

Winkler, Erwin

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Diverging paths: Labor reallocation, sorting, and wage inequality*

Erwin Winkler[†]
Job Market Paper

November 14, 2019

This paper provides evidence that labor reallocation from the manufacturing into the non-manufacturing sector causes an increase in sorting of high-skilled (low-skilled) workers into high-paying (low-paying) firms and thereby triggers a rise in wage inequality. I use data on 50% of all West German male employees and exploit industry-level variation in trade-induced labor reallocation into the non-manufacturing sector, stemming from Germany's trade integration with China and Eastern Europe. The results suggest that labor reallocation into the non-manufacturing sector causes an increase in sorting because low-educated workers performing routine and codifiable tasks are less likely to move to high-paying service firms than more skilled workers. These results are not specific to trade-induced labor reallocation, but carry over to any shock or policy which causes a contraction of the manufacturing sector and labor reallocation into the service sector. A back-of-the-envelope calculation suggests that total observed labor reallocation into the non-manufacturing sector explains at least 30% of the rise in sorting and 10% of the rise in wage inequality between 1990 and 2010 in Germany.

JEL-Classification: J31, J62, F14

Keywords: Labor reallocation, wage inequality, sorting, firms, international trade

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[†]University of Wuerzburg and Wharton School (University of Pennsylvania). Current address: 415A Vance Hall, 3733 Spruce Street, 19104 Philadelphia. Email: erwin.winkler@uni-wuerzburg.de

1. Introduction

Wage inequality has increased substantially in the USA, Germany, and other industrialized countries during the last decades (e.g. Dustmann et al. 2009; Acemoglu and Autor 2011; Antonczyk et al. 2018). To fully understand the causes of this phenomenon, it is crucial to understand the role that firms play for the wage structure. The idea that some firms pay higher wages than others for similarly skilled workers has a long tradition in the economic literature (e.g. Slichter 1950; Dickens and Katz 1987; Krueger and Summers 1988). Existing firm-specific wage premiums contribute to the overall wage dispersion in different countries (e.g. Card et al. 2013; Card et al. 2016; Alvarez et al. 2018; Song et al. 2019).¹

In the presence of firm-specific wage premiums, changes in sorting of workers across high-paying and low-paying firms affect wage inequality. Indeed, recent evidence suggests that the allocation of workers across firms has changed fundamentally during the last decades. In the USA and Germany, high-skilled (low-skilled) workers have become more likely to be employed by high-paying (low-paying) firms. This increase in sorting accounts for about one third of the rise in wage inequality in both countries (Card et al. 2013; Song et al. 2019). Despite its relevance for wage inequality, the causes of the increase in sorting are not yet fully explored.

This paper analyzes the impact of structural change, in the form of labor reallocation from the manufacturing into the non-manufacturing sector, on sorting, and the resulting effect on wage inequality. Structural change is a salient feature in many industrialized countries. In Germany, manufacturing employment has decreased by about 20% from 1994 through 2014 (Dauth et al. 2017). Partly, the decline in manufacturing employment and the simultaneous expansion of the service sector have been fueled by labor mobility between sectors. A common explanation for the secular decline in manufacturing employment is labor-saving technological progress in the manufacturing sector (Herrendorf et al. 2014).² Understanding the distributional effects of decreasing manufacturing employment is especially relevant as manufacturing employment might further decline due to technological progress or other reasons in the future.

How can labor reallocation cause an increase in sorting? In a first step, I make use of data on 50% of all West German male employees from 1985 through 2010 to provide two novel descriptive findings which suggest a channel through which labor reallocation affects sorting. To this end, I build on Abowd et al. (1999) and decompose log wages of

¹Building on Abowd et al. (1999), these studies control for observable and unobservable differences in workforce composition across firms and obtain measures of a proportional wage premium or discount which the firm pays to all its employees. See section 2 for more details.

²Other potential explanations are rising income levels paired with non-homothetic preferences over manufacturing and service goods (Herrendorf et al. 2014) and rising import competition from low-wage countries (e.g. Autor et al. 2013; Pierce and Schott 2016). See Herrendorf et al. (2014) for a more detailed overview of the trends in structural change and potential causes.

workers into a permanent worker component which is assumed to be portable across firms and a firm component. The firm component reflects a wage premium or discount that the firm pays to all its employees.

First, I provide evidence that estimated firm wage premiums differ between the manufacturing and the non-manufacturing sector. The manufacturing sector offers comparatively high wage premiums, potentially because of the strong role that unions play in this sector.³ The non-manufacturing sector, in contrast, contains a segment of firms paying wage premiums that are comparable to those in the manufacturing sector, and a segment of firms paying substantially lower wage premiums. Partly, the dispersion within the non-manufacturing sector reflects a divide between high-end service industries like financial intermediation and low-wage service industries such as industrial cleaning. Firm wage premiums, however, also differ across firms within industries.

The second main descriptive finding suggests that manufacturing workers with low formal education performing routine and codifiable tasks have lower access to high-paying non-manufacturing firms than more skilled manufacturing workers.⁴ Potential reasons are inherent differences in the skill requirements between high-paying and low-paying non-manufacturing firms or skill-biased technological change in high-paying non-manufacturing industries or firms. As low-skilled and high-skilled manufacturing workers tend to be employed by firms paying similar wage premiums, this implies that a contraction of the manufacturing sector which triggers labor reallocation into the non-manufacturing sector causes an increase in sorting and wage inequality. Importantly, in this case, sorting and wage inequality increase even if high-skilled and low-skilled workers are equally likely to move into the non-manufacturing sector in response to a given shock or policy.

In the main empirical analysis, I then isolate a shock which generates labor mobility from the manufacturing into the non-manufacturing sector for all skill groups. I exploit industry-level variation in labor reallocation from the manufacturing into the non-manufacturing sector, stemming from Germany's trade integration with China and Eastern Europe. Triggered to a large extent by China's transformation into a market economy and the fall of the Iron Curtain, Germany's exports to and imports from China and Eastern Europe increased by more than 1,000% between 1990 and 2010. This trade shock played out differently across manufacturing industries and thereby created variation in involuntary labor reallocation into the non-manufacturing sector. Workers employed in import-exposed industries experience increasing rates of displacement at their initial firm. In the light of the overall contraction of the manufacturing sector, moving into the non-manufacturing sector is the most viable path for displaced workers. Growing imports

³See for example Hirsch and Mueller (2018) who find that German firms bound by collective bargaining agreements and firms with a works council pay higher wage premiums on average.

⁴High-paying firms are firms whose estimated firm wage premium is in the upper tercile in the whole economy in a given year. Analogously, low-paying firms are firms in the lowest tercile.

therefore accelerate the ongoing process of labor reallocation by moving workers into the non-manufacturing sector at higher rates. Growing export opportunities, in contrast, constitute a positive demand shock on the industry and translate into increased job stability for workers employed in these industries. Rising exports therefore slow down the process of labor reallocation by retaining manufacturing jobs.⁵ In the main empirical analysis, I focus on worker mobility from the manufacturing into the non-manufacturing sector over a period of ten years and exploit variation in increasing net import exposure across manufacturing industries over time, conditional on a variety of controls at the worker, firm, industry, and region level.

As expected, the results suggest that workers initially employed in manufacturing industries that experience a higher increase in net import exposure face a higher probability of leaving the initial industry, which translates into a higher probability of moving into the expanding service sector. Consistent with the idea that growing import competition constitutes a negative demand shock on the whole industry, this effect is identical across skill groups.

In contrast, the allocation to high-paying and low-paying non-manufacturing firms differs substantially across skill groups. The results provide robust evidence that high-skilled and low-skilled workers initially employed in manufacturing firms paying similar wage premiums sort into firms paying different wage premiums within the non-manufacturing sector. Highly educated workers performing complex tasks mostly move to high-wage non-manufacturing firms and thereby curb the resulting loss in firm wage premiums and wages. Low-educated workers performing routine and codifiable tasks more often reallocate to low-wage non-manufacturing firms and therefore experience a loss in firm wage premiums and wages, relative to more skilled workers. Through the resulting increase in sorting upon formal education and tasks, labor reallocation causes an increase in the skill premium and in residual wage inequality. The effects are the result of sorting between and within non-manufacturing industries. High-skilled workers are better able to reallocate into high-paying service industries, especially in the business services industry, and more often move to the highest-paying firms within the respective service industry.

Overall, the results provide evidence that the rise in sorting documented by Card et al. (2013) and Song et al. (2019) for Germany and the USA is strongly related to labor reallocation from the manufacturing into the non-manufacturing sector. These results are not specific to trade-induced labor reallocation. They carry over to any shock or policy which causes a contraction of the manufacturing sector and thereby triggers labor mobility into the non-manufacturing sector. Importantly, the results suggest that sorting and wage inequality increase even if a given shock causes higher mobility into the non-manufacturing

⁵The previous literature provides strong evidence in favor of the accelerating and decelerating effects of trade with China and Eastern Europe on labor reallocation (e.g. Autor et al. 2014; Dauth et al. 2014; Dauth et al. 2017; Dauth et al. 2019a; Utar 2018). The literature, however, does not focus on sorting of workers across high-paying and low-paying firms within the non-manufacturing sector.

sector to the same extent for all skill groups. The most conservative back-of-the-envelope calculation suggests that total observed labor reallocation from the manufacturing into the non-manufacturing sector and the resulting relative loss of firm wage premiums for low-wage workers explains at least 30% of the rise in sorting and 10% of the rise in wage inequality between 1990 and 2010.

The findings imply that a further decline of manufacturing employment, potentially driven by technological progress, a negative demand shock, or any other cause, might go along with increasing wage inequality in the future. From the perspective of a policymaker who aims to curb the resulting distributional effects, the analysis in this paper suggests a strong focus on the set of skills which enable a worker to take up a high-paying job in the service sector. In contrast, a mere focus on bringing displaced manufacturing workers into full-time employment in the expanding service sector is not sufficient to fully curb the distributional effects.

This paper is related to Goldschmidt and Schmieder (2017) who provide evidence that high-paying firms have increasingly outsourced workers in low-wage occupations to low-wage business service firms (domestic outsourcing), contributing to the rise in sorting and wage inequality in Germany. To the extent that domestic outsourcing is performed by manufacturing firms, it also involves labor reallocation from manufacturing into non-manufacturing. In Goldschmidt and Schmieder (2017), this reallocation causes a rise in sorting because a selected group of low-skilled workers are moved into low-wage service firms, whereas more skilled workers remain employed in the manufacturing firm. In contrast, this paper provides evidence that sorting increases even if the initial shock triggering structural change in the form of labor mobility is homogeneous across skill groups. The results in this paper therefore speak to structural change more generally and carry over to all shocks or policies which trigger a contraction of manufacturing industries and thereby induce labor reallocation into non-manufacturing.

The previous literature offers globalization and technological progress as potential drivers of increased sorting. A number of studies emphasize the effects of technological progress on sorting in the context of complementarities between skills and technologies (Acemoglu 1999; Kremer and Maskin 1996; Håkanson et al. 2015). Globalization can affect sorting as it allows firms to decrease the range of tasks performed within the firm through outsourcing (Feenstra and Hanson 1996; Grossman and Rossi-Hansberg 2008) and as it allows high-skilled workers to match with foreign high-skilled workers rather than with domestic low-skilled workers (Kremer and Maskin 2006). The previous empirical literature on the impact of international trade on sorting across high-paying and low-paying firms focuses on sorting within industries or sectors (Davidson et al. 2014; Baziki et al. 2016; Borrs and Knauth 2016).⁶ This paper, in contrast, provides evidence

⁶More generally, research along the lines of Melitz (2003) focuses on the effects of trade on the intra-industry reallocation of economic activity towards the most productive firms and the resulting effects

on a systematic link between trade-induced labor reallocation into the non-manufacturing sector on economy-wide sorting and wage inequality. As most of the low-paying firms in the economy are non-manufacturing firms, a focus on within-industry or within-sector sorting potentially understates the overall effects on sorting and wage inequality

The paper also contributes to the literature on the distributional effects across workers of imports from China and in some cases Eastern Europe (Autor et al. 2014; Dauth et al. 2014; Ashournia et al. 2014; Nilsson Hakkala and Huttunen 2016; Dix-Carneiro and Kovak 2017; Utar 2018; Dauth et al. 2019a; Keller and Utar 2019; Huber and Winkler 2019). This literature typically focuses on the effects of import exposure on cumulative earnings or employment over several years and thereby potentially captures purely transitional effects, for example coming from temporary unemployment or temporarily depressed wages, and more long-run effects which persist in the new equilibrium after the economy has adjusted. The relative magnitude of these two types of effects are not yet fully explored. This paper provides evidence on a mechanism through which distributional effects persist in the medium-run and long-run, even after workers of all skill levels have moved out of import-exposed industries and found full-time employment in non-manufacturing. In particular, this paper suggests that bringing trade-displaced workers into full-time employment in the service sector is not sufficient to fully curb the resulting distributional effects.⁷ By emphasizing long-run distributional effects of import exposure, the paper is related to the literature about the long-lasting effects of job loss on workers' earnings (e.g. Jacobson et al. 1993).

