.[25]

$Trade_{jt}$ contains export exposure (EX_{jt}) and import exposure (IM_{jt}) on industry j in which worker i is employed in the base year t. They are defined as follows:

$$EX_{jt} = \frac{\Delta Exports_{jt}^{Ger \to C+E}}{10{,}000 \times WageSum_{jt}}$$

$$IM_{jt} = \frac{\Delta Imports_{jt}^{C+E \to Ger}}{10{,}000 \times WageSum_{jt}}$$

EX_{jt} captures the degree to which industry j benefits from increased exports to China and Eastern Europe from t through $t+10$ and is defined as the increase in annual exports during the respective ten-year interval, $\Delta Exports_{jt}^{Ger \to C+E}$, normalized by the industry

[25]For the sake of readability, I leave out indices for worker types, firm types, and regions.

wage bill in the base year t. The normalization controls for size differences across industries. Import exposure on an industry, IM_{jt} is computed analogously. From the perspective of the domestic 3-digit industry, this can reflect either import competition in the final goods market or, if the imports are used in exactly that same industry as intermediates, offshoring. Given that I cannot observe the use of the imports at the level of 3-digit industries, I cannot differentiate between these two types of imports.

Importantly, I interact the trade exposure variables with dummies for medium-wage workers (D_{it}^{MW}) and high-wage workers (D_{it}^{HW}). With low-wage workers being the reference group, the coefficients on EX_{jt} and IM_{jt} capture the impact of industry-level export and import exposure on the probability of employment by a certain firm type at year $t+10$ for low-wage workers. The coefficients on the interaction effects capture the extent to which export and import exposure affect medium-wage and high-wage workers differently from low-wage workers.

By varying the outcome variable and restricting the regression to workers initially employed by a given firm type, it is possible to provide a picture about how trade affects the mobility pattern of workers across firm types. If I focus on workers employed by high-wage firms in the base year t and define the outcome variable as a dummy for being employed by a high-wage firm at year $t+10$, I capture the impact of trade on job stability at high-wage firms (see table 3 in the following section). Alternatively, if I define the outcome variable as a dummy for being employed by a low-wage firm at $t+10$, I capture the effect of trade on mobility from high-wage towards low-wage firms (see table 4 in the following section).

X_{ijt} contains a large battery of control variables at the worker, firm, industry, and regional level, which are held constant at the base-year level. First, it contains a dummy to differentiate between the two base years. To control for age- and education-specific mobility across firm types, it includes dummies for three age groups (20-30, 30-40, 40-50) and a dummy for high formal education (college or university degree). To control for task-specific effects of technological progress and the corresponding effects on worker mobility, X_{ijt} includes dummies for performing routine-intensive tasks and codifiable tasks (measured at the 3-digit occupation level, see section 2.2) and 2-digit occupation dummies.[26] Finally, to control for mobility based on initial match-specific effects, X_{ijt} contains dummies for the tercile of the individual in the distribution of residuals from equation 1.[27]

To control for firm-specific effects related to size, X_{ijt} includes dummies for firm size groups (number of employees: 1-10, 10-100, 100-1,000, >1,000). The regression also

[26]See for example Autor et al. (2003), Autor et al. (2008), and Goos et al. (2014) for the effect of technological progress on workers performing routine tasks.

[27]Note, however, that the residuals generally are very small. The R squared of an estimation of equation 1 is at around 90%. See table A1. In a robustness check in section 4, I additionally drop observations in the top and bottom tercile of the residual distribution.

includes a battery of industry-specific controls. To control for differences between broad industry groups, X_{ijt} includes five industry group dummies (food, consumer goods, capital goods, production goods (without automobile sector), automobile sector). To control for the industry-specific workforce and establishment composition, it includes the mean estimated worker effect and mean estimated firm wage premium in the 3-digit industry. Additionally, X_{ijt} contains the log number of firms in the 3-digit industry in the base year. To control for industry-specific pre-trends in employment which could be confounded with the effects of trade exposure, X_{ijt} includes the change in log number of employees during the five years preceding the base year. To control for institutional factors such as the strength of collective bargaining agreements or works councils, the regression controls for the mean wage of workers with low formal education in the 3-digit industry.[28] Finally, to make sure than region-specific shocks are not confounded with the effects of trade exposure, X_{ijt} includes dummies for labor market regions.

The goal of the empirical exercise is to compare workers who have very similar demographic characteristics, are initially employed in similar firms and industries, work in the same local labor market, but are differently affected by Germany's trade integration with Eastern Europe and China due to differences in initial industry affiliation. Equation 3 is essentially a triple-differences estimation. It compares the outcomes over time of trade-exposed workers to similar non-exposed workers, separately by worker type.

To further mitigate endogeneity concerns, I apply the instrumental variable strategy pioneered by Autor et al. (2014) and adapted to the German context by Dauth et al. (2018) to purge the estimates from industry-level demand and technology shocks, which might be correlated with trade exposure and at the same time influence the workers' employment pattern of different firm types. More specifically, I instrument export and import exposure measures by trade exposure on a group of instrument countries:

$$EX_{jt}^{Ins} = \frac{\Delta Exports_{jt}^{Ins \to C+E}}{10{,}000 \times WageSum_l}$$

$$IM_{jt}^{Ins} = \frac{\Delta Imports_{jt}^{C+E \to Ins}}{10{,}000 \times Emp_{jt}}$$

where $Exports_{jt}^{Ins \to C+E}$ ($Imports_{jt}^{C+E \to Ins}$) denotes the increase in exports to (imports from) China and Eastern Europe in industry j of a group of instrument countries, namely Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. Underlying to this strategy is the idea that China and Eastern Europe experienced rapid productivity growth due to their transition to a market economy which

[28] One could try to directly control for the existence of collective bargaining agreements and work councils with the respective variables from the IAB Establishment Panel. However, due to the low number of observations in this panel, the variable would not be representative at the 3-digit industry level. Note that one should not control for the change in union density over time in a given industry, since this might be partly an outcome of the trade shock. See for example Dustmann et al. (2014) who argue that the fall of the Iron curtain, by making the threat of relocation of production abroad more credible, changed the power equilibrium between employers and employee associations and eventually contributed to the decentralization of the wage bargaining process.

went along with capital accumulation, migration to rural areas and improvement of the infrastructure (Naughton 2007; Hsieh and Klenow 2009; Burda and Severgnini 2009). The productivity growth translated into a strong increase in export capabilities in certain industries. For China, this effect was amplified through its entry into the WTO at the beginning of the 2000s. This effect should not only be present for Germany in the form of increasing imports in these industries, but also in other high-income countries. Then, instrumenting German industry-level import exposure with industry-level import exposure of these high-income countries should isolate the exogenous increase in import exposure that is related to the productivity growth in China and Eastern Europe. Similarly, the export exposure instrument is supposed to isolate the exogenous part of German export exposure that is driven by the rise of China and Eastern Europe. For this strategy to be valid, trade exposure of the instrument countries must not have an impact on German industries and industry-level supply and demand shocks in these countries should not be strongly correlated with those for German industries. The instrument group therefore does not contain any direct neighbors to Germany, no members of the European Monetary Union, and excludes the U.S.A. See also Autor et al. (2014) and Dauth et al. (2014) for a discussion.

3. Results

3.1. Trade and job stability at high-wage firms

Table 3 provides the estimates of the impact of industry-level trade exposure on the probability of employment by a high-wage firm in year $t + 10$, conditional on employment by a high-wage firm in year t. It thereby captures the extent to which exports and imports affect job stability at high-wage firms. Columns (1)-(4) provide the baseline estimates in which I do not differentiate between employment in the same versus in a different firm/industry/sector as in t. In columns (5)-(10), I then explicitly differentiate between these cases.