Studies with more structural approaches estimate sizable adjustment costs arising to workers who move between sectors (e.g. Lee and Wolpin 2006; Artuc et al. 2010; Dix-Carneiro 2014). The results in this paper suggest that the degree of adjustment costs that arise for a worker who reallocates into the non-manufacturing sector is intimately related to the ability of moving into high-paying firms, both between and within non-manufacturing industries. By emphasizing the role that tasks performed on the job play for the ability to reallocate to high-paying firms, the paper contributes to a growing literature which documents the important role that tasks performed at the workplace play for the distributional effects of technological progress and globalization (e.g. Autor et al. 2003; Spitz-Oener 2006; Autor et al. 2008; Gathmann and Schoenberg 2010; Becker et al. 2013; Goos et al. 2014; Hummels et al. 2014; Ebenstein et al. 2014; Becker and Muendler 2015).

on within-industry wage inequality (e.g. Helpman et al. 2010; Egger and Kreickemeier 2012; Krishna et al. 2014; Egger et al. 2016; Helpman et al. 2016). See Helpman (2016) or Muendler (2017) for more extensive overviews of the literature.

⁷Dauth et al. (2019a) provide evidence for Germany that more skilled workers garner higher cumulative earnings in the non-manufacturing sector than less skilled workers, in response to growing import competition. However, this difference can be driven by faster reallocation and lower temporary unemployment (i.e. transitional effects) and do not necessarily reflect higher wages conditional on employment in the non-manufacturing sector.

With its focus on structural change and wage inequality, the paper is related to Cravino and Sotelo (2019) who analyze the effects of trade-induced structural change on the skill premium in a quantitative trade model. Buera and Kaboski (2012) theoretically and empirically analyze the link between the rise in skill-intensive service industries and the rise in the skill premium. These studies do not focus on worker-firm sorting and its effects on the skill premium. The results in this paper are consistent with their finding that structural change raises the skill premium. Finally, the paper is also related to Dauth et al. (2019b) who analyze the role of agglomeration effects for within-city sorting of workers across firms.

2. Data and AKM estimation

2.1. Main data sources

The main data source in this paper is the Employee History Dataset (BeH, V.09.05.00), provided by the Institute for Employment Research in Nuremberg, Germany. The BeH contains information on all German workers subject to social security contributions. It is based on employers' notifications to the social security insurance and therefore is highly reliable. The dataset contains information on workers' wages, industry-affiliation, location, and a large battery of socio-economic variables on a daily basis. Crucially for the question in this paper, the data allow to follow workers over time as they move between firms⁸, between and within industries, sectors, occupations, and regions. I make use of a 50% random sample of all West German male full-time employees in the BeH. I impute missing and inconsistent education data with the help of Fitzenberger et al. (2005)'s approach. 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).⁹

The data on exports and imports stem from the United Nations Commodity Trade Database (Comtrade). This database provides 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. I then match them to the BeH with the help of the industry identifier.

Finally, I use data from the BIBB/BAuA Employment Surveys. These surveys are carried out by the German Federal Institute for Vocational Training and the Institute for

⁸I use the terms 'firm' and 'establishment' interchangeably. With the datasets used in this paper, 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).

⁹The data do not allow to observe workers who are unemployed, self-employed, or employed in the public sector as civil servants.

Employment Research. They contain a random sample of about one tenth of a percent of the German labor force in a given year. The surveys provide information about workplace characteristics and requirements that I use to construct measures for tasks performed at the workplace.

2.2. AKM estimation

The wage decomposition pioneered by Abowd et al. (1999) and applied to the German context by Card et al. (2013) forms the basis of the analysis in this paper. I carry out the wage decomposition separately for five six-year intervals: 1985-1990, 1990-1995, 1995-2000, 2000-2005, and 2005-2010. Following Card et al. (2013), I select the worker-firm observation with the highest cumulative earnings among all full-time worker-firm observations within a given year. The resulting sample consists of 30-35 million observations in each interval. I estimate the following 'AKM regression' separately for each interval:

$$y_{i\tau} = \alpha_i + \psi_{J(i\tau)} + x'_{i\tau}\beta + r_{i\tau} \quad (1)$$

In this equation, $y_{i\tau}$ denotes the log daily wage of worker i in year τ . α_i reflects the worker component of the wage. It captures all time-invariant observable and unobservable worker characteristics that influence his wage and is assumed to be portable across employers. It captures the effects of formal education as most of the workers in the sample have already completed their education. It also captures time-invariant effects of the worker's occupation and tasks performed on the job as well as time-invariant unobservables like motivation and unobserved ability.

$J(i\tau)$ is a function that gives the identity of firm j that employs worker i in year τ . ψ_j can be interpreted as a proportional wage premium or wage discount that firm j pays to its employees, i.e. all workers for which $J(i\tau) = j$. A potential explanation for the existence of these wage premiums and the resulting deviation from the law of one price for skill is rent sharing. The results of several studies for different countries suggest that rent sharing indeed is an important explanation. For example, in line with the idea of rent sharing, Card et al. (2016) find that more productive Portuguese firms pay higher wage premiums on average. This result is consistent with a link between the productivity dispersion across firms and the wage dispersion found in the previous literature (e.g. Faggio et al. 2010; Barth et al. 2016). Using German data, Hirsch and Mueller (2018) find that firms bound by collective bargaining agreements and firms with a works council pay higher wage premiums, conditional on productivity. While this paper is largely agnostic about the underlying causes of firm wage premiums, the results are consistent with rent sharing being an important factor.¹⁰

¹⁰A further potential explanation is that firms pay wage premiums of different size to compensate workers for differences in non-wage job characteristics (e.g. Mas and Pallais 2017). While I cannot rule out that

$x'_{i\tau}$ 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, $r_{i\tau}$ is the error term, for which I assume mean zero and orthogonality to worker and firm effects, conditional on the control variables. This empirical specification closely follows Card et al. (2013).¹¹ Appendix A provides more details on the estimation of equation 1.

Terciles. In parts of the main empirical analysis, I group all firms in the sample in a given year (manufacturing and non-manufacturing) into three terciles, based on the estimated firm wage premiums $\hat{\psi}_j$: high-wage, medium-wage, and low-wage firms. I do this separately for three years: 1990, 2000, and 2010. These years correspond to the start and end dates of the two intervals 1990-2000 and 2000-2010 for which I carry out the main analysis. To group firms into terciles in 1990 (2000, 2010), I use the estimated firm wage premiums from interval 1985-1990 (1995-2000, 2005-2010).

A potential concern in the estimation of equation 1 is measurement error of the estimated firm wage premiums (Andrews et al. 2008). By using the tercile of the firm by which a worker is employed as an outcome variable in the main analysis, I allow for a substantial degree of measurement error in the estimated firm wage premium. A potential downside of this strategy is that it discards differences in firm wage premiums within terciles. Therefore, I also employ the estimated firm wage premium directly as an outcome. Analogously to the procedure for firms, I rank workers into three terciles based on their estimated worker component $\hat{\alpha}_i$: high-wage, medium-wage, and low-wage workers.

3. Descriptives on labor reallocation and sorting

3.1. Aggregate trends

Figure 1 illustrates that the rise in wage inequality and the increase in labor market sorting in Germany coincided with a decline in the manufacturing employment share. The blue lines in figure 1 show that wage inequality, as measured by the variance of log daily wages for male full-time employed workers, increased by about 13 log points between the first and the last interval.¹² The red lines show that the increase in sorting accounts for around one third of the rise in wage inequality. More specifically, based on the estimation of equation 1, one can apply a variance decomposition to give a descriptive

some changes in wage premiums are compensated by non-wage characteristics, the focus in this paper on comparatively large changes in wage premiums makes it unlikely that non-wage characteristics provide a full compensation for the estimated effects.

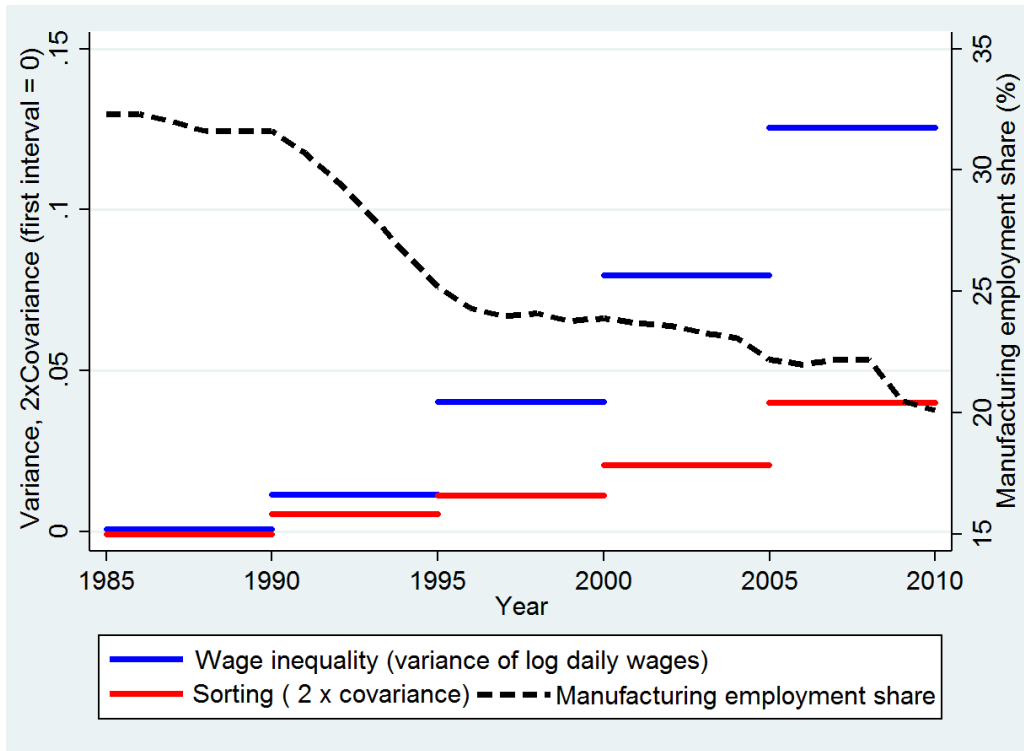
¹¹For the purpose of this paper, I choose slightly different time intervals for the decomposition than Card et al. (2013). Another difference is that I employ a 50% sample, whereas Card et al. (2013) have access to the full universe of West German employees. The results of the variance decomposition are very similar to those in Card et al. (2013). I am grateful to Linda Borrs and Florian Knauth for sharing their Matlab code for the decomposition.

¹²In this figure, I pool all observations in a given 6-year-interval. Alternatively, figure A1 in the appendix shows the same trend by plotting various annual wage percentiles over time.

overview of the role of worker and firm components as well as the role of sorting for the rise in wage inequality. The part of the variance of log wages which is driven by sorting in a given interval is $2cov(\hat{\alpha}_i, \hat{\phi}_{J(i\tau)})$.¹³ The increase of the covariance over time suggests that high-skilled workers have become relatively more likely to be employed by high-paying firms. This result is consistent with the findings by Card et al. (2013) for Germany. In a recent study, Song et al. (2019) provide results of similar magnitude for the USA.

Finally, figure 1 plots the evolution of the manufacturing employment share in Germany over time. This share has decreased from about 33% in 1985 to about 20% in 2010. The manufacturing sector has also contracted in absolute terms. Dauth et al. (2017) report that total manufacturing employment has decreased by about 20% from 1994 through 2014. Figure A2 in the appendix illustrates that other countries experienced very similar decreases in the manufacturing employment share.

Figure 1: Wage inequality, sorting, and structural change



Notes: The dashed line depicts the manufacturing employment share in Germany in a given year. See figure A2 for a cross-country comparison. The blue lines depict the level of wage inequality, as measured by the variance of log daily wages of full-time employed workers in a given interval, as a deviation from the level of wage inequality in the first interval 1985-1990. The red lines depict the level of sorting, as measured by twice the covariance between estimated worker components and firm wage premiums in a given interval, as a deviation from the level of sorting in the first interval 1985-1990. See section 2 for a more detailed explanation of the data preparation and wage decomposition. Data sources: BeH and U.S. Bureau of Labour Statistics.

¹³The total variance decomposition reads as follows: $var(\hat{y}_{i\tau}) = var(\hat{\alpha}_i) + var(\hat{\phi}_{J(i\tau)}) + var(\hat{\beta}'_{i\tau}) + 2cov(\hat{\alpha}_i, \hat{\phi}_{J(i\tau)}) + 2cov(\hat{\alpha}_i, \hat{\beta}'_{i\tau}) + 2cov(\hat{\phi}_{J(i\tau)}, \hat{\beta}'_{i\tau}) + var(\hat{\epsilon}_{i\tau})$. See appendix A for more details.