Baseline estimates. The estimates in columns (1)-(4) of table 3 provide evidence that industry-level import exposure reduces job stability at high-wage firms. The coefficients on the interaction terms suggest that the negative job stability effect is strongest for low-wage workers. This pattern is robust across all specifications. It even holds in the most demanding specification in column (4) in which I identify the effects within local labor market regions.[29] In addition, the estimates in columns (1)-(4) of table 3 provide evidence that industry-level export exposure has a positive effect on job stability at high-wage firms. Interestingly, the coefficients on the interaction terms suggest that this effect

[29] All estimates have a strong first stage with the F-statistics being above 200 in all cases. The estimation therefore does not suffer from weak instrument problems. See figure A3 for a visual representation of the first stage. The detailed first stage results are available upon request.

occurs mostly for low-wage and medium-wage workers and is much smaller for high-wage workers. Again, this pattern is highly robust across different specifications. In the preferred specification in column (4), there is no job stability effect at all for high-wage workers. Finally, the estimates of the coefficients on the dummy variables for worker types (without interactions) provide evidence that high-wage workers in general have a higher job stability at high-wage firms than medium-wage and low-wage workers.

Implications for the sorting pattern. To gauge the magnitude of the effects on the sorting pattern, consider the raw difference in job stability at high-wage firms between high-wage workers and low-wage workers. According to table 2, high-wage workers are 15.74 percentage points more likely to be employed by a high-wage firm in $t + 10$, conditional on starting in a high-wage firm in t ($72.57\% - 56.83\% = 15.74\%$). Evaluated at the sample mean of 0.11 (see table A2), import exposure explains about 5% of this difference ($(0.11 * 0.0714)/(0.1574) \approx 0.05$).[30] In contrast, the positive job stability effect of exports is stronger for low-wage workers and export exposure therefore works into the opposite direction. Using the sample mean of export exposure of 0.12 (see table A2), the estimates imply that job stability at high-wage firms for high-wage workers would be 18.3% higher in absence of export exposure ($(0.12 * (-0.2401)/(0.1574) \approx -0.183$). To obtain a more complete picture about the the effects on the sorting pattern, see section 3.2 which additionally investigates downward mobility out of high-wage firms.

Detailed mobility. The differential effects of export and import exposure across worker types documented in columns (1)-(4) can be due to either differences in job stability at the original high-wage employer or differences in mobility between high-wage firms. Columns (5) and (6) of table 3 decompose the effects from column (4) into the probability of employment at the same high-wage firm as in t and the probability of employment at a different high-wage firm. Strikingly, column (5) provides evidence that the effect of import exposure on the displacement probability at the initial firm does not differ between worker types. This result is reflected in the small and statistically insignificant interaction effects. As column (6) shows, in response to import exposure, however, high-wage and medium-wage workers have a higher probability of being employed by a different high-wage firm. Column (6)-(10) further show that this is driven by employment at a different high-wage firm in a different industry in a different sector (column (10)). Consequently, conditional on displacement from the original high-wage firm in the manufacturing sector, high-wage workers have a substantially higher probability of moving to a different high-wage firm in the non-manufacturing sector and this drives the differences detected in the baseline

[30] The contribution of export and import exposure to sorting does not only depend on the size of the point estimate on the interaction terms, but also on the extent to which different worker types experience different levels of export and import exposure. Table A2 shows that differences in export and import exposure between workers types on average are very small. For example, the difference in mean export exposure between high-wage and low-wage workers is only 0.01. For simplicity, I therefore abstract from these small differences in the back-of-the-envelope calculations and impose the overall sample means of export and import exposure of 0.12 and 0.11, respectively.

estimates. Columns (5)-(10) further show that the differences in the effect of export exposure across worker types is driven exclusively by a higher job stability at the initial firm in the initial industry and sector for low-wage and medium-wage workers. See section 3.4 for potential explanations of these effects.

Table 3: Trade and Job Stability at High-wage Firms

Dep. var.: HW firm in $t+10$	**(1)-(4): Baseline results**				**(5)-(10): Detailed mobility: same vs. different firm/industry/sector**					
Sample: HW firm in t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
					Same firm		**Same 3-dig. industry**		**Diff. industry, same sector**	
					Yes	**No**	**Yes**	**No**	**Yes**	**No**
IM	-0.0710	-0.0637**	-0.1440***	-0.1472***	-0.1282***	-0.0190	-0.1638***	0.0166	-0.0085	0.0251*
	(0.0509)	(0.0263)	(0.0299)	(0.0297)	(0.0331)	(0.0191)	(0.0315)	(0.0181)	(0.0144)	(0.0138)
IM*MW worker	0.0306	0.0361**	0.0485***	0.0481***	-0.0215	0.0696***	-0.0121	0.0602**	0.0264	0.0338**
	(0.0191)	(0.0169)	(0.0158)	(0.0162)	(0.0217)	(0.0243)	(0.0206)	(0.0236)	(0.0277)	(0.0157)
IM*HW worker	0.0313	0.0445	0.0795***	0.0714**	0.0048	0.0667	-0.0004	0.0718	-0.0088	0.0806**
	(0.0403)	(0.0310)	(0.0158)	(0.0308)	(0.0362)	(0.0481)	(0.0476)	(0.0611)	(0.0153)	(0.0372)
EX	0.4261***	0.2368***	0.2215***	0.2195***	0.2216**	-0.0020	0.2337**	-0.0142	-0.0019	-0.0123
	(0.0881)	(0.0591)	(0.0839)	(0.0826)	(0.1060)	(0.0659)	(0.1169)	(0.0689)	(0.0058)	(0.0462)
EX*MW worker	-0.0651	-0.0459	-0.0237	-0.0352	0.1688**	-0.2040	0.0820	-0.1172*	-0.1096*	-0.0076*
	(0.0422)	(0.0345)	(0.0593)	(0.0617)	(0.0806)	(0.0794)	(0.0674)	(0.0619)	(0.0624)	(0.0401)
EX*HW worker	-0.1777**	-0.1328*	-0.2100**	-0.2401**	-0.1909	-0.0492	-0.2219*	-0.0182	0.0900*	-0.1082
	(0.0853)	(0.0708)	(0.0977)	(0.1029)	(0.1400)	(0.1670)	(0.1284)	(0.1717)	(0.0512)	(0.0877)
MW worker	0.1219***	0.0920***	0.0874***	0.0875***	0.0509***	0.0366***	0.0725***	0.0150*	0.0112	0.0038
	(0.0038)	(0.0040)	(0.0071)	(0.0073)	(0.0096)	(0.0113)	(0.0075)	(0.0088)	(0.0099)	(0.0118)
HW worker	0.1726***	0.1308***	0.1368***	0.1400***	0.1151***	0.0248	0.1417***	-0.0017	-0.0072	0.0055
	(0.0073)	(0.0064)	(0.0108)	(0.0113)	(0.0189)	(0.0216)	(0.0180)	(0.0221)	(0.0124)	(0.0050)
Worker controls	√	√	√	√	√	√	√	√	√	√
Firm controls		√	√	√	√	√	√	√	√	√
Industry controls		√	√	√	√	√	√	√	√	√
Region controls				√	√	√	√	√	√	√
R2	0.06	0.10	0.10	0.11	0.12	0.07	0.13	0.07	0.07	0.07
N					2,201,073					

Notes: See equation 3. Sample is restricted to workers who are employed by a high-wage firm in base year t (1990 or 2000). Columns (1)-(4): Dependent variable is 1 if worker is employed by a high-wage firm in $t+10$, zero otherwise. Column (5): Dependent variable is 1 if worker is employed in $t+10$ by the same high-wage firm as in t, zero otherwise. Columns (6)-(10) analogously. Controls are held constant at t. 'Worker controls': three age groups (20-30, 30-40, 40-50), a dummy for high education (college or university), a dummies for routine-intensive and codifiable jobs, 2-digit occupation dummies, a dummy for the tercile in the residual distribution. 'Firm controls': four size groups (number of employees): 0-10, 10-100, 100-1000, >1000. 'Industry': five dummies for broad industry groups, mean worker effect and mean firm wage premium in the 3-digit industry, mean wage of low-skilled workers (no tertiary education) in the 3-digit industry, log number of firms, log change in industry employment during five years before t. 'Region': dummies for labor market regions. All regressions contain a dummy to differentiate between the base years t (1990 and 2000). Standard errors are clustered at the 3-digit industry x base year level (in parentheses). See section 2 for the data preparation. Levels of significance: *10%, **5%, ***1%

3.2. Trade and downward mobility out of high-wage firms

Baseline results. Industry-level import exposure decreases the probability of remaining employed by a high-wage firm, especially for low-wage workers. To provide a complete picture of the consequences for the sorting pattern, table 4 provides estimates on the reallocation of workers out of high-wage firms in response to import exposure. The estimates suggest that import exposure increases the likelihood of downward mobility from high-wage firms into medium-wage and low-wage firms and also increases the likelihood of dropping out of the sample. Not surprisingly, given the previous estimates in table 3, the estimated effect of import exposure on downward mobility is strongest for low-wage workers. The point estimates on export exposure in table 4 also provide the mirror picture of the estimates in table 3. Through its positive effect on job stability at high-wage firms, export exposure shields workers from downward mobility into medium-wage and low-wage firms. The point estimates of the interaction terms suggest that this effect is strongest for low-wage and medium-wage workers - which is not surprising given that the estimated job stability effect at high-wage firms is strongest for medium-wage and low-wage workers.

Implications for the sorting pattern. An important implication of these estimates is that industry-level import exposure triggers an increase in sorting and wage inequality since its downward mobility effect is biased towards low-wage workers. How much of the differences in downward mobility from high-wage towards medium-wage and low-wage firms between worker types can export and import exposure explain? According to table 2, low-wage workers are 5.19 percentage points more likely to move from high-wage to low-wage firms than high-wage workers ($7.46\% - 2.27\% = 5.19\%$). Evaluated at its sample mean of 0.11 (see table A2), import exposure explains about 9.3% of this difference ($(0.11 * 0.0437)/0.0519 \approx 0.093$). In terms of downward mobility from high-wage to medium-wage firms in response to import exposure (column (1)), the estimates do not detect a difference between low-wage and medium-wage workers. They, however, suggest that there is a difference between high-wage workers on the one hand and low- and medium-wage workers on the other hand. Evaluated at its mean, import exposure explains about 8.1% of the difference between high-wage and low-wage workers in terms of downward mobility from high-wage to medium-wage firms ($0.11 * 0.0302/0.0409 \approx 0.081$). Taken together, these results imply that, through the sorting channel, import exposure triggers an increase in wage inequality both at the upper tail and at the lower tail of the wage distribution.

Export exposure, in contrast, counteracts this effect. For example, using mean export exposure in the sample (0.12, see table A2), the estimates imply that the difference in downward mobility from high-wage to low-wage firms between high-wage and low-wage workers would have been 16.6% higher in absence of export exposure ($(0.12 * 0.0719)/0.0519 \approx 0.166$). Export exposure, through its effect of sorting across firms, therefore works towards a decrease of wage inequality, especially in the upper tail of the wage distribution. The strong job stability effect detected in this paper is in line with the results in Dauth et al. (2014), who show that increased exports to Eastern Europe and China have helped retaining jobs in the manufacturing sector. The paper at hand provides complementary evidence on how this job stability effect differs between workers and thereby affects wage inequality through the sorting pattern.

What is the net effect of export and import exposure on wage inequality through the sorting channel? While it is not possible to exactly compute the predicted impact, the estimates imply that the sign and the strength of the impact differs between industries, depending on their actual levels of export and import exposure. The estimates in table 4 provide evidence that the negative effect of export exposure on sorting is slightly stronger than the positive effect of import exposure on sorting. To see this, compare for example the coefficient on the interactions of export and import exposure with the dummy for high-wage workers in table 4, column (2) (-0.0437 vs. 0.0719). The net effect therefore works towards an increase in sorting and inequality if industry-level import exposure exceeds industry-level export exposure by a factor of 1.65 or more. This is the case for about 34% of the worker-year observations in the sample.[31]

Detailed mobility. Columns (4)-(9) of table 4 allow a closer look at downward mobility from high-wage towards low-wage firms in response to import exposure. Given that I allow worker and firm types to vary over time, which is in line with Card et al. (2013), the estimates could technically be driven by workers remaining employed by firms which move from high-wage to low wage status over time. However, reassuringly, the estimates in columns (4) and (5) provide evidence that workers experience 'real' mobility by moving to a different firm. Do workers, in response to import exposure, experience downward mobility within the same industry or sector? Columns (6)-(9) suggest that workers experience downward mobility mostly through a switch into the non-manufacturing sector. To sum up, all worker types increasingly reallocate from the manufacturing into the non-manufacturing sector in response to import exposure. However, the paths strongly differ between worker types. While high-wage workers often manage to move to a different high-wage firm, low-wage workers predominantly experience downward mobility during the process of reallocation. Finally, the estimates in columns (4)-(9) show that export-exposure, in contrast, shields workers from downward mobility into low-wage firms in the non-manufacturing sector. Again, this is the mirror picture of the estimates on job stability at high-wage firms.

[31] Technically, one could also gauge the magnitude on sorting based on the corresponding interaction effects in table 3, for example column (4) (0.0714 vs. -0.2401). These estimates implicitly do not only contain the effect on mobility into low-wage and medium-wage firms but also out of the sample. While dropping out of the sample is an important outcome variable, it is not a meaningful outcome variable for the question about sorting. Note that the variance decomposition in Card et al. (2013) does not contain these workers by construction. Therefore, I prefer to use the direct estimates for downward mobility into low-wage and medium-wage firms in table 4 to quantify the effect on sorting.