3.2. Descriptives on potential channels

3.2.1. Differences between sectors

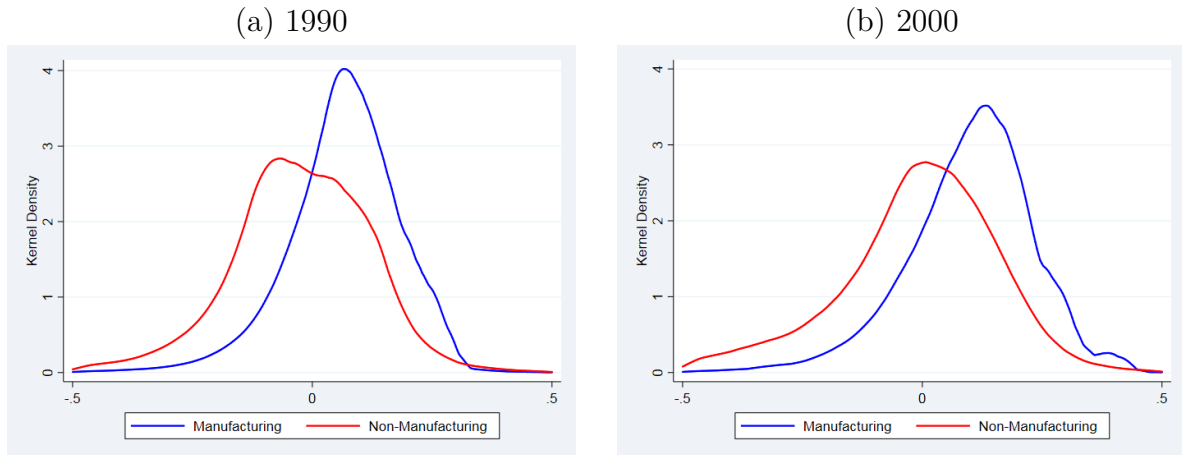
The first main descriptive finding is that the absolute size and the dispersion of firm wage premiums differ between the manufacturing and the non-manufacturing sector. Figure 2 plots the employment-weighted distribution of estimated firm wage premiums in 1990 and 2000, separately by sector. First, it shows that estimated firm wage premiums on average are higher in the manufacturing sector. In 1990, the difference in the employment-weighted average firm wage premium between the manufacturing and the non-manufacturing sector amounts to ten log points. A plausible explanation for the difference in levels across sectors is the higher collective bargaining density in manufacturing, illustrated for example by Oberfichtner and Schnabel (2018). Hirsch and Mueller (2018) provide evidence that German firms bound by collective bargaining agreements and firms with a works council pay higher wage premiums on average.

Additionally, figure 2 illustrates that the distribution of firm wage premiums in the non-manufacturing sector is larger than in the manufacturing sector. In particular, the upper part of the distribution within the non-manufacturing sector overlaps with parts of the distribution in the manufacturing sector. This means that the non-manufacturing sector contains a segment of high-paying firms which offer wage premiums that are comparable to or higher than in the average manufacturing firm. However, it also contains a segment of low-paying firms which offer substantially lower wage premiums than in manufacturing. Partly, the dispersion within non-manufacturing reflects a divide between high-end service industries and low-skill service industries. For example, in 1990, the mean firm wage premium in a service industry like financial intermediation (0.10) is slightly higher than in the average manufacturing firm (0.07). In contrast, the mean wage premium in the hotel industry (-0.28) is substantially lower. Table A1 in the appendix provides a list of mean firm wage premiums in selected industries. It is, however, important to note that firm wage premiums also vary substantially within industries, as reflected by the high standard deviations in table A1.¹⁴

Overall figure 2 illustrates the large heterogeneity in estimated firm wage premiums. The mean firm wage premium within the upper tercile in the economy in 1990 is about 50 (20) log points higher than the mean wage premium in the lower (middle) tercile. For comparison, the wage gap between a worker at the 75th and a worker at the 25th percentile in the raw data in 1990 (2000) amounts 43 (50) log points. Mobility between firms located at different part of the distribution of firm wage premiums therefore corresponds to substantial mobility in the overall earnings distribution.

¹⁴The pattern which is illustrated by figure 2 is robust across time. Figure A3 shows the same result for the year 2010.

Figure 2: Firm wage premiums: manufacturing vs. non-manufacturing



Notes: The figure depicts the employment-weighted distribution of estimated firm wage premiums in 1990 and 2000, separately for the manufacturing and the non-manufacturing sector. Multiply the numbers on the horizontal axis by 100 to obtain log points. See section 2 for a more detailed explanation of the data preparation and wage decomposition.

3.2.2. Access to high-paying non-manufacturing firms

The second main descriptive result suggests that low-skilled manufacturing workers have less access to high-paying non-manufacturing firms than high-skilled manufacturing workers. In what follows, I focus on manufacturing workers aged 20-50 in 1990 or 2000 (the base years t) in full-time employment and follow these workers over a period of ten years. With these restrictions, I end up with two intervals (1990-2000, 2000-2010) that contain a total of 3,369,473 worker-base year observations.¹⁵ Based on the estimated worker components, I group workers into three terciles, separately for both base years: high-wage, medium-wage, and low-wage workers.

Panel (a) of figure 3 shows that high-wage, medium-wage, and low-wage workers differ in terms of observable characteristics. High-wage workers on average have a higher level of formal education than medium-wage and low-wage workers. Panel (a) of figure 3 also shows that the worker groups differ in terms of the tasks they perform on the job. Low-wage workers on average perform more routine-intensive and codifiable tasks than medium-wage and high-wage workers. The variables for the tasks content of work are based on the worker's occupation.¹⁶

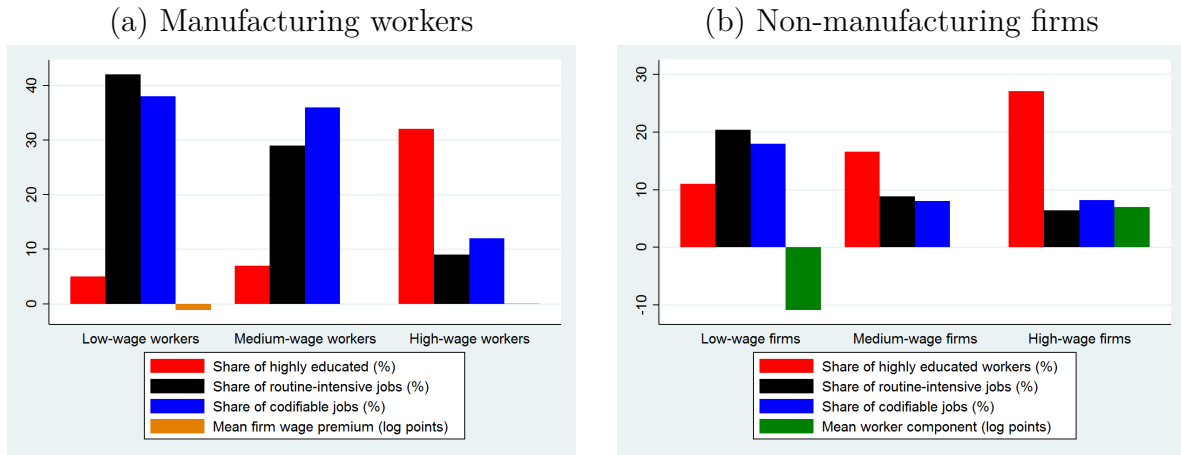
Finally, panel (a) of figure 3 suggests that high-wage, medium-wage, and low-wage manufacturing workers on average are employed in firms that pay similar wage premiums

¹⁵See table A2 for basic summary statistics on the resulting sample.

¹⁶I use the 1985/86 BIBB/BAuA 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.

in the base years. This means that there is only little or not sorting by skill across high-paying and low-paying manufacturing firms in the base years. More specifically, the figure plots the mean firm wage premium for low-wage and high-wage workers, as a deviation from the mean firm wage premium of medium-wage workers. It turns out that the mean firm wage premium is virtually identical across all skill groups.¹⁷

Figure 3: Characteristics of workers and firms



Notes: Workers (firms) are grouped into terciles according to the estimated worker component (firm wage premium) in equation 1. $N=3,369,473$ manufacturing workers in panel in panel (a). $N=1,478,790$ non-manufacturing firms (b). The mean firm wage premium in panel (a) is displayed as a deviation from the mean firm wage premium of medium-wage workers. The mean worker component in panel (b) is displayed as a deviation from the mean worker component in medium-wage firms. Values in panel (a) refer to the base years t (1990 and 2000). Values in panel (b) refer to $t + 10$. See section 2 for a more detailed explanation of the data preparation and wage decomposition.

Table 1 suggests that low-wage workers who reallocate into the non-manufacturing sector have lower access to high-paying non-manufacturing firms than reallocating high-wage workers. This table provides a look at reallocation into the non-manufacturing sector between the years t and $t + 10$ for the sample of manufacturing workers in t . Overall, 14.6% of the manufacturing workers move into the non-manufacturing sector between years t and $t + 10$. Columns (2)-(4) provide evidence that most of this mobility is absorbed by high-wage non-manufacturing firms, i.e. firms which belong to the top tercile of the distribution of firm wage premiums in the economy in $t + 10$. Table 1 hints at substantial differences between workers of different skill groups in the reallocation into high-paying and low-paying non-manufacturing firms. The vast majority of high-wage workers who reallocate into non-manufacturing move to high-wage firms. In contrast, low-wage workers more often move to low-wage non-manufacturing firms. In fact, for low-wage workers, mobility is relatively balanced across the firm types with equal shares of worker moving to high-wage, medium-wage, and low-wage firms. To the extent that the

¹⁷Table A3 in the appendix provides additional summary statistics on the different skill groups. It shows for example that high-wage workers on average are employed in more skill-intensive occupations.

descriptive findings in table 1 reflect lower access to high-paying non-manufacturing firms for low-skilled manufacturing workers, a contraction of the non-manufacturing causes an increase in sorting and wage inequality. Table A5 further differentiates between initial firm types in the manufacturing sector. The basic conclusion remains unchanged.

Table 1: Reallocation into non-manufacturing and sorting

Manufacturing in t	Non-manufacturing in $t + 10$ (%)			
	Firm type:			
	All firms	High-wage	Medium-wage	Low-wage
	(1)	(2)	(3)	(4)
All workers	14.6	6.8	4.6	3.2
High-wage workers	13.0	8.6	3.0	1.4
Medium-wage workers	13.9	6.4	4.7	2.8
Low-wage workers	16.7	5.5	5.8	5.4

Notes: N=3,369,473. Sample includes full-time employed manufacturing workers aged 20-50 in 1990 or 2000 (t). Column (1) shows the share of workers who are full-time employed in the non-manufacturing sector in $t + 10$. Columns (2)-(4) split up the share from column (1) into employment by high-wage, medium-wage, and low-wage firms (terciles of the distribution of firm wage premiums in $t + 10$). See section 2 for a more detailed explanation of the data preparation and wage decomposition.

Panel (b) of figure 3 supports the idea that low-wage manufacturing workers have lower access to high-paying non-manufacturing firms from a different angle. It provides evidence that high-paying non-manufacturing firms produce more skill-intensive than low-paying non-manufacturing firms. High-wage non-manufacturing firms employ a higher share of workers with high formal education than medium-wage and low-wage firms in $t + 10$. In addition, the figure suggests that high-wage firms employ a lower share of workers that perform routine-intensive and codifiable tasks than medium-wage and low-wage firms. As a consequence, high-wage non-manufacturing firms also employ workers with a higher estimated worker component on average.

The differences in panel (b) of figure 3 might be driven by inherent differences in the skill requirements between firms and industries. Additionally, they might accrue endogenously, for example in response to technological progress which decreases the number of routine and codifiable jobs at high-paying non-manufacturing firms (Autor et al. 2003). Spitz-Oener (2006) provides evidence that computerization triggered a decrease in routine jobs and educational upgrading in Germany. The pattern in (b) of figure 3 suggests that this process did not take place uniformly across high-paying and low-paying non-manufacturing firms industries. Acemoglu (1999) provides a model in which technological change can trigger an increase in the segregation of skills across heterogeneous firms.

4. Conceptual framework

The previous descriptive results indicate a potential link between a contraction of the manufacturing sector and economy-wide labor market sorting. To fix ideas, this subsection provides a conceptual framework which serves to illustrate this link and which guides the subsequent empirical analysis.

4.1. Firms

Consider an economy which consists of four firms: one manufacturing firm and three non-manufacturing firms. Suppose that wages in this economy are additive in a worker component and a firm wage premium, as in equation 1. The manufacturing firm pays a wage premium of ψ_{Man} . The non-manufacturing sector consists of one high-wage firm, one medium-wage firms, and one low-wage firm, where $\psi_{Non}^H > \psi_{Non}^M > \psi_{Non}^L$. Further, suppose that the wage premium in the high-wage non-manufacturing firm is equal to the wage premium in the manufacturing firm: $\psi_{Man} = \psi_{Non}^H > \psi_{Non}^M > \psi_{Non}^L$. Under the assumption that each firm employs a mass of workers larger than zero, this set-up captures the descriptive results from figure 2 in a stylized way. First, the employment-weighted average firm wage premium is larger in the manufacturing than in the non-manufacturing sector. Second, the distributions of the two sectors overlap, such that the non-manufacturing sector contains a segment of firms that pay wage premiums comparable to the manufacturing sector.

In the AKM estimation of 1, the estimated firm wage premiums constitute dummy variables which need to be interpreted relative to a reference group. In what follows, I will treat the medium-wage non-manufacturing firm as the reference group, such that $\psi_{Non}^M = 0$ and $\psi_{Non}^L < 0$ by construction.

4.2. Workers

The manufacturing sector contains low-skilled and high-skilled workers, each with a mass of one. The worker component of the wage for high-skilled workers exceeds the worker component of the wage for low-skilled workers: $\alpha^H > \alpha^L$. Consistent with the descriptives in panel (a) of figure 3, one can think of the differences in the worker component as the result of differences in formal education and tasks performed on the job. By construction, this stylized economy captures the descriptive result in panel (a) of figure 3 that high-skilled and low-skilled workers in the manufacturing sector are employed in firms that pay very similar wage premiums, i.e. there is very little or no sorting by skill in the manufacturing sector in the base years. For simplicity of the exposition, I abstract from initial employment in the non-manufacturing sector and assume that all workers are

employed in the manufacturing sector.¹⁸

4.3. Sorting and wage inequality

In this simple framework, a natural measure for the degree of sorting by skill across high-paying and low-paying firms in the economy is the difference in average firm wage premiums across skill groups. By construction, this difference amounts to zero in this economy. Wage inequality, therefore is captured exclusively by the difference in the worker components across high-skilled and low-skilled workers.