Table 4: Trade and Downward Mobility out of High-wage Firms

Sample: HW firm in t	**(1)-(3): Baseline results**			**(4)-(9): Detailed mobility: same vs. different firm/industry/sector**					
				Dependent variable: Employed by.......firm in $t+10$					
	medium-wage	**low-wage**	**out**	**low-wage**	**low-wage**	**low-wage**	**low-wage**	**low-wage**	**low-wage**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Same firm		**Same industry**		**Different industry, same sector**	
				Yes	**No**	**Yes**	**No**	**Yes**	**No**
IM	0.0468***	0.0469***	0.0535***	0.0042	0.0427***	0.0040	0.0429***	0.0057***	0.0372***
	(0.0127)	(0.0093)	(0.0144)	(0.0031)	(0.0076)	(0.0041)	(0.0071)	(0.0016)	(0.0063)
IM*MW worker	-0.0036	-0.0318***	-0.0127	-0.0051**	-0.0267**	-0.0057*	-0.0261***	-0.0211***	-0.0211***
	(0.0091)	(0.0074)	(0.0136)	(0.0023)	(0.0070)	(0.0032)	(0.0071)	(0.0067)	(0.0067)
IM*HW worker	-0.0302***	-0.0437***	0.0024	-0.0046*	-0.0391***	-0.0058	-0.0379***	-0.0319***	-0.0319***
	(0.0116)	(0.0109)	(0.0212)	(0.0026)	(0.0095)	(0.0036)	(0.0089)	(0.0076)	(0.0076)
EX	-0.0489	-0.0791***	-0.0916**	-0.0059	-0.0732**	-0.0177*	-0.0614**	-0.0108**	-0.0506**
	(0.0418)	(0.0287)	(0.0380)	(0.0071)	(0.0290)	(0.0105)	(0.0284)	(0.0047)	(0.0258)
EX*MW worker	0.0059	0.0209	0.0084	0.0063	0.0146	0.0130	0.0079	0.0019	0.0060
	(0.0349)	(0.0207)	(0.0371)	(0.0051)	(0.0200)	(0.0081)	(0.0204)	(0.0045)	(0.0181)
EX*HW worker	0.0923	0.0719***	0.0759*	0.0062	0.0657**	0.0160*	0.0559*	0.0095**	0.0464*
	(0.0715)	(0.0296)	(0.0445)	(0.0066)	(0.0288)	(0.0097)	(0.0288)	(0.0045)	(0.0261)
MW worker	-0.0066	-0.0234***	-0.0574***	-0.0012	-0.0222***	-0.0024*	-0.0213***	-0.0014**	-0.0199***
	(0.0043)	(0.0041)	(0.0044)	(0.0008)	(0.0038)	(0.0013)	(0.0038)	(0.0007)	(0.0034)
HW worker	-0.0247***	-0.0381***	-0.0771***	-0.0014	-0.0367***	-0.0021	-0.0357***	-0.0033***	-0.0324***
	(0.0080)	(0.0051)	(0.0058)	(0.0009)	(0.0049)	(0.0012)	(0.0049)	(0.0007)	(0.0044)
R2	0.06	0.04	0.05	0.03	0.03	0.04	0.02	0.01	0.02

Notes: See equation 3. Sample is restricted to workers who are employed by a high-wage firm in t (1990 or 2000). All control variables are included (cf. column 4 of table 3). Standard errors clustered at the 3-digit industry x base year level in parentheses. See section 2 for the data preparation. Levels of significance: *10%, **5%, ***1%

3.3. Workers initially employed by medium-wage and low-wage firms

The analysis so far was restricted to workers initially employed by high-wage firms. Does import and export exposure affect sorting of workers initially employed by medium-wage and low-wage firms? Tables A5 and A6 summarize the job stability and mobility effects for workers starting in medium-wage and low-wage firms in year t. The results point to no systematic effects of trade exposure on sorting for this group of workers and firms. The coefficients on industry-level import exposure are small and statistically insignificant. Especially the coefficients on the interaction terms are close to zero and statistically insignificant, suggesting that import exposure does not affect the sorting pattern for workers initially employed by medium-wage and low-wage firms. It is important to note that the sample of workers initially employed by medium-wage and low-wage firms is substantially smaller than the sample of workers initially employed by high-wage firms. 64% of the workers are employed by a high-wage firm in the base year and only 24% (12%) are employed by a medium-wage (low-wage) firm. So even for a given point estimate, the implications for overall sorting and wage inequality are much smaller for the estimate which is related to the smaller sample of workers employed by low-wage and medium-wage firms. Most coefficients on export exposure and the respective interactions effects are statistically insignificant as well. There is thus no evidence on favor of an effect of export exposure on sorting for this group of workers.[32]

3.4. What drives the effects? Observed vs. unobserved skills

The results in sections 3.1 and 3.2 suggest that export and import exposure affects job stability and mobility of high-wage, medium-wage, and low-wage workers differently. The estimated worker fixed effects, which are usually used as a proxy for the skill level of a worker, capture all time-invariant factors which influence his wage. They capture both purely unobserved factors (e.g. unobserved ability, motivation) and observed factors (education, occupations, tasks) as long as they are time-invariant.[33] In fact, table 1 documents that high-wage workers on average have a higher formal education level, are employed in more skill-intensive occupations, and perform different tasks than medium-wage and low-wage workers.

In the following exercise, the goal is to provide evidence on the characteristics that drive the differences between low-, medium-, and high-wage workers in the degree to which they are affected by export and import exposure. I focus on formal education, occupational

[32] One exception is the positive and statistically significant effect of export exposure on upward mobility of medium-wage workers from low-wage to high-wage firms. However, this effect is not robust across different specifications (not shown in the tables).

[33] Of course, it is not possible to directly observe the task performed at the workplace for a given worker. However, I will refer to the task content of work as an observable factor as compared to motivation or unobserved mobility for which there is no variable readily available.

groups, tasks, and unobserved differences within skill groups defined by formal education, occupation, and industry. Moreover, I focus on the job stability effect at high-wage firms to illustrate the role of observable and unobservable characteristics. The results for the downward mobility effect are very similar.

In panel (a) of table 5, I interact the trade exposure variables with education, occupation, and task dummies. In column (1), I interact trade exposure with a dummy for high formal education (college or university degree). In columns (2) and (3), I interact them with dummies for jobs with a high degree of non-routineness and non-codifiability, instead.[34] Column (4) interacts the trade exposure variables with dummies for occupational groups. The omitted reference category consists of manual and unskilled service occupations.

Column (1) of table 5 provides evidence that import exposure affect workers with low formal education more negatively than workers with high formal education. The differences between workers of high and low formal education are very similar to the differences between high-wage and low-wage workers in table 3. Consequently, import exposure works towards an increase of the skill premium as measured by the wage difference between workers with college and university education and other workers. Column (2) suggests that workers performing routine-intensive tasks at their workplace are more negatively affected by import exposure than others. The same is true for workers performing codifiable tasks. However, the interaction effect in column (3) is not statistically significant. Column (4) in addition suggests that less skill-intensive occupations experience a larger drop of job stability in response to import exposure than more skill-intensive occupations. The results in columns (2)-(4) point to an increase in residual inequality in response to import exposure.[35]

A look at the corresponding effects of export exposure shows that workers with low-formal education, employed in low-skill occupations, performing routine and codifiable tasks benefit more from the job stability effect of exports than others. Taken together, the results in panal (a) suggest that at least part of the differences between low-wage, medium-wage, and high-wage workers detected in sections 3.1 and 3.2 are driven by differences in education, occupation, and tasks performed on the job.

However, do differences in tasks and formal education fully explain the different effects on low-wage, medium-wage, and high-wage workers? In fact, table A4 shows that a

[34]The variables are measured at the 3-digit occupation level and are based on the following questions from the 1985/86 wave of the BIBB/BAuA data: 1) Are the contents of your job minutely described by the employer? (codifiable) 2) Does the job sequence repeat itself regularly? (routine) I compute the share of workers within 3-digit occupations who report 'almost always' for a given question. Finally, I label the top 25% of occupations with the highest share as routine/codifiable.

[35]It is not possible to separate the effect of formal education from the effect of occupations and tasks because these dimensions are very strongly correlated. However, it is unlikely that the effects are exclusively driven by either one. For example, an estimation of the specifications in columns (2) and (3) separately for education groups yields similar results for the effects of tasks. The results are available upon request.

regression of the estimated worker effect on controls for education, routine and codifiable jobs, 2-digit occupation and 3-digit industry fixed effects as well as labor market region fixed effects yields an R squared of about 40%. There is thus substantial variation in estimated worker effects within commonly defined skill groups. To provide evidence on whether unobserved skill differences within commonly defined skill groups matter as well, I rank workers **within** skill groups in panel (b) of table 5. In column (5), I rank workers according to their estimated worker fixed effect within formal education groups (high vs. low education). In this case, a high-wage worker is a worker whose fixed effect is in the top tercile within his education group. In column (6), I rank workers according to their fixed effect within 2-digit occupation-3-digit industry groups. I thereby shut down most of the effect that comes from formal education and tasks, since workers are very homogeneous in terms of these characteristics within 2-digit occupation-3-digit industry groups. If the pattern documented in sections 3.1 and 3.2 remains, this indicates that trade affects the sorting based on unobserved skill differences within skill groups and not only sorting based on observables.

The results in columns (5) and (6) of table 5 suggest that the effects of import exposure do not differ across unobservable skills within skill groups. Especially in column (6), which ranks workers within narrowly defined skill groups, the coefficients on the interactions effects are small and close to zero. This result suggests that the effects of import exposure on sorting are well-summarized by differences in terms of formal education, occupations, and tasks between low-wage, medium-wage, and high-wage workers. This is in stark contrast to the results for export exposure. It turns out that workers with low unobserved skills benefit more from the job stability effect than workers with high unobserved skills. The effect of export exposure on sorting therefore is the result of differences in observable and unobservable characteristics between worker types.

3.5. Discussion of the results

The job stability effect of export exposure. The estimates in the previous sections suggest that export exposure generates a strong job stability effect for workers at high-wage firms. Interestingly, this effect is strongest for high-wage and medium-wage workers and is virtually non-existent for high-wage workers. How can this difference between worker types be explained?

A potential explanation is that workers who are more vulnerable to negative demand shocks of any kind benefit more from a positive demand shock in the form of increasing export opportunities. Two results support this claim. First, the coefficients on the dummies (without interaction) for high-wage and medium-wage workers (for example in table 3) provide evidence that high-wage workers have a higher job stability at high-wage firms in general. Second, a closer look at the job stability effect in section 3.4 shows that it oc-

Table 5: Observable vs. unobservable characteristics

	(a) Interactions with observable characteristics			
Dep.var.: HW firm in $t+10$	(1)	(2)	(3)	(4)
Sample: HW firm in t	Education	Non-Routine	Non-Codifiable	Occupation groups
IM	-0.1227***	-0.1542***	-0.1422***	-0.1372***
	(0.0240)	(0.0419)	(0.0534)	(0.0306)
IM*High	0.0610**	0.0650*	0.0528	
	(0.0275)	(0.0346)	(0.0493)	
IM*(Technician/Qual. Services/Admin)				0.0517*
				(0.0281)
IM*(Manager/Engineer/Professional)				0.0798**
				(0.0345)
EX	0.1682**	0.2283***	0.1915**	0.2171***
	(0.0752)	(0.0853)	(0.0877)	(0.0783)
EX*High	-0.2270**	-0.1556*	-0.1034	
	(0.0976)	(0.0825)	(0.0782)	
EX*(Technician/Qual. Services/Admin)				-0.2087***
				(0.0660)
EX*(Manager/Engineer/Professional)				-0.2963***
				(0.0955)
R2	0.11	0.10	0.11	0.10

	(b) Interactions with unobservable characteristics	
Dep.var.: HW firm in $t+10$	(5)	(6)
Sample: HW firm in t	Ranking of workers within...groups	
	education	2-digit occ.-3-digit industry
IM	-0.1228***	-0.1051***
	(0.0234)	(0.0182)
IM*MW worker (within)	0.0321*	-0.0033
	(0.0172)	(0.0127)
IM*HW worker (within)	0.0356	0.0072
	(0.0217)	(0.0181)
EX	0.1912***	0.2096**
	(0.0654)	(0.0864)
EX*MW worker (within)	-0.0713	-0.1081*
	(0.0498)	(0.0595)
EX*HW worker (within)	-0.1617**	-0.1809**
	(0.0787)	(0.0843)
R2	0.11	0.10

Notes: Sample is restricted to workers who are employed by a high-wage firm in t (1990 or 2000). Dependent variable is 1 if worker is employed by a high-wage firm in $t+10$. Column (1) of panel (a) includes interaction terms with a dummy variable for high formal education (college or university). Columns (2) and (3) include interaction terms with dummies for performing non-routine and non-codifiable tasks. Column (4) includes interactions with dummies for occupation groups: manual and unskilled services are the omitted reference category. Panel (b) includes interaction terms with indicators for being a high-/medium-/low-wage worker **within** a given skill group. In column (5), the dummy for being a high-wage worker is 1 for workers whose estimated worker component is among the top tercile within his education group (high or low). Analogously, in column (6), workers are ranked within groups of 3-digit industries and 2-digit occupations. The dummy variables without interactions are omitted to save space. All control variables are included (cf. column (4) of table 3). Standard errors clustered at the 3-digit industry x base year level in parentheses. See section 2 for the data preparation. Levels of significance: *10%, **5%, ***1%

curs mostly for workers with low observed and unobserved skills. These workers typically have a much lower job stability. They are the marginal workers in the presence of a negative shock and this is why they benefit much more from a positive demand coming from increasing export opportunities. A closely related explanation touches the institutional background in Germany. Labor unions and works councils traditionally play a strong role in Germany and their presence increases job stability for workers, especially for low-skilled workers who increasingly face the risk of displacement due to technological progress or outsourcing. In such an environment, it is particularly difficult for firms to justify layoffs in the presence of a positive demand shock stemming from increased exports to Eastern Europe and China.

The downward mobility effect of import exposure. The estimates in the previous section point to formal education and tasks as important drivers for the way in which import exposure influences sorting. In that sense, the result is in line with a large and increasing literature which emphasizes the role of tasks and education for labor market outcomes of workers in response to technological progress and international trade (e.g. Autor et al. 2003; Goos et al. 2014; Hummels et al. 2014; Autor et al. 2014; Ebenstein et al. 2014; Dauth et al. 2018). However, to understand the underlying mechanisms, it is important to note that the effects of import exposure on sorting are not driven by higher separation rates of low-wage workers from high-wage firms. In fact, low-wage, medium-wage, and high-wage workers are equally likely to separate from their initial high-wage employer and to reallocate to the non-manufacturing sector in response to import exposure. The main difference is that, upon separation from their original high-wage firm, high-wage workers move to a high-wage firm in the non-manufacturing sector, whereas low-wage workers move to a low-wage firm in the non-manufacturing sector.

A potential explanation for this result is that high-wage workers, due to their high education and the tasks they perform on their workplace, have a higher transferability of skills and therefore are more employable by high-wage non-manufacturing firms than low-wage workers. Routine-biased technological progress (Autor et al. 2003), which might be strongest in high-wage firms who are early adopters of new technologies, potentially plays an important role for this mechanism by reducing the number of routine-intensive jobs at high-wage non-manufacturing firms. It thereby limits the scope for reallocation of low-wage workers to high-wage non-manufacturing firms and this is why they are forced to move to low-paying non-manufacturing jobs. Similarly, workers with high formal education might find it easier to learn the new skills and techniques required at high-wage non-manufacturing firms.

4. Robustness

4.1. Drop special subgroups of workers

Managers. Around 3% of the sample of workers in the base years consists of managers. One could argue that managers are a special group and are not affected in the same way by a given shock as the rest of the employees in a firm. To test whether the results documented in the main section of the paper is driven by managers, I drop this group in a robustness check. Column (1) of table A7 shows that the results are unaffected by this manipulation.

Food, cleaning, security, logistics. Goldschmidt and Schmieder (2017) provide convincing evidence that German firms paying high wage premiums have increasingly engaged in domestic outsourcing of low-skilled workers in food, cleaning, security, and catering occupations, arguably to exclude them from firm-specific rents. Domestic outsourcing triggered a mobility of these workers from high-wage towards low-wage firms and thereby contributed to the increase in sorting and wage inequality. First, note that the inclusion of 2-digit occupation fixed effects should already control for domestic outsourcing of certain occupational groups. To further mitigate concerns that the effects documented in this paper in fact reflect mobility in response to domestic outsourcing and not in response to import exposure, I drop workers in food, cleaning, security, and catering occupations from the sample in a robustness check. Column (2) of table A7 shows that the results are robust to this manipulation.