4.4. Labor reallocation, sorting, and wage inequality

Now suppose that a share of low-skilled workers (β^L) and a share of high-skilled workers (β^H) is being displaced from the manufacturing firm and reallocates into the non-manufacturing sector. Importantly, I assume that this share is equal across both skill groups: $\beta^L = \beta^H = \beta$. This (skill-unbiased) reallocation into the non-manufacturing sector can be the result of labor-saving technological progress in the manufacturing sector, lower demand for manufacturing goods in the context of non-homothetic preferences and rising incomes, or any negative demand shock on the manufacturing sector, for example from increased import competition.

Conditional on being displaced from the manufacturing sector, high-skilled (low-skilled) workers move to the high-wage non-manufacturing firm with probability κ^H (κ^L) and to the medium-wage non-manufacturing firm with probability λ^H (λ^L). With the remaining probability of $1-\kappa^H-\lambda^H$ ($1-\kappa^L-\lambda^L$), high-skilled (low-skilled) workers move to the low-wage manufacturing firm.

The descriptives on labor reallocation and sorting in table 1 as well as the descriptives on the composition of non-manufacturing firms in panel (b) of figure 3 suggest that $\kappa^H > \kappa^L$. In other words, conditional on reallocating into the non-manufacturing sector, high-skilled workers are more likely to move to the high-paying non-manufacturing firm than low-skilled workers. They also suggest that $(1-\kappa^L-\lambda^L) > 1-\kappa^H-\lambda^H$, i.e. conditional on moving into the non-manufacturing sector, low-skilled workers are more likely to move to a low-wage firm. I assume that the worker components of the wage, α^H and α^L , remain unaffected by the labor reallocation. The effects on sorting therefore translate one-to-one into effects on wage inequality.¹⁹

¹⁸An alternative would be to assume that workers initially employed in the non-manufacturing sector are unaffected by the subsequent labor reallocation. See section 4.4.

¹⁹This assumption is consistent with the empirical exercise which isolates the effects coming from relative gains and losses of firm wage premiums. There are reasons to expect that changes in worker components work into the same direction, contributing to the rise in wage inequality. See for example Cravino and Sotelo (2019) who argue that a decline of the manufacturing sector raises the skill premium because the non-manufacturing sector is more skill-intensive than the manufacturing sector. In an AKM framework, this would show up as an increase in $(\alpha^H - \alpha^L)$.

How does labor reallocation in this context affect sorting? Provided that initial sorting as measured by the difference in firm wage premiums between skill groups is zero by construction, the change in sorting is given by the difference in expected average firm wage premiums across skill groups. For high-skilled workers, the expected average firm wage premium after reallocation reads:

$$E(\psi|H) = \beta[\kappa^H \psi_{Non}^H + (1 - \kappa^H - \lambda^H) \psi_{Non}^L] + (1 - \beta) \psi_{Man} \quad (2)$$

Setting up an analogous equation for low-skilled workers, taking the difference, and simplifying the resulting terms, one obtains the expected increase in sorting and wage inequality:

$$E(\psi|H) - E(\psi|L) = \beta[(\kappa^H - \kappa^L) \psi_{Non}^H - (\kappa^H - \kappa^L + \lambda^H - \lambda^L) \psi_{Non}^L] \quad (3)$$

This equation provides several important insights. For a given dispersion of firm wage premiums, reflected by the absolute size of ψ_{Non}^H and ψ_{Non}^L (<0), the sorting and wage inequality effects of a given labor reallocation ($\beta > 0$) increase with the extent to which high-skilled workers are more likely to move to high-wage firms ($\kappa^H > \kappa^L$) and to medium-wage firms ($\lambda^H > \lambda^L$) than low-skilled workers. If high-skilled and low-skilled workers were equally likely to move to the respective different non-manufacturing firms ($(\kappa^H = \kappa^L)$ and $(\lambda^H = \lambda^L)$), skill-unbiased labor reallocation would not affect sorting. It is important to note that the effects on sorting and wage inequality between skill groups do not depend on the absolute size of the parameters κ^H , κ^L , λ^H and λ^L .²⁰ Finally, for a given difference in firm wage premiums within non-manufacturing and a given $(\kappa^H - \kappa^L)$ and $(\lambda^H - \lambda^L)$, the sorting and wage inequality effects increase with β , the share of workers who reallocate in response to a given shock.

In a last step, I bring β into the brackets and obtain an equation which can be used to perform a back-of-the-envelope calculation of the effects of a given labor reallocation on sorting and wage inequality:

$$E(\psi|H) - E(\psi|L) = [(\beta\kappa^H - \beta\kappa^L) \psi_{Non}^H - (\beta\kappa^H - \beta\kappa^L + \beta\lambda^H - \beta\lambda^L) \psi_{Non}^L] \quad (4)$$

The empirical analysis will yield estimates for β as well as for $(\beta\kappa^H - \beta\kappa^L)$ and $(\beta\lambda^H - \beta\lambda^L)$. The latter two terms reflect the differences in the probability to reallocate to a high-wage and medium-wage non-manufacturing firm in response to a given shock with

²⁰The effects on absolute wages, however, depend on the absolute sizes of κ^H , κ^L , λ^H and λ^L , as they govern the likelihood to experience wage losses through mobility to firms paying lower wage premiums as the manufacturing firm. Additionally, their size affects the effects on wage inequality within the groups of high-skilled and low-skilled workers. In the empirical exercise, I focus on sorting and wage inequality between skill groups as defined by the estimated worker components, formal education, and tasks performed on the job.

a given β . Together with the estimated firm wage premiums, this gives rise to a back-of-the-envelope calculation of the sorting and wage inequality effects of a labor reallocation with a given β . The empirical exercise identifies sorting and wage inequality effects for manufacturing workers. To end up with an estimation for economy-wide sorting and wage inequality, the results can be scaled down by the manufacturing employment share. Implicitly, this is to assume that sorting and wage inequality among the group of incumbent non-manufacturing workers and new entrants is not affected by labor reallocation from manufacturing into non-manufacturing.

The conceptual framework imposes $\beta^L = \beta^H = \beta$ because the empirical exercise identifies a shock whose initial effect of bringing workers into the non-manufacturing sector is similar across skill groups. Table 1, however, suggests that less skilled workers are more likely to move into the non-manufacturing sector, i.e. $\beta^H < \beta^L$. Given that low-wage manufacturing workers more often perform routine-intensive tasks (see figure 3), this pattern is consistent for example with technological progress adversely affecting workers performing routine-intensive tasks as in Autor et al. (2003). To the extent that a given labor reallocation is biased against low-skilled workers, the estimates for the effects on sorting and wage inequality in this paper are a lower bound for the total effect.

5. Identifying the link between labor reallocation and sorting

The differential mobility pattern between skill groups documented in the descriptive table 1 do not necessarily reflect the mechanism outlined in section 4. Overall labor reallocation into the non-manufacturing sector is most likely a cause of a variety of different shocks, or more generally speaking, reflects a variety of different causes. The differences in the mobility pattern therefore can be driven for example by high-skilled and low-skilled workers being affected by different types shocks.

The main empirical analysis identifies a shock which has a common initial effect across all skill groups by bringing them into the non-manufacturing sector at higher rates ($\beta \approx \beta^H \approx \beta^L > 0$). Conditioning on a variety of controls at the worker, firm, industry, and regional level, this shock allows to test whether, all else being equal, more skilled workers are more likely to move to high-paying non-manufacturing firms than low-skilled workers in response to this shock ($\beta \kappa^H > \beta \kappa^L$).

5.1. Trade-induced labor reallocation

Analogously to the descriptives on labor reallocation in section 3.2.2, I focus on manufacturing workers aged 20-50 in 1990 or 2000 (the base years t) in full-time employment

and follow these workers over a period of ten years. I estimate variants of the following specification:

$$Non_i^{t+10} = \beta \Delta NetImp_k^{t,t+10} + \xi X_{ikt} + \epsilon_{ikt} \quad (5)$$

Non_i^{t+10} is a dummy variable which has the value 1 if worker i initially employed in manufacturing industry k in year t is full-time employed in the non-manufacturing sector in year $t+10$. The main explanatory variable in this regression is the change in net import exposure in industry k in which worker i is initially employed in year t :

$$\Delta NetImp_k^{t,t+10} = \frac{\Delta Imports_k^{t,t+10} - \Delta Exports_k^{t,t+10}}{10,000 \times WageSum_{kt}}$$

$\Delta NetImp_k^{t,t+10}$ captures the extent to which industry k experiences net import exposure from China and Eastern Europe during t and $t+10$ and is defined as the increase in net imports ($\Delta Imports_k^{t,t+10} - \Delta Exports_k^{t,t+10}$) normalized by the initial industry wage bill to control for size differences across industries.²¹

Variation in the growth of net import exposure creates quasi-exogenous variation in trade-induced labor reallocation into the non-manufacturing sector. To the extent that growing net import exposure constitutes a negative demand shock on the industry, it generates increasing rates of displacement at the initial firm for all skill groups. In the light of the ongoing contraction of the manufacturing sector, displaced workers are expected to move into the non-manufacturing sector rather than into other manufacturing sectors. Growing net import exposure therefore is expected to accelerate the ongoing process of structural change. The opposite is true for growing net export exposure. The effects of growing net export exposure can work through different channels. First, the positive demand shock associated with growing export opportunities might (partly) offset any negative demand shock and thereby translate into a positive job stability effect for workers, relative to workers in industries which do not experience an increase in exports. Second, growing exports might decelerate labor reallocation in response to labor-saving technological progress. This is because, in the context of strong unions, it might be harder to justify layoffs in the presence of a substantial positive demand shock stemming from increased exports.²²

I allow the effects to differ across skill groups by interacting the growth of net import exposure in equation 5 with indicators for the skill level of a worker. If the coefficients

²¹From the perspective of the domestic 3-digit industry, $\Delta Import_k^{t,t+10}$ 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.

²²Figure A4 graphically illustrates the variation in net import exposure in the sample. Figure A5 illustrates the rapid increase in exports to and imports from China and Eastern Europe, starting in the early 1990s. The extent of this trade shock was not anticipated and trade with China and Eastern Europe grew much stronger as trade with the rest of the world, as illustrated by panel (b) of figure A5. Table A6 further provides a list of top exporting and importing industries.

on the interaction effects are close to zero and statistically insignificant, the effects of growing net import exposure on reallocation into the non-manufacturing sector are equal across skill groups, i.e. $\beta \approx \beta^H \approx \beta^L > 0$.

X_{ikt} contains control variables at the worker, firm, industry, and regional level, held constant at the base year t . It contains dummies for worker types and initial firm types (terciles), dummies for age groups (30-40 and 40-50 years of age in the base year), a dummy for high formal education (college or university degree), binary variables for performing routine-intensive and codifiable tasks and dummies for tenure (2-5 and >5 years). X_{ikt} also includes firm size dummies (number of employees: 10-100, 100-1,000, >1,000) and dummies for broad industry groups (food, consumer goods, capital goods, with production goods being the reference group). Finally, X_{ikt} contains dummies for labor market regions.

5.2. Trade-induced labor reallocation and sorting

To study the effects on sorting across high-paying and low-paying firms within the non-manufacturing sector, I modify the dependent variable:

$$PremiumNon_i^{t+10} = \beta \Delta NetImp_k^{t,t+10} + \xi X_{ikt} + \epsilon_{ikt} \quad (6)$$

$PremiumNon_i^{t+10}$ is equal to 1 if the worker is full-time employed by a given firm type (high-wage, medium-wage, or low-wage) in non-manufacturing in $t + 10$. The firm type reflects the tercile of the firm in the distribution of firm wage premiums in the economy in $t + 10$.

Trough interaction effects of net import exposure with dummies for skill groups, this specification allows to test whether certain skill groups are more or less likely to move to a high-paying non-manufacturing firms than others in response to the shock. For example, it allows to test whether $\beta \kappa^H > \beta \kappa^L$. I also employ the estimated firm wage premium in $t + 10$ as an alternative outcome variable.

Overall, the goal of equations 5 and 6 is to implicitly compare workers who have very similar demographic characteristics, are initially employed in similar firms and industries in the same local labor market, but are differently affected by Germany's trade integration with China and Eastern Europe due to differences in industry affiliation in year t . Through the interaction effects of growing net import exposure, I make this kind of comparison separately for different skill groups and thereby allow the estimated effect to differ across skill groups. In that sense, the estimation resembles a triple-differences regression which compares trade-exposed to non-exposed workers over time, separately by skill group.²³ In the baseline specification, I interact net import exposure with dummies for worker

²³See Dauth et al. (2019a) for a similar empirical exercise in the context of trade with China and Eastern Europe. They, however, do not analyze sorting into high-paying and low-paying non-manufacturing firms.

types as reflected by terciles of the estimated firm components in the base year (high-wage, medium-wage, and low-wage workers). At a later stage, I employ interactions with variables for formal education and tasks performed on the job.