4.2. Non-monotonicities

Even though figure 2 provides evidence that mobility between firm types indeed goes along with substantial wage effects, one might have concerns that there could be systematic deviations for certain types of workers. One concern is related to the strong monotonicity assumption implied by the functional form of the fixed effects specification in equation 1, which implies that switching to a firm of lower type (e.g. from a high-wage to a low-wage firm) always goes along with a wage loss, regardless of the worker type. Models that incorporate search frictions and wage bargaining into a world with complementarity between workers and firms predict deviations from monotonicity, with wages decreasing to the left and to the right of the 'ideal' match that corresponds to perfect assortative matching (see e.g. Gautier and Teulings 2006; Eeckhout and Kircher 2011; Hagedorn et al. 2017; Melo 2017).[36] This non-monotonicity is at odds with the log additive structure in

[36] In a world without frictions, the existence of complementarities between worker and firm types would imply perfect positive assortative matching as in Becker (1973). In a world with search frictions, firms and workers must accept deviations from the ideal match. Wages are maximized at the ideal match and apart from the ideal match, wages are smaller because workers need to compensate firm for the foregone option value of continuing to search. The log additive structure of the AKM model allows

equation 1.

A closely related point of critique is the potential existence of match-specific effects. There is a class of trade models which emphasizes the existence of match-specific productivity draws (Helpman et al. 2010; Helpman 2016). Match-specific effects constitute a violation of the AKM assumption and, similar to non-monotonicity, a threat to the following empirical analysis.

First, note that strong non-monotonicities and match-specific effects imply high residuals in the AKM estimation. As Card et al. (2013) emphasize, the residual are generally very small, which is also reflected in the high R squared of around 90%. In addition, replacing the separate worker and establishment fixed effect by job fixed effects does only yield a minor improvement of the model fit of around two percentage points. However, the residuals are large for some observations and this could reflect systematic violations of the AKM assumptions.

While I do not want to make the case that non-monotonicities and match-specific effect play no role in practice, I want to ensure that their existence does not interfere with my empirical strategy in a systematic way. First, note that the main empirical specification includes dummies for terciles of individuals in the distribution of residuals from the initial AKM estimation. To further mitigate concerns about non-monotonicities interfering with the documented results, I conduct two robustness checks. The first one is based on the finding by Lochner and Schulz (2016). Reconciling the AKM specification with models with search frictions and wage bargaining, they emphasize that log additivity provides a valid approximation of the wage structure for a large part of the data. They, however, find deviations from monotonicity (implying high residuals) for the least skilled workers, who seem to select into low-type firms where they maximize their earnings. Observing a switch from a high-wage to a low-wage firm for these types of workers, I would wrongly conclude that this goes along with a wage loss. To mitigate this concern, I drop the bottom 5% of workers with the lowest fixed effects in one robustness check. The results, shown in column (4) of table A7 remain robust.

The second robustness check directly concerns the estimated residuals. Consider the residuals from the initial AKM estimation for the base years 1990 and 2000. Comparing workers with high residuals to workers with low residuals might be problematic as the difference in mobility in response to trade between these groups might be due to differences in the quality of the worker-firm match as for example in Helpman et al. (2010) or due to non-monotonicities. As a robustness check, I drop workers in the top and bottom decile of the residual distribution in each base year. The estimates in column (3) of table A7 show that this does not change the basic results.

for some degree of complementarity. To see this, note that in absolute terms, the wage increase of switching to a higher-type firm is larger for high-wage workers than for low-wage workers.

4.3. Ranking firms within industries

In the main empirical analysis, I group firms into terciles based on their rank in the distribution of estimated wage premiums in the whole sample, regardless of their rank in the 3-digit industry. Trade models along the lines of Melitz (2003) would suggest that the rank within the industry matters in the sense that only the most productive firms within a given industry select into exporting. To the extent that the overall rank in the economy for a given firm differs from its rank within the industry, this might be a problem for the estimation. To mitigate this concern, I restrict the sample to firms that are not only in the top tercile in the whole sample of firms but also in the top tercile within their 3-digit industry. Column (5) of table A7 shows that this does not change the results in a qualitative way. The results for import exposure are almost completely unaffected. The positive job stability effect of exports becomes slightly smaller but is still sizeable.

4.4. Time-varying controls

Equation 1 includes year dummies and a quadratic and cubic term in age fully interacted with education dummies as in Card et al. (2013). In the main empirical analysis, however, I rank workers exclusively based on the estimated worker effect. As a robustness check, I add the predicted impact of the time-varying controls to the estimated worker effect and rank workers accordingly. Column (6) of table A7 provides evidence that this does not change the results in a qualitative way. Especially the estimated interaction effects, which are crucial for the main question about sorting, remain very robust.

4.5. Alternative ranking of firms

In the main empirical analysis, I rank firms based on the estimated firm wage premium in equation 1. In a robustness check, I alternatively rank firms based on the mean log daily wage paid in the respective year. Models that incorporate rent sharing into a setting with heterogeneous firms would predict that the most productive firms, which eventually select into exporting, pay higher wages on average (Egger and Kreickemeier 2009; Amiti and Davis 2011; Egger and Kreickemeier 2012). Column (7) of table A7 shows the resulting estimates. The estimated impact on sorting in this robustness check, as reflected by the interaction effects, is even stronger than in the main empirical analysis.

4.6. Continuous firm wage premium

In the main empirical analysis, the outcome is based on the tercile of the firm in the distribution of estimated firm wage premiums. As a robustness check, I alternatively use the estimated firm wage premium directly as the dependent variable. With this specification, I do not only capture mobility between firms and the corresponding effects on sorting, but also changes of firm wage premiums on the job over time. The downside of this approach is that it is much more vulnerable to measurement error in the estimated firm wage premium. Column (8) of table A7 shows that the basic pattern documented so far remains robust even in this specification. However, the coefficients of export exposure are less precisely measured which might be a consequence of measurement error in the dependent variable.

5. Conclusion

Using a large administrative dataset, this paper provides evidence on the impact of Germany's trade integration with Eastern Europe and China on the sorting of workers across firms that differ in terms of their wage setting. The paper emphasizes the detailed mobility pattern of workers which is underlying to the aggregate changes in the sorting pattern. It also stresses the important role of observable and unobservable skills for the questions whether a worker benefits or loses from the aggregate changes in the sorting pattern in response to the trade integration.

The results suggest that industry-level import exposure triggers an increase in sorting and wage inequality by pushing low-skilled workers out of high-wage firms in the manufacturing sector and into low-wage firms in the non-manufacturing sector. More skilled workers also move into the non-manufacturing sector in response to import exposure. However, in contrast to their less skilled counterparts, they more often manage to reallocate to a different high-wage firm and thereby avoid downward mobility and the associated wage effects. In export-oriented industries, in contrast, the effects are quite different. Mainly workers with low observable and unobservable skills benefit from a positive job stability effect. Increased exports shield low-skilled workers from downward mobility out of high-wage firms and therefore work towards a decrease in wage inequality.