In the baseline estimates, I pool all workers in the manufacturing sector, regardless of the firm wage premium of the initial firm of employment. In an extension, I differentiate between effects on workers initially employed in high-paying and low-paying manufacturing firms. This differentiation allows to provide a closer look at whether workers experience gains and losses of firm wage premiums upon moving into non-manufacturing.

5.3. Instruments

Remaining threats to identification are industry-level demand and productivity shocks which might be correlated with trade exposure and at the same time influence the workers' mobility pattern. For example, in the context of domestic demand shocks which drive increased imports, the point estimates of increasing net import exposure will be biased towards zero. I apply the instrumental variable strategy pioneered by Autor et al. (2014) and adapted to the German context by Dauth et al. (2019a) More specifically, I instrument growing net import exposure with growing net import exposure on a group of instrument countries:

$$\Delta NetImp_k^{t,t+10,Ins} = \frac{\Delta Imports_k^{t,t+10,Ins} - \Delta Exports_k^{t,t+10,Ins}}{10,000 \times WageSum_{kt}}$$

where $\Delta Imports_k^{t,t+10,Ins} - \Delta Exports_k^{t,t+10,Ins}$ denotes the increase in net imports from China and Eastern Europe in industry k 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 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 net imports in these industries, but also in other high-income countries. Then, instrumenting German industry-level net import exposure with industry-level net import exposure of these high-income countries should isolate the exogenous increase in net import exposure that is related to the productivity growth in China and Eastern Europe. For this strategy to be valid, net import exposure of the instrument countries must not have a direct 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 USA. See also Autor et al. (2014) and Dauth et al. (2014) for a discussion. To instrument for the interaction effects in the regression, I employ interactions of the instrument with dummies for skill groups.

6. Results

6.1. Baseline estimates

Table 2 provides the main estimates. Panel (a) starts with a simple specification without interaction effects and therefore captures the average effect across all skill groups. Panels (b) and (c) allow the estimates to differ across skill groups.

Column (1) of panel (a) provides evidence that net import exposure does generate structural change in the form of labor reallocation from manufacturing into non-manufacturing. The estimate suggests that manufacturing workers who experience a stronger increase in net import exposure between t and $t + 10$ are more likely to be employed in the non-manufacturing sector in $t + 10$. To gauge the magnitude of the effect, compare a worker at the 75th percentile of increasing net import exposure (0.02) to a worker at the 25th percentile (-0.10). The point estimate implies a 1.3 percentage points higher probability for the former group to be employed in non-manufacturing in $t + 10$ ($0.11 * 0.12 \approx 0.013$). This effect amounts to almost ten percent of the raw probability of moving into non-manufacturing (or mean dependent variable) of 14.6% displayed in table 1. Variation in net import exposure therefore generates non-negligible variation in labor reallocation. Columns (2)-(4) decompose the point estimate of 0.11 into the effects of being employed by a high-wage, medium-wage, and low-wage non-manufacturing firm in $t + 10$. It turns out that most of the mobility into the non-manufacturing sector is absorbed by high-wage firms. Finally, column (5) employs the estimated firm wage premium in $t + 10$ as a dependent variable. Consistent with the finding that the level of firm wage premiums is lower in non-manufacturing (see figure 2), net import exposure goes along with lower firm wage premiums on average in $t + 10$.

Turning to the estimates in panel (b), column (1) shows that the initial effect of bringing workers into the non-manufacturing sector is very similar across skill groups. The estimated interaction effects are positive, but small and statistically insignificant. This result is consistent with the idea the increased import exposure constitutes a negative demand shock on the industry which increases the likelihood of displacement for all skill groups. Referring to the conceptual framework in section 4, this result corresponds to $\beta^L \approx \beta^H$. Table A7 in the appendix confirms this result from a different angle. It shows that the negative effect of import exposure on employment in the initial firm and in the manufacturing sector is virtually identical across skill groups. The slightly positive (but statistically insignificant) interaction effects in column (1) of table 2 are mirrored by a

slightly higher probability of less skilled workers to be out of the sample in $t + 10$.

While the initial effect of bringing workers into the non-manufacturing sector is identical across skill groups, the resulting allocation within the non-manufacturing sector is not. Columns (2)-(4) provide evidence that high-skilled and low-skilled workers sort into different tails of the distribution of firm wage premiums in the non-manufacturing sector. Column (2) shows that high-wage workers are substantially more likely to reallocate to a high-wage non-manufacturing firm than low-wage workers. The point estimate for high-wage workers ($0.04+0.06=0.1$) is 2.5 times bigger than the point estimate for low-wage workers (0.4) and is statistically significant. Column (4) shows that low-wage workers, in contrast, are more likely to move to low-wage non-manufacturing firms than high-wage workers.

Finally, column (5) of panel (b) displays the differential effects on the firm wage premium in $t + 10$. In response to increased import exposure, low-wage workers experience a decrease in the firm wage premium in $t + 10$. High-skilled workers, in contrast, are better able to move to high-wage non-manufacturing firms and therefore manage to reallocate into the non-manufacturing sector without major losses in firm wage premiums. As a consequence, this result suggests that labor reallocation generates an increase in sorting and wage inequality as high-skilled workers are relatively more likely to transition into well-paying non-manufacturing firms. Panel (c) shows that the OLS/LPM estimates are qualitatively very similar. Consistent with the idea that part of the observed increase in imports are in fact driven by a rise in domestic demand, the point estimates are slightly lower.²⁴

A natural question to ask is whether sorting would also have increased to the same extent if workers remained within the manufacturing sector. First, note that the scope for an increase in sorting within the manufacturing sector is constrained by the lack of low-paying firms in the manufacturing sector, as illustrated by figure 2. The figure shows that most of the low-wage firms in the economy are non-manufacturing firms. However, it is still possible that, in absence of the shock causing labor reallocation into non-manufacturing, low-wage workers disproportionately move to low-paying manufacturing firms, with an increase in sorting as the result. Column (1) of table A7 in the appendix provides evidence that this is not the case. The result suggests that, in absence of the shock, workers of all skill groups remain in their initial manufacturing firm. Finally, note that the results in table 2 pool all manufacturing workers and thereby abstracts from the dispersion of firm wage premiums within the manufacturing sector. Table A8 in the appendix provides separate results for workers initially employed in high-wage, medium-wage, and low-wage manufacturing firms. The basic results remain unchanged. See section 7 for an explanation.

²⁴The first stages are strong with F statistics of more than 200. Figure A7 in the appendix shows a visual representation of the first stage relationship for export and import exposure.

Table 2: Baseline estimates

Dependent variable:	(1)	(2)	(3)	(4)	(5)
	All firms	High-wage	Medium-wage	Low-wage	Premium in $t + 10$
[2SLS]	(a) Average effects across all skill groups				
Δ NetImp	0.11*** (0.03)	0.07*** (0.02)	0.03*** (0.00)	0.01** (0.00)	-0.03** (0.01)
R2	0.05	0.03	0.02	0.02	0.47
[2SLS]	(b) Sorting by skill group (2SLS)				
Δ NetImp	0.10*** (0.02)	0.04*** (0.01)	0.03*** (0.01)	0.03*** (0.01)	-0.06*** (0.02)
Δ NetImp*Medium-wage worker	0.02 (0.01)	0.03** (0.01)	0.00 (0.00)	-0.01*** (0.00)	0.02*** (0.01)
Δ NetImp*High-wage worker	0.02 (0.03)	0.06** (0.03)	-0.01*** (0.01)	-0.02*** (0.01)	0.05*** (0.01)
R2	0.05	0.03	0.02	0.02	0.47
[OLS]	(c) Sorting by skill group (OLS)				
Δ NetImp	0.07*** (0.01)	0.03*** (0.01)	0.02*** (0.00)	0.02*** (0.01)	-0.02*** (0.01)
Δ NetImp*Medium-wage worker	0.01 (0.01)	0.01 (0.01)	-0.00 (0.00)	-0.00 (0.00)	0.01** (0.01)
Δ NetImp*High-wage worker	0.01 (0.01)	0.03** (0.01)	-0.01*** (0.00)	-0.01** (0.01)	0.03** (0.01)
R2	0.05	0.03	0.02	0.02	0.47

Notes: N=3,369,473. See equations 5 and 6. Sample includes full-time employed manufacturing workers aged 20-50 in 1990 or 2000 (t). In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t + 10$. In column (2), the dependent variable is 1 if the worker is employed in a high-wage non-manufacturing firm in $t + 10$ (top tercile of the distribution of firm wage premiums in $t + 10$). Analogously for columns (3) and (4). Column (5) shows the results with the estimated firm wage premium in $t + 10$ as a dependent variable. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 2 and 5 for a more detailed explanation. Levels of statistical significance: *10%, **5%, ***1%.

6.2. Back-of-the-envelope calculation

What do the estimates in table 2 imply for the effects of labor reallocation on sorting and wage inequality? Note that the trade shock on net does not explain any of the labor reallocation and sorting, because the increase in import exposure on average is negative and close to zero (see table A2). This result is consistent with Dauth et al. (2014) and Dauth et al. (2019a) who argue that increased trade with China and Eastern Europe on net has retained German manufacturing jobs.

However, variation in trade exposure across industries generates variation in labor reallocation which allows to draw conclusions about the effects of labor reallocation on sorting. A potential exercise is to compute the change in sorting that would have occurred if all the labor reallocation observed in the data were driven by the shock with the properties displayed in table 2.

Based on equation 4 derived in section 4, one can use the interaction effects in columns (2) and (3) of panel (b), which yield estimates for $(\beta\kappa^H - \beta\kappa^L)$ and $(\beta\lambda^H - \beta\lambda^L)$, as well as the average difference in firm wage premiums between firm types at $t + 10$ ($\psi_{Non}^H = 21.5$, $\psi_{Non}^L = -35.2$), to obtain a back-of-the-envelope calculation on the sorting and wage inequality effects.²⁵ Two adjustments need to be made. First, the interaction effects in table 2 refer to a shock which brings roughly 10% of workers into the non-manufacturing sector (see column (1)). I scale up the effect by the factor of 1.46 to match the observed probability of moving into the non-manufacturing sector of 14.6% (table 1). Second, the estimates only refer to manufacturing workers and not to non-manufacturing workers. I therefore multiply the effect by the average manufacturing employment share in the sample (41%).²⁶

The estimates imply that the firm wage premium gap between low-wage and high-wage workers grew by 1.83 log points in response to labor reallocation between t and $t + 10$.²⁷ This corresponds to 31.0% of the rise in sorting as measured by the rise in the difference in average firm wage premiums between high-wage and low-wage workers between t and $t + 10$. Analogously, it corresponds to 11.3% of the rise in wage inequality as measured by the rise in the wage gap between high-wage and low-wage workers between t and $t + 10$.²⁸

An alternative back-of-the-envelope calculation relies on the effects on the continuous firm wage premium in column (5). The estimates in panel (b) of table 2 imply that a shock which brings 10% of the workers into the non-manufacturing sector (column 1) leads to a loss of firm wage premiums of 5 log points for low-wage workers relative to

²⁵See table A2 for an overview of the values that are necessary to conduct the back-of-the-envelope calculation.

²⁶This share is relatively high as the BeH do not include most of the workers in the public sector, for example civil servants. These workers are also not covered in Card et al. (2013). The aggregate statistics displayed in figure 1 include the public sector and therefore show a smaller manufacturing employment share.

²⁷ $[0.06 * 21.5 + (0.06 - 0.01) * 35.2] * 1.46 * 0.41 \approx 1.83$. See equation 4.

²⁸ $1.83/5.9 \approx 31.0\%$ and $1.83/16.2 \approx 11.3\%$.

high-wage workers (column 5). Scaling up to the observed probability of reallocation and adjusting for the manufacturing employment share as above, the effect implies a loss of firm wage premiums of 3.0 log points for low-wage workers relative to high-wage workers between t and $t + 10$.²⁹ This corresponds to 50.8% of the rise in sorting and 18.5% of the rise in wage inequality between t and $t + 10$.³⁰

In both alternatives, labor reallocation explains a substantial share of the rise in sorting and wage inequality. Note that in this back-of-the envelope calculation, I assume that worker components remain unchanged. Further, I assume that the allocation of workers initially employed in non-manufacturing across firms is not affected by the reallocation of manufacturing workers.

6.3. Sorting between versus within sectors

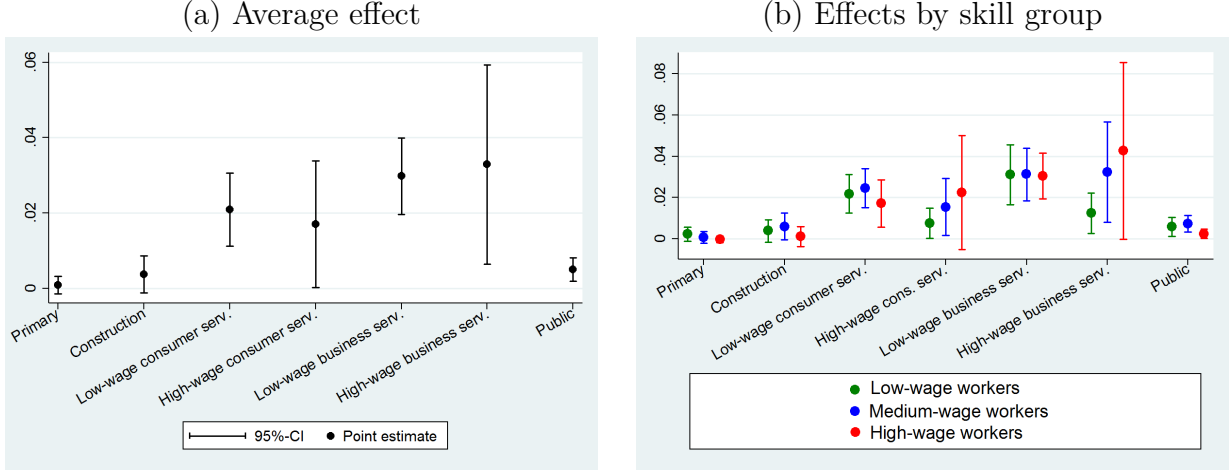
Firm wage premiums differ both between and within non-manufacturing industries. It is therefore natural to ask whether the estimates documented so far reflect sorting of high-skilled and low-skilled workers into high-paying and low-paying non-manufacturing industries versus sorting into high-paying and low-paying firms within non-manufacturing industries. It turns out that both is the case.

Sorting between industries. Figure 4 provides a look at sorting into different sub-sectors of the non-manufacturing sector. I divide the non-manufacturing sector into the following sub-sectors: the primary sector, the construction sector, low-wage business services (e.g. industrial cleaning), high-wage business services (e.g. financial intermediation), low-wage personal services (e.g. hotels), high-wage personal services (e.g. radio and television), and the public sector. I divide business and personal service industries into high-wage and low-wage based on the median firm wage premium within the respective group. Figure 4 provides the point estimates of the impact of increasing net import exposure on employment in one of these sub-sectors. Panel (a) first depicts the average effect across all skill groups. Not surprisingly, most of the workers reallocating into non-manufacturing move into business and personal service firms, with mobility into business services having a slightly higher probability. Panel (b) displays the point estimates of separate regressions by skill group. Even though, partly driven by the sample split, the confidence intervals are large, a clear pattern emerges. High-wage workers are substantially more likely to move into high-wage business service firms than less skilled workers. Less skilled workers, in contrast, are more likely to move into low-wage personal services, the construction sector, and the public sector. Therefore, a lower access for the least skilled workers to high-wage business service firms seems to be part of the explanation for the sorting effects of labor reallocation.

²⁹ $1.46 * 5 * 0.41 \approx 3.0$.

³⁰ $3.0/5.9 \approx 50.8\%$ and $3.0/16.2 \approx 18.5\%$.

Figure 4: Sorting between non-manufacturing industries



Notes: Panel (a) depicts the effect of the increase in net import exposure on full-time employment in one of the sub-sectors of non-manufacturing. Panel (b) provide separate estimates by worker type. High-wage (low-wage) consumer service industries are industries with a mean firm wage premium above (below) the median firm wage premium across all consumer service industries. Analogously for business service industries. Across all outcome variables, the point estimates sum up to the respective point estimate in table 2.

Table 3: Sorting within non-manufacturing industries

	(1)	(2)	(3)	(4)
Dependent variable: (ranking within industry)	Dummy: Non-manufacturing in $t + 10$			
	All	High-wage	Medium-wage	Low-wage
Δ NetImp	0.10*** (0.02)	0.06*** (0.02)	0.02** (0.01)	0.02* (0.01)
Δ NetImp*Medium-wage worker	0.02 (0.01)	0.03** (0.01)	0.00 (0.00)	-0.01*** (0.00)
Δ NetImp*High-wage worker	0.02 (0.03)	0.04** (0.01)	-0.01* (0.01)	-0.01** (0.01)
R2	0.05	0.03	0.02	0.02

Notes: N=3,369,473. In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t + 10$. In column (2), the dependent variable is 1 if the worker is employed in a firm with an estimated firm wage premium in the top tercile **within** the industry. Analogously for columns (3) and (4). Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 2 and 5 for a more detailed explanation. Levels of statistical significance: *10%, **5%, ***1%.

Sorting within industries. Table 3 provides evidence on the effects on sorting within non-manufacturing industries. In the underlying regressions, I construct the outcome vari-

ables in columns (2)-(4) by ranking firms by their estimated firm wage premium **within** industries. Table 3 provides two main insights. First, the relatively large point estimates for all skill groups in column (2) suggest that most of the mobility into the manufacturing sector is absorbed by the highest-paying firms in the respective target industry. Second, and more importantly for the question in this paper, high-skilled workers are relatively more likely to move into the highest paying firms within the respective industry than less skilled workers. To sum up, the results in figure 4 and table 3 provide evidence that the overall effects on sorting are the result of differential sorting between and within industries.

6.4. Effects on the skill premium and residual wage inequality

The descriptives in figure 3 show that high-wage workers on average have a higher level of formal education and perform more complex tasks than medium-wage and low-wage workers. In this section, I therefore analyze to what extent the differential effects across high-wage, medium-wage, and low-wage workers documented so far are driven by formal education and tasks performed on the job. This exercise is interesting in itself, but also provides evidence on the nature of wage inequality which is affected by labor reallocation. An increase in sorting upon formal education triggers a rise in the skill premium, whereas an increase in sorting upon tasks or occupations, conditional on formal education, triggers a rise in residual wage inequality.

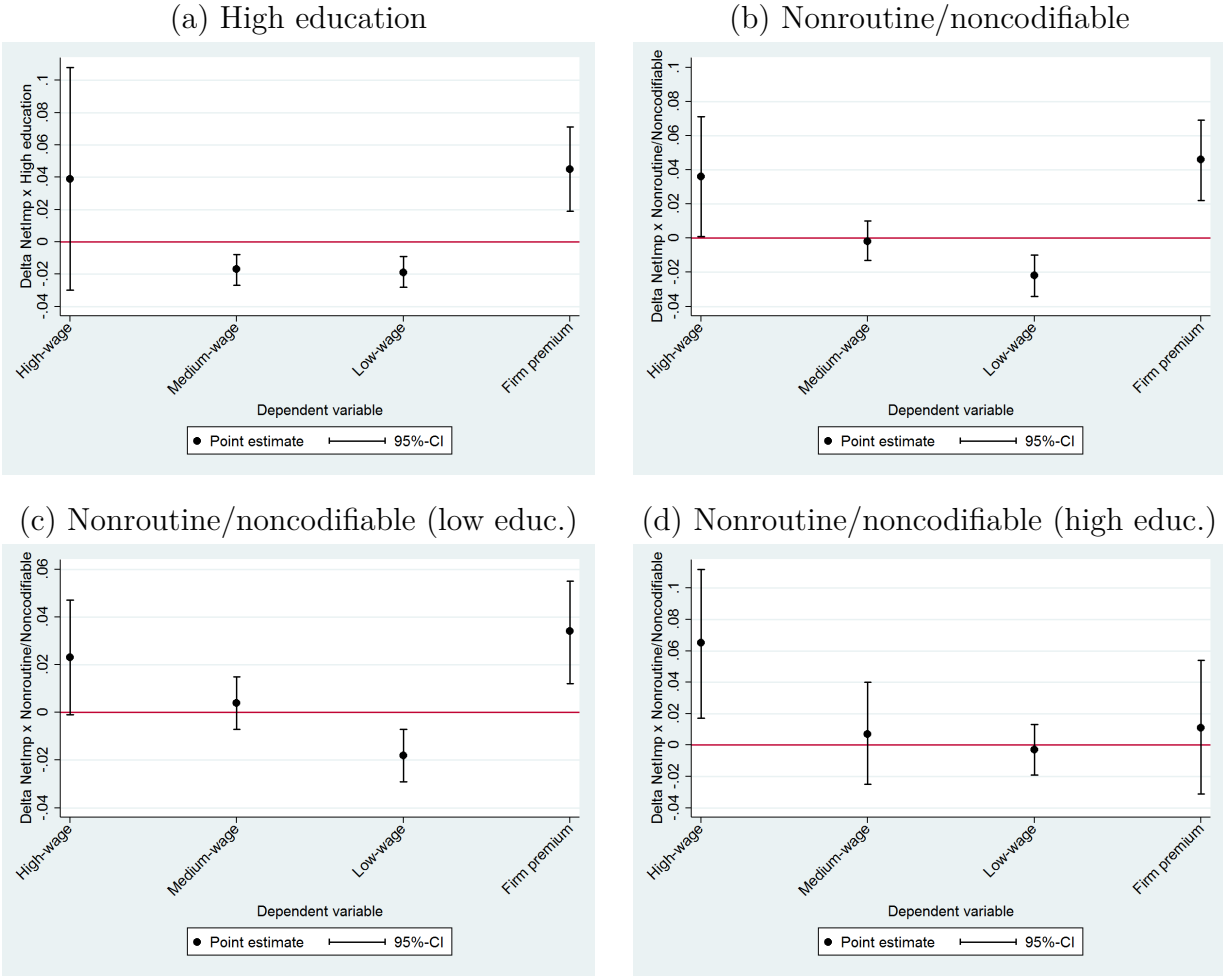
Panel (a) of figure 5 provides evidence that labor reallocation triggers a rise in sorting by formal education and thereby raises the skill premium. The figure plots the point estimates on the interaction effect of net import exposure with a dummy for formal education, for four different outcome variables: full-time employment by high-wage, medium-wage, and low-wage firms in the non-manufacturing sector as well as the estimated firm wage premium in $t + 10$. The estimates suggest that, in response to increasing net import exposure, workers with high formal education are relatively more likely to move to a high-paying and relatively less likely to move into a low-paying non-manufacturing firm. This translates into a relatively higher firm wage premium in $t + 10$ for workers with high formal education.

Panel (b) of figure 5 shows evidence in favor of increased sorting by tasks performed on the job in response to labor reallocation. Analogously to panel (a), the figure shows interactions of net import exposure with a dummy for performing non-routine and non-codifiable tasks at the manufacturing workplace. The figure suggests that workers who initially perform more complex tasks find it substantially easier to reallocate to a high-paying non-manufacturing firm than workers initially performing routine and codifiable tasks.

Panels (c) and (d) of figure 5 show that this effect is also present conditional on formal

education. The effect of tasks is especially strong within the group of workers with low formal education. It follows from panels (b)-(d) that labor reallocation also increases residual wage inequality as it favors workers who initially perform more complex tasks in the manufacturing sector.

Figure 5: The role of education and tasks



Notes: Panel (a) depicts the point estimate of the coefficient on the change in net import exposure interacted with a dummy for high formal education, for four different outcome variables: full-time employment by a high-wage, medium-wage, and low-wage non-manufacturing firm in $t + 10$ as well as the estimated firm wage premium in $t + 10$. Analogously, panel (b) provides estimates for interactions with a dummy for performing nonroutine and noncodifiable tasks. Panels (c) and (d) restrict the sample on workers with low and high formal education, respectively. See equations 5 and 6.

7. Robustness and Extensions

7.1. Upward versus downward mobility

Table A8 in the appendix provides separate estimates for worker initially employed in high-wage, medium-wage, and low-wage manufacturing firms in t . It thereby allows to differentiate between downward mobility from high-wage manufacturing towards low-wage non-manufacturing firms and upward mobility from low-wage and medium-wage manufacturing towards high-wage non-manufacturing firms. Due to the higher level of firm wage premiums in manufacturing as compared to non-manufacturing, and because high-wage firms on average are larger than low-wage firms, about 73% of manufacturing workers are employed by high-wage firms and only about 5% are employed by low-wage firms.

It turns out that the effects on labor reallocation, depicted in column (1), are strongest for workers initially employed by high-wage manufacturing firms. This result is consistent with Dauth et al. (2019a) who show that the negative effect of growing imports on cumulative earnings are largest for the group of workers employed by high-wage manufacturing firms. To the extent that the firm wage premiums reflect rent sharing through collective bargaining, a plausible explanation for this finding is that the effects of rising import competition are strongest for industries which are less competitive due to a higher level of wages. Importantly for the purpose of this paper, the main finding that high-wage workers are more likely to move to high-wage non-manufacturing firms in response to rising net import exposure (column (2)) is robust across all sub-samples. Column (5) shows that the losses in firm wages premiums are largest for low-wage workers starting in high-wage manufacturing firms. This is a natural consequence of the difference in wage premiums between high-wage, medium-wage, and low-wage firms. Overall, table A8 suggests that trade-induced structural change triggers an increase in sorting and wage inequality, mostly driven by higher downward mobility among low-wage workers who are initially employed by high-wage manufacturing firms.

7.2. Domestic outsourcing

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, logistics, and catering occupations, arguably to exclude them from firm-specific rents. Domestic outsourcing triggered mobility of these workers from high-wage towards low-wage firms and thereby contributed to the increase in sorting and wage inequality. To mitigate concerns that the effects documented in this paper in fact reflect mobility in response to domestic outsourcing and not in response to increasing net import exposure, I drop workers in food, cleaning, security, logistics and catering occupations in a robustness check, which reduces the sample size by about 7%. A closer

inspection shows that these workers tend to be concentrated in the group of low-wage workers (as expected). They, however, do not seem to be over- or underrepresented in industries experiencing large increases in net import exposure. It is therefore not surprising that table A9 shows very similar results as table 2.