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A. Appendix

Table A1: Variance Decomposition by Interval

	(1) 1985-90	(2) 1995-00	(3) 2005-10	(4) Change (1) → (3)	(5) Share (%)
var(y_{it})	0.1349	0.1752	0.2604	0.1255	100
var(α_i)	0.0818	0.1038	0.1405	0.0587	46.8
var($\psi_{J(it)}$)	0.0264	0.0354	0.0534	0.0270	21.5
var($x'_{it}\beta$)	0.0174	0.0095	0.0128	-0.0046	-3.7
var(r_{it})	0.0102	0.0115	0.0128	0.0026	2.1
2cov(α_i,$\psi_{J(it)}$)	-0.0044	0.0067	0.0310	0.0354	28.2
2cov(α_i,$x'_{it}\beta$)	-0.0007	0.0033	0.0001	0.0008	0.7
2cov($\psi_{J(it)}$,$x'_{it}\beta$)	0.0042	0.0050	0.0098	0.0056	4.5
Obs.	33,632,346	33,813,233	31,291,461		
Adjusted R2	0.87	0.89	0.92		

Notes: Table displays variance decomposition applied to equation 1. See section 2 for data preparation and estimation. See Card et al. (2013), page 994 for comparison. Data source: Integrated Employment Biographies (IEB), 50%-sample.

Table A2: Descriptives (Base Years 1990 and 2000)

	Mean	Median	p75	p25	N
Log daily wage (imputed)	4.48	4.44	4.68	4.25	3,336,402
High education	0.14	0	0	0	3,336,402
Routine job	0.27	0	0	1	3,336,402
Codifiable job	0.33	0	0	1	3,336,402
Age	35.72	36	42	29	3,336,402
Estimated worker effect	4.38	4.34	4.51	4.21	3,336,402
Estimated firm wage premium	0.08	0.08	0.16	0.01	3,336,402
EX (All)	0.12	0.10	0.17	0.05	3,336,402
EX (LW Workers)	0.12	0.10	0.16	0.05	1,088,174
EX (MW Workers)	0.13	0.10	0.18	0.05	1,092,994
EX (HW Workers)	0.13	0.11	0.17	0.05	1,155,234
IM (All)	0.11	0.06	0.15	0.03	3,336,402
IM (LW Workers)	0.11	0.07	0.15	0.03	1,088,174
IM (MW Workers)	0.11	0.06	0.15	0.03	1,092,994
IM (HW Workers)	0.12	0.06	0.14	0.03	1,155,234

Notes: The table provides summary statistics for the sample in the base years 1990 and 2000. See section 2 for a detailed explanation of the data preparation and wage decomposition.

Table A3: Top Exporting and Importing Industries

3-digit industry	Change 1990-2010
(a) Top exporting industries	
Motor vehicles	17.92
Parts for motor vehicles	12.85
Machines for prod. and use of mech. power	8.42
Other machinery	7.72
Electricity distribution apparatus	6.58
(b) Top importing industries	
Office machinery	13.56
Motor vehicles	8.69
Parts for motor vehicles	8.60
Electronic components	8.22
Television and radio	6.50

Notes: Table displays the industries with the largest increase in exports and imports from 1990 through 2010, respectively. All values in billions of 2010-euros. Data source: Comtrade.

Table A4: Explaining the variation of estimated worker effects

Dep. var.: Estim. Worker effect	(1)	(2)	(3)	(4)	(5)
High education	0.2930***	0.2463***	0.2239***	0.0412***	0.0407***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Routine job		-0.0747***	-0.0752***	-0.0254***	-0.0250***
		(0.0003)	(0.0004)	(0.0005)	(0.0005)
Codifiable job		-0.0814***	-0.0865***	-0.0054***	-0.0055***
		(0.0003)	(0.0003)	(0.0006)	(0.0006)
R2	0.19	0.25	0.27	0.40	0.40
Tasks		√	√	√	√
3-digit industry FE			√	√	√
2-digit occupation FE				√	√
Labor market region FE					√

Notes: The tables shows the results of a regression of the estimated worker effect on various explanatory variables, all the the base year level. All specifications include a cubic term in age and a dummy to differentiate between the cross-sections 1990 and 2000. See section 2 for the data preparation. Levels of significance: *10%, **5%, ***1%

Table A5: Job stability and mobility of workers starting in medium-wage firms

Dep. Var.:	Employed by........firm in $t+10$			
	high-wage	medium-wage	low-wage	out
Sample: MW firm in t	(1)	(2)	(3)	(4)
IM	-0.0253	0.0286	-0.0019	-0.0014
	(0.0346)	(0.0192)	(0.0167)	(0.0146)
IM*MW worker	-0.0227	0.0007	0.0035	0.0186*
	(0.0177)	(0.0160)	(0.0097)	(0.0111)
IM*HW worker	-0.0048	-0.0265	0.0027	0.0285**
	(0.0302)	(0.0225)	(0.0037)	(0.0120)
EX	0.0473	-0.0961	0.0009	0.0479
	(0.1008)	(0.0648)	(0.0551)	(0.0341)
EX*MW worker	0.0845	-0.0093	-0.0006	-0.0745*
	(0.0624)	(0.0713)	(0.0287)	(0.0392)
EX*HW worker	-0.0143	0.0786	-0.0065	-0.0577
	(0.0896)	(0.0811)	(0.0588)	(0.0446)
MW worker	0.0760***	0.0376***	-0.0311***	-0.0825***
	(0.0070)	(0.0071)	(0.0032)	(0.0041)
HW worker	0.1065***	0.0294***	-0.0433***	-0.0916***
	(0.0108)	(0.0098)	(0.0057)	(0.0053)
R2	0.10	0.03	0.04	0.05
N	881,731	881,731	881,731	881,731

Notes: See equation 3. Sample is restricted to workers who are employed by a medium-wage firm in t (1990 or 2000). All control variables are included (cf. column 4 of table 3). Standard errors clustered at the 3-digit industry x base year level in parentheses. See section 2 for the data preparation. Levels of significance: *10%, **5%, ***1%

Table A6: Job stability and mobility of workers starting in low-wage firms

Dep. Var.:	Employed by........firm in $t+10$			
	high-wage	medium-wage	low-wage	out
Sample: MW firm in t	(1)	(2)	(3)	(4)
IM	-0.0250	0.0385	0.0139	-0.0274
	(0.0152)	(0.0334)	(0.0291)	(0.0228)
IM*MW worker	-0.0169	-0.0008	0.0121	0.0056
	(0.0161)	(0.0167)	(0.0147)	(0.0193)
IM*HW worker	-0.0083	-0.0007	-0.0082	0.0172
	(0.0266)	(0.0230)	(0.0295)	(0.0224)
EX	-0.0111	-0.0088	-0.1267	0.1466
	(0.0501)	(0.0917)	(0.1514)	(0.1282)
EX*MW worker	0.1346***	0.0403	0.0155	-0.1905
	(0.0497)	(0.0895)	(0.0640)	(0.1222)
EX*HW worker	-0.0266	0.0088	0.1666	-0.1488
	(0.1084)	(0.0929)	(0.1487)	(0.1437)
MW worker	0.0370***	0.0705***	-0.0019	-0.1056***
	(0.0054)	(0.0092)	(0.0067)	(0.0103)
HW worker	0.0717***	0.0782***	-0.0287**	-0.1212***
	(0.0108)	(0.0104)	(0.0123)	(0.0132)
R2	0.06	0.05	0.03	0.05
N	267,703	267,703	267,703	267,703

Notes: See equation 3. Sample is restricted to workers who are employed by a low-wage firm in t (1990 or 2000). All control variables are included (cf. column 4 of table 3). Standard errors clustered at the 3-digit industry x base year level in parentheses. See section 2 for the data preparation. Levels of significance: *10%, **5%, ***1%