7.3. Non-monotonicities

A potential 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 the same log 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 2018).³¹ This non-monotonicity is at odds with the log additive structure in 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). Systematic 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. The residuals 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 (Card et al. 2013). However, the residuals are large for some observations and this could reflect systematic violations of the AKM assumptions.

The robustness check I conduct 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 very 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

³¹In 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 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.

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 10% of workers with the lowest fixed effects in one robustness check. The results, shown in table A10 remain robust to this manipulation.

7.4. Separate effects of import and export exposure

As a final robustness check, I employ import and export exposure separately as explanatory variables in the regression. These measures are computed analogously to the measure in the main specification and the respective instruments are also constructed analogously. Table A11 shows the results.

The results for import exposure are very similar to the results for net import exposure in the baseline specification. As expected, growing import exposure increases the likelihood for all skill groups to move into the non-manufacturing sector. Conditional on moving into the non-manufacturing sector, high-wage workers more often move to high-paying firms than low-wage workers.

Table A11 also shows that growing export exposure generates lower mobility into the non-manufacturing sector for all skill groups. However, this effect is smaller for high-wage workers than for medium-wage and low-wage workers. This result can be explained by the different channels through which growing exports might affect job stability within manufacturing. First, growing exports potentially (partly) offset any negative demand shock on the respective industry or firm which would have triggered displacement of workers. This effect should play out similarly for all skill groups, just as the effects of growing import exposure are similar across all skill groups. On top of that, however, growing exports might shield workers who are at risk of displacement from technological progress. 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. As low-wage and medium-wage workers tend to specialize in routine-intensive and codifiable tasks (see figure 3), they are at risk of being adversely affected by routine-biased technological progress, and therefore they benefit most from this effect.

8. Conclusion

Using a large administrative dataset, this paper provides robust evidence on the link between labor reallocation from the manufacturing into the non-manufacturing sector, sorting, and wage inequality. Exploiting the large and sudden increase in Germany's

exports to and imports from China and Eastern Europe, I provide evidence that labor reallocation resulting from a contraction of a manufacturing industry results in an increase in sorting by skill across high-paying and low-paying firms. The results emphasize the crucial role that worker characteristics such as education and tasks performed on the job play for the mobility pattern which is underlying to the change in sorting.

The results in this paper carry over to any shock or policy which triggers a contraction of the manufacturing sector and thereby causes labor reallocation into the non-manufacturing sector. In the light of the rapid pace of technological progress experienced in the last years, the manufacturing employment share can be expected to further decrease in the upcoming years. The results in this paper suggest that the welfare gains from these technological advances might be unequally distributed within the economy. By pushing low-wage workers out of high-wage firms at higher rates, a contraction of the manufacturing sector creates persistent distributional effects. First, there is an immediate distributional effect which stems from an increasing wage gap, driven by the (relative) loss of firm wage premiums for low-wage workers. Second, there are reasons to believe that the increased sorting goes along with distributional effects in the longer-run as well. Abowd et al. (2018) for example show that employment at a high-wage firm facilitates upward-mobility in the earnings distribution in the following years. From the perspective of a policymaker who aims to curb the distributional effects of technological progress, international trade, or any other factor which triggers a contraction of manufacturing employment, is therefore crucial to focus on the skills and the human capital which enable workers to move into high-paying firms in the service sector.

This paper also provides new insights on the discussion about the distributional effects of trade with low-wage countries. Previous studies focus on the effects of growing import competition on cumulative earnings and typically find that the negative effects are largest for low-wage workers (e.g. Autor et al. 2014; Dauth et al. 2019a; Utar 2018). It is still an open discussion to what extent these results reflect transitional effects, coming for example from temporary unemployment or temporarily depressed wages, or more long-term effects which persist even after the economy has adjusted to the new equilibrium. The results in this paper isolate a specific component of inequality which is long-term in nature. It therefore suggests that growing imports do indeed generate persistent effects on wage inequality. Relatedly, the results in this paper suggest that bringing trade-displaced workers into full-time employment in the service sector is not sufficient to fully curb these adjustment costs and the resulting distributional effects.

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A. Appendix: AKM estimation

This section provides further details on the estimation of the following empirical specification, which dates back to Abowd et al. (1999):

$$y_{i\tau} = \alpha_i + \psi_{J(i\tau)} + x'_{i\tau}\beta + r_{i\tau} \quad (\text{A1})$$

Section 2 explains the interpretation of the components $y_{i\tau}$, α_i , $\psi_{J(i\tau)}$ and $x'_{i\tau}$. It is worthwhile to have a closer look at the error term which consists of three components for which I assume mean zero and orthogonality to worker and firm effects conditional on the control variables:

$$r_{i\tau} = \eta_{iJ(i\tau)} + \xi_{i\tau} + \epsilon_{i\tau} \quad (\text{A2})$$

The error term $r_{i\tau}$ consists of a worker-firm match component $\eta_{iJ(i\tau)}$, a unit-root component $\xi_{i\tau}$, which captures a potential drift in workers' wages, and a transitory error, $\epsilon_{i\tau}$.

Match effects. Especially the match effect $\eta_{iJ(i\tau)}$ deserves close attention. The estimation of the firm effects ψ_j relies on mobility of workers between firms. The difference in the firm wage premium between two firms captures systematic wage changes for workers that move between those firms. When workers moving into a given firm experience high wage gains, conditional on α_i and $x'_{i\tau}$, the estimated firm wage premium of this firm will be high. However, the wage change that workers experience by moving between two firms can be due to differences in the firm wage premium or due to differences in the average worker-firm match component between those firms. Systematic mobility of certain workers into firms based on a worker-firm match component therefore will be picked up by ψ_j , but precludes its interpretation as a ceteris paribus wage premium that every worker employed by this firm receives. Therefore, I need to assume that $\eta_{iJ(i\tau)}$ has mean zero and is orthogonal to worker and firm effects.

Card et al. (2013) check the plausibility of this assumption for the German case in different ways. First, in an event-study, they observe wage changes of workers moving from one firm to another to the wage change of movers into the opposite direction. They find that wage gains for workers moving from low coworker-wage firms to high coworker-wage firms are about as large as the losses of workers moving into the opposite direction. In the presence of strong match-specific effects, the wage changes should not be symmetric. In extreme cases with very strong match effects, wage changes should be positive for movers in both directions. Second, they compare the fit of equation A1 to the fit of a model with fixed effects for every worker-firm match. The R-squared of the baseline model is very high with values around 90% and stable over time. Match-effects, which are part of the residual, therefore are relatively small on average. Inclusion of match-specific fixed effects

instead of worker and firm effects improves the R-squared by only 2 percentage points on average. The additive specification in equation A1, which abstracts from match-specific effects therefore seems to provide a very good fit to the data. Lochner and Schulz (2016) argue that this assumption might be violated for the least skilled workers in Germany. As a robustness check, therefore, I drop workers in the bottom 10% of the distribution of worker effects.

Worker mobility. In contrast, equation A1 is consistent with non-random mobility of workers with different worker components across firms. This is because the estimator conditions on the actual sequence of firms by which a given worker is employed. The main empirical analysis in this paper, which investigates whether trade induces non-random mobility of workers with different worker effects across firms that pay different wage premiums, therefore is consistent with equation Equation A1.

Worker and firm effects in equation A1 can only be separately identified within a connected set of firms which are linked by worker mobility. Following Card et al. (2013), I focus on the largest connected set in each interval. The largest connected set comprises about 95% of the workers in the raw data. In the main analysis which focuses on the effects of trade, I drop workers who belong to the largest connected set in t but not in $t + 10$. In an alternative estimation, keep them in the analysis and code them as 'out'. The results remain unchanged and are available upon request.

Variance decomposition. Having estimated equation A1, one can perform a decomposition of the variance of log wages into the respective worker- and firm-related components as done in Card et al. (2013):

$$\begin{aligned} \text{var}(y_{i\tau}) &= \text{var}(\alpha_i) + \text{var}(\phi_{J(i\tau)}) + \text{var}(\beta x'_{i\tau}) \\ &+ 2\text{cov}(\alpha_i, \phi_{J(i\tau)}) + 2\text{cov}(\alpha_i, \beta x'_{i\tau}) + 2\text{cov}(\phi_{J(i\tau)}) \\ &+ \text{var}(r_{i\tau}) \quad (\text{A3}) \end{aligned}$$

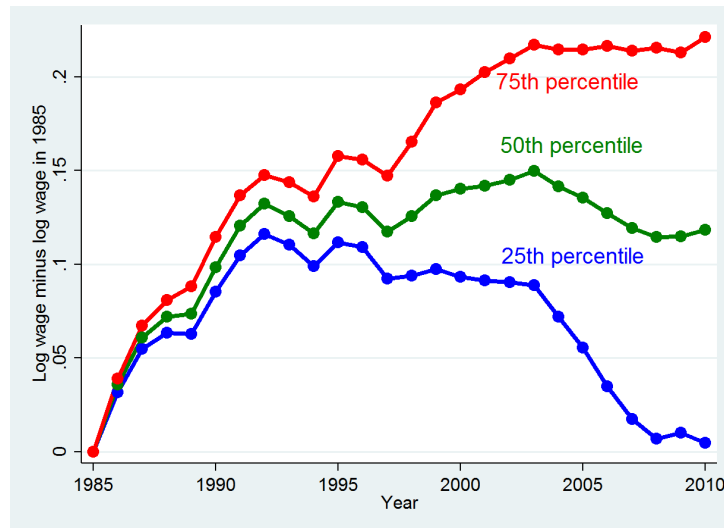
Using equation A3, Card et al. (2013) decompose cross-sectional wage inequality as well as the rise in wage inequality. It turns out that the rise in wage inequality is driven by three main factors: a rise in the dispersion of the worker components $\text{var}(\alpha_i)$, a rise in the dispersion of firm wage premiums $\text{var}(\phi_{J(i\tau)})$, and a rise in worker-firm sorting as reflected by the covariance between worker components and firm wage premiums $2\text{cov}(\alpha_i, \phi_{J(i\tau)})$.

For the purpose of this paper, I use slightly different time intervals as Card et al. (2013). For example, my first interval comprises the years 1985-1990, whereas the first interval in Card et al. (2013) contains the years 1985-1991. The results of the variance decomposition however are very similar. Figure A6 plots the variance of wages as well as the three main

components for the intervals I use in the empirical analysis (1985-1990, 1995-2000, 2005-2010), and for the sake of completeness, the intervals 1990-1995 and 200-2005. In the cross-section, the variance of worker components is clearly the dominant component of wage inequality. However, looking at the change in wage inequality over time, the increase in sorting is almost as important as the increase in the variance of worker components. The increase in sorting from the first to the last interval explains roughly 30% of the increase in the variance of wages between these intervals.

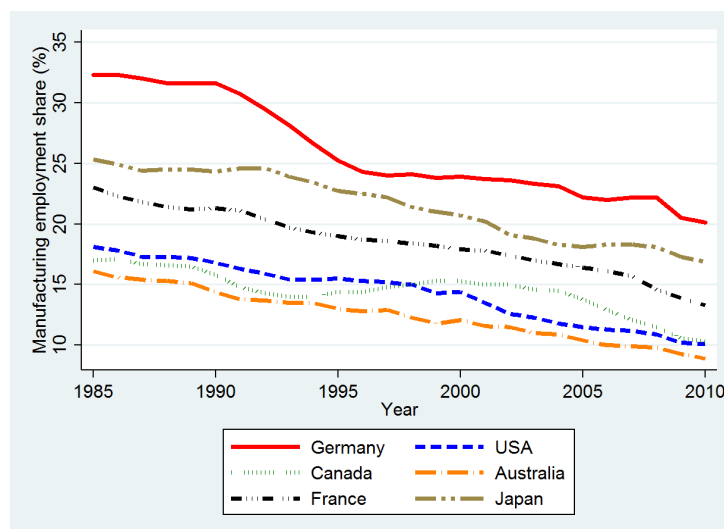
B. Appendix: Figures and Tables

Figure A1: Wage inequality: percentiles



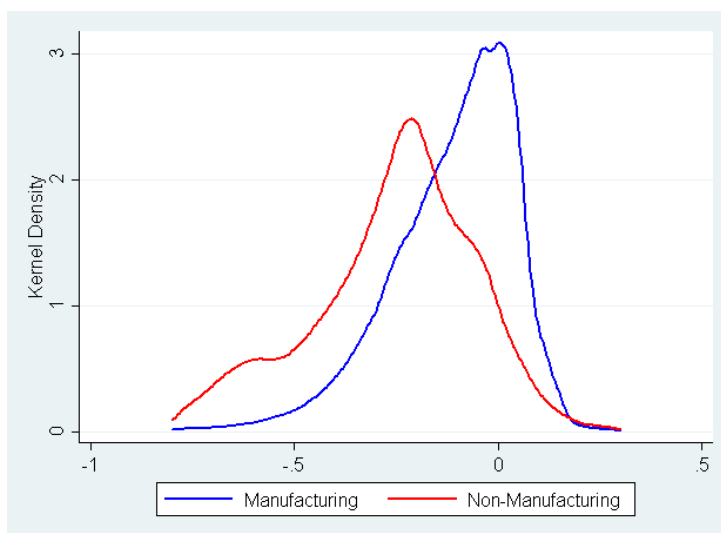
Notes: The table denotes the log daily wage in the 75th, 50th and 25th percentile in the overall wage distribution (manufacturing plus non-manufacturing) minus the respective log wage in the percentile in 1990. The table includes 50% of all male full-time employed employees subject to social security contributions in West Germany. See section 2 for more information on the data.