Table A7: Job Stability at High-wage Firms: Robustness Checks

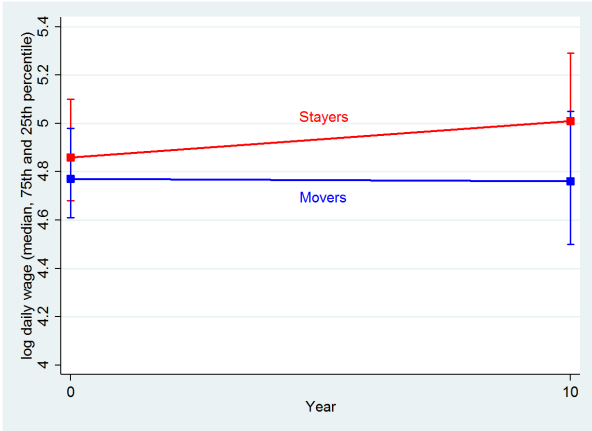
Dep. var.: HW firm in $t+10$ Sample: HW firm in t	(1) Drop managers	(2) Drop FCSL	(3) Drop Residuals	(4) Drop 5%	(5) Within industry	(6) Add observables	(7) Wage ranking	(8) Continuous premium
IM	-0.1481***	-0.1472***	-0.1505***	-0.1395***	-0.1477***	-0.1162***	-0.1259***	-0.0519***
	(0.0294)	(0.0297)	(0.310)	(0.0297)	(0.0280)	(0.0309)	(0.0291)	(0.0115)
IM*MW worker	0.0482***	0.0481***	0.0506***	0.0404***	0.0524***	0.0135	0.0693***	0.0340***
	(0.0161)	(0.0162)	(0.0161)	(0.0146)	(0.0168)	(0.0175)	(0.0173)	(0.0079)
IM*HW worker	0.0751**	0.0714**	0.0646*	0.0622**	0.0676**	0.0718**	0.0804**	0.0413***
	(0.0313)	(0.0308)	(0.0339)	(0.0305)	(0.0324)	(0.0298)	(0.0322)	(0.0121)
EX	0.2213***	0.2195***	0.2131***	0.1970**	0.1654*	0.1939**	0.3259***	0.0819
	(0.0826)	(0.0826)	(0.0826)	(0.0797)	(0.0868)	(0.0871)	(0.1046)	(0.0641)
EX*MW worker	-0.0380	-0.0352	-0.0338	-0.0172	-0.0892	-0.0100	-0.0803	-0.0300
	(0.0615)	(0.0617)	(0.0662)	(0.0571)	(0.0652)	(0.0868)	(0.0496)	(0.0248)
EX*HW worker	-0.2338***	-0.2401**	-0.2191**	-0.2204**	-0.2574**	-0.2243**	-0.3301***	-0.0927*
	(0.1034)	(0.1029)	(0.1024)	(0.0976)	(0.1209)	(0.1011)	(0.0789)	(0.0482)
MW worker	0.0880***	0.0875***	0.0831***	0.0695***	0.0925***	0.1324***	0.0954***	0.0258***
	(0.0073)	(0.0073)	(0.0075)	(0.0063)	(0.0082)	(0.0110)	(0.0086)	(0.0042)
HW worker	0.1395***	0.1400***	0.1275***	0.1193***	0.1403***	0.1935***	0.1640***	0.0448***
	(0.0113)	(0.0113)	(0.0111)	(0.0103)	(0.0133)	(0.0121)	(0.0124)	(0.0070)
R2	0.11	0.11	0.10	0.10	0.11	0.12	0.10	0.51

Notes: See equation 3. Sample is restricted to workers who are employed by a high-wage firm in base year t (1990 or 2000). Dependent variable is 1 if worker is employed by a high-wage firm in $t+10$. Columns (1) and (2) show the results after dropping managers and food/cleaning/security/logistics workers. In column (3), I drop workers in the top and bottom decile of the AKM residual distribution in a given base year. In column (4), I drop the bottom 5% of estimated worker effects. Column (5) restricts on firms that additionally belong to the top tercile within their 3-digit industry. Column (6) adds the estimated effect of controls in the AKM estimation to the worker effect and rank workers accordingly. In column (7), firms are grouped into terciles based on their mean log wage. Column (8) employs the estimated firm wage premium in $t+10$ as an outcome, controlling for the initial estimated firm wage premium in the base year t. Standard errors are clustered at the 3-digit industry x base year level (in parentheses). See section 2 for the data preparation. Levels of significance: *10%, **5%, ***1%

Figure A1: Wage effects of moving from a high- to a medium-wage firm: a descriptive look

(a) Low-wage workers

(b) High-wage workers



Notes: Panel (a) includes low-wage workers employed by a high-wage establishment in year 0 (the base year 1990 or 2000). It plots median wages as well as the 75th and 25th percentile of wages in the base year and ten years later (2000 or 2010). The group of 'stayers' in red includes all workers who are still employed at a high-wage establishment ten years later (not necessarily the same establishment). The group of 'movers' in blue includes all workers who are employed at a low-wage establishment ten years later. Panel (b) shows the same results for high-wage workers employed by a high-wage establishment in year 0. See section 2 for a more detailed description.

Figure A2: Wage effects of moving from a low- to a high-wage firm: a descriptive look

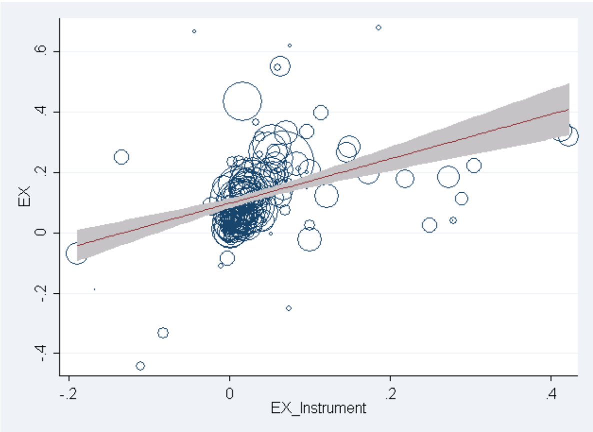
(a) Low-wage workers

(b) High-wage workers

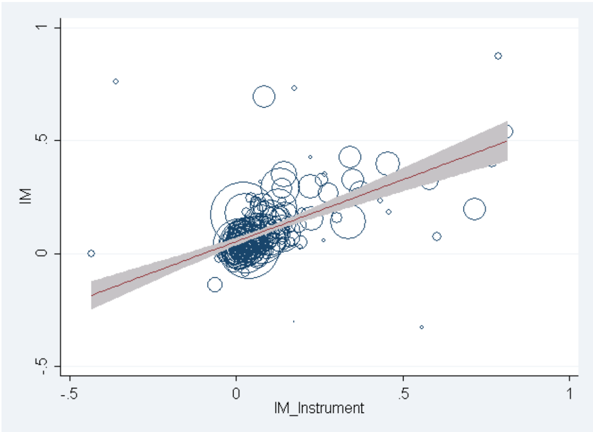
Notes: Panel (a) includes low-wage workers employed by a high-wage establishment in year 0 (the base year 1990 or 2000). It plots median wages as well as the 75th and 25th percentile of wages in the base year and ten years later (2000 or 2010). The group of 'stayers' in red includes all workers who are still employed at a high-wage establishment ten years later (not necessarily the same establishment). The group of 'movers' in blue includes all workers who are employed at a low-wage establishment ten years later. Note that in 1990 establishments are partitioned into terciles based on the wage decomposition for the interval 1985-1990. See section 2 for a more detailed description.

Figure A3: First Stage

(a) Export Exposure



(b) Import Exposure



Notes: The graphs represent the first stage for export and import exposure at the industry-year level. The size of the circle reflects the number of workers employed in the industry as of the base year t. The shaded area reflects a 95% confidence interval.