Figure A2: The decline in the manufacturing employment share in selected countries



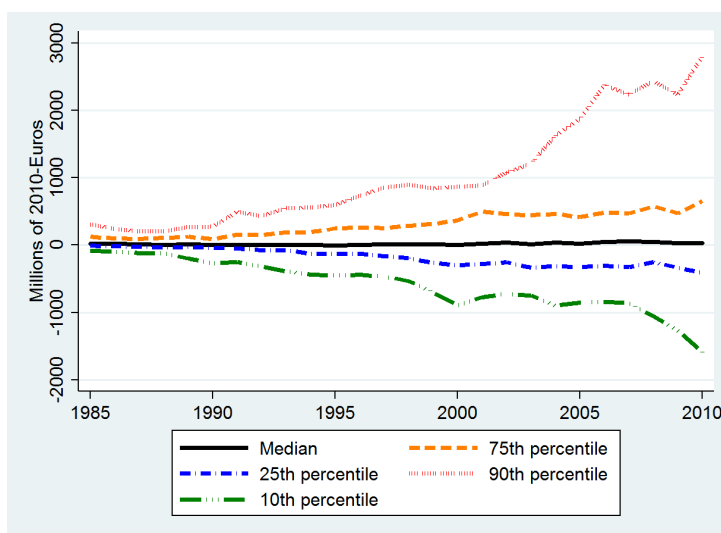
Notes: The figure plots the manufacturing employment share over time for selected countries. Data source: U.S. Bureau of Labour Statistics.

Figure A3: Dispersion of firm wage premiums, by sector, 2010



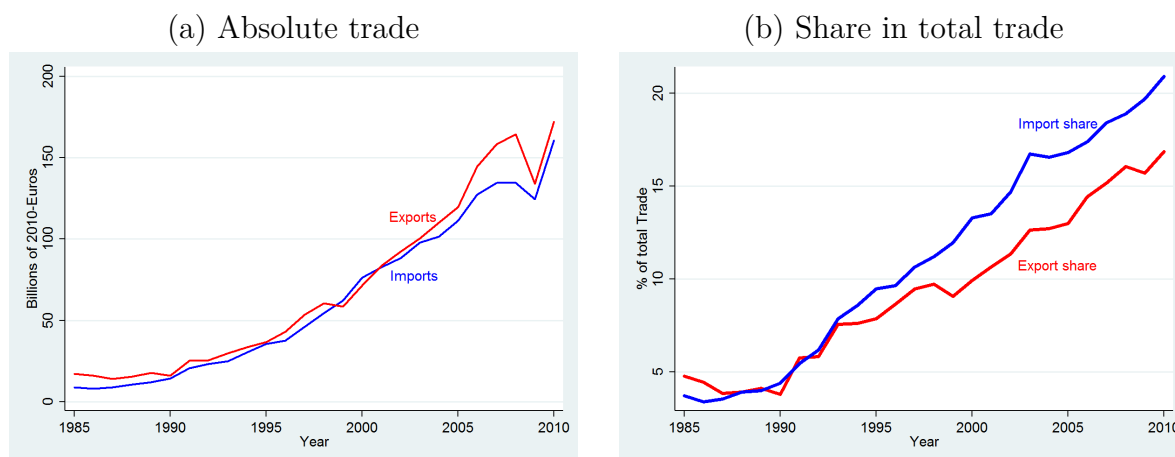
Notes: The figure depicts the employment-weighted distribution of estimated firm wage premiums in 2010, separately for the manufacturing and the non-manufacturing sector. See section 2 for a more detailed explanation of the data preparation and wage decomposition.

Figure A4: Variation in net imports across industries



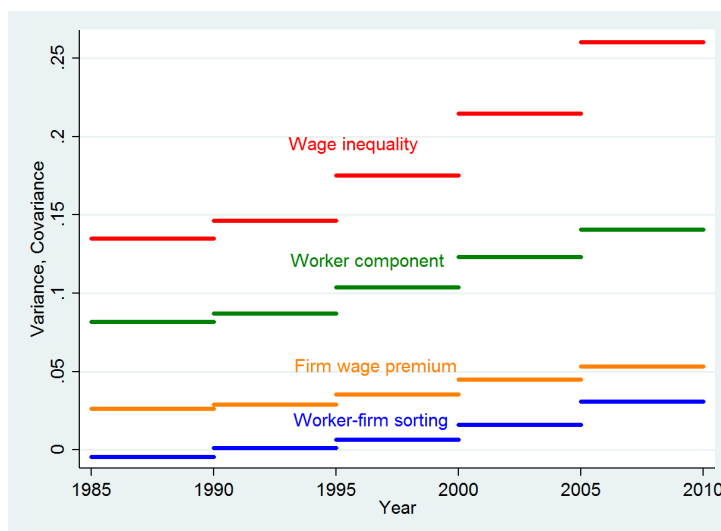
Notes: The figure depicts annual net German imports from China and Eastern Europe of industries at various percentiles. Eastern Europe includes: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, the former USSR, and its successor states the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. See sections 2 for a more detailed explanation of the data.

Figure A5: Trade with China and Eastern Europe



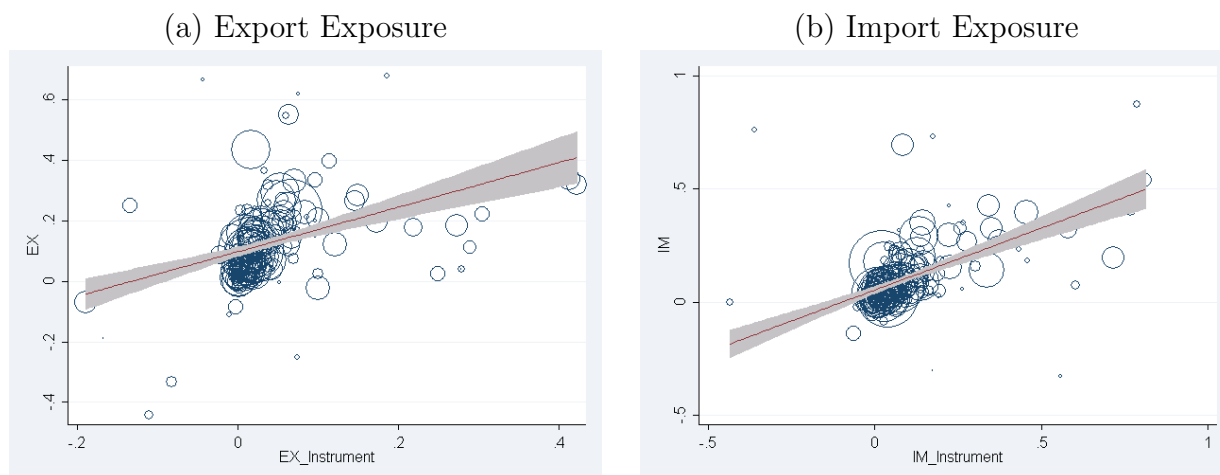
Notes: Panel (a) depicts the value of German exports to and imports from China and Eastern Europe in each year. Panel (b) depicts the share of German exports to and imports from Eastern Europe and China in total German export and imports. Eastern Europe comprises the following countries: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, the former USSR, and its successor states the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. See sections 2 for a more detailed explanation of the data.

Figure A6: AKM decomposition: main components



Notes: The figure plots the main components of the variance decomposition explained in appendix A. 'Wage inequality' denotes the variance of log daily wages. 'Worker component' denotes the variance of estimated worker components. 'Firm wage premium' denotes the variance of estimated firm wage premiums. 'Worker-firm sorting' denotes twice the covariance of estimated worker components and firm wage premiums. The decomposition is based on 50% of all male full-time employed employees subject to social security contributions in West Germany. See section 2 for a more detailed explanation of the data preparation and wage decomposition.

Figure A7: First Stage



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.

Table A1: Estimated firm wage premiums in selected industries

3-digit industry	Mean	Standard Deviation	Number of firms
(a) Manufacturing			
Refined petroleum	0.12	0.15	136
Basic chemicals	0.06	0.16	822
Other general purpose machinery	0.02	0.17	3624
Furniture	-0.09	0.24	6558
Other wearing apparel	-0.12	0.27	1258
(b) Non-manufacturing			
Monetary intermediation	0.10	0.20	9809
Insurance and pension	0.04	0.17	2009
Advertising	-0.07	0.33	2721
Industrial cleaning	-0.11	0.30	3495
Hotels	-0.28	0.29	5565

Notes: The table displays summary statistics about estimated firm wages premiums in selected industries in 1990 and 2000. See sections 2 and 5 for the data preparation and wage decomposition.

Table A2: Sample descriptives

	Mean	Median	p75	p25	N
(a) General descriptives					
Log daily wage (imputed)	4.48	4.44	4.68	4.25	3,369,473
High education	0.14	0	0	0	3,369,473
Age	35.75	36	29	42	3,369,473
Occupational groups:					
Manager/engineer/professional	0.09	0	0	0	3,369,473
Technician, qual. services, admin.	0.21	0	0	0	3,369,473
Manual/simple services	0.70	1	1	0	3,369,473
Tasks:					
Routine job	0.28	0	1	0	3,369,473
Codifiable job	0.33	0	1	0	3,369,473
AKM effects:					
Estimated worker effect ($\hat{\alpha}_i$)	4.38	4.34	4.51	4.21	3,369,473
Estimated firm wage premium ($\hat{\psi}_{J(it)}$)	0.08	0.09	0.16	0.01	3,369,473
(b) Descriptives on trade exposure					
Change in net import exposure:					
Δ NetImp (All workers)	-0.01	-0.03	0.02	-0.10	3,369,473
Δ NetImp (Low-wage workers)	-0.01	-0.03	0.02	-0.10	1,131,725
Δ NetImp (Medium-wage workers)	-0.02	-0.04	0.02	-0.11	1,218,432
Δ NetImp (High-wage workers)	-0.01	-0.03	0.02	-0.10	1,019,316
Change in export exposure:					
Δ EX (All workers)	0.13	0.10	0.18	0.06	3,369,473
Δ EX (Low-wage workers)	0.12	0.10	0.17	0.05	1,131,725
Δ EX (Medium-wage workers)	0.13	0.10	0.18	0.05	1,218,432
Δ EX (High-wage workers)	0.13	0.10	0.19	0.06	1,019,316
Change in import exposure:					
Δ IM (All workers)	0.12	0.07	0.15	0.03	3,369,473
Δ IM (Low-wage workers)	0.11	0.07	0.04	0.03	1,131,725
Δ IM (Medium-wage workers)	0.11	0.07	0.05	0.03	1,218,432
Δ IM (High-wage workers)	0.12	0.07	0.16	0.03	1,019,316
(c) Descriptives for back-of-the-envelope calculation					
Change in wage gap $t, t + 10$					
High-wage worker/low-wage worker	16.2 log points				
High-wage worker/medium-wage worker	8.1 log points				
Medium-wage worker/low-wage worker	8.1 log points				
Change in firm wage premium gap $t, t + 10$					
High-wage worker/low-wage worker	5.9 log points				
High-wage worker/medium-wage worker	2.0 log points				
Medium-wage worker/low-wage worker	3.9 log points				
Average firm wage premium in $t + 10$					
High-wage firms	21.5 log points (dev. from medium-wage firms)				
Low-wage firms	-35.2 log points (dev. from medium-wage firms)				

Notes: Panels (a) and (b) provide summary statistics for the main estimation sample in the base years 1990 and 2000. Panel (c) provides the basic variables needed for the back-of-the-envelope calculation of labor reallocation on sorting and wage inequality. The numbers in panel (c) refer to the whole economy (manufacturing plus non-manufacturing). See section 2 and 3 for a detailed explanation of the data preparation and wage decomposition.

Table A3: Descriptives on worker groups

[Sample means]	Worker type (tercile of $\hat{\alpha}_i$):		
	High-wage	Medium-wage	Low-wage
(a) General			
Estimated worker component ($\hat{\alpha}_i$)	4.69	4.36	4.13
Log daily wage (imputed)	4.84	4.43	4.22
High education	0.32	0.07	0.05
(b) Occupational groups:			
Manager/Engineer/Professional	0.25	0.03	0.01
Technician/Qual. services/Admin.	0.42	0.16	0.08
Manual/Simple services	0.33	0.80	0.91
(c) Job tasks:			
Routine job	0.09	0.29	0.42
Codifiable job	0.12	0.36	0.48
(d) Firm type:			
High-wage firm	0.77	0.74	0.70
Medium-wage firm	0.18	0.22	0.25
Low-wage firm	0.05	0.04	0.05
N	1,019,316	1,218,432	1,131,725

Notes: Descriptives on the main estimation sample (N=3,369,473) for the base years t (1990 and 2000). Each value denotes the sample mean of the respective variable. Workers 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.

Table A4: Explaining the variation of estimated worker effects

Dep. var.:	(1)	(2)	(3)	(4)	(5)
Estim. Worker effect					
High education	0.2930*** (0.0004)	0.2463*** (0.0004)	0.2239*** (0.0004)	0.0412*** (0.0004)	0.0407*** (0.0004)
Routine job		-0.0747*** (0.0003)	-0.0752*** (0.0004)	-0.0254*** (0.0005)	-0.0250*** (0.0005)
Codifiable job		-0.0814*** (0.0003)	-0.0865*** (0.0003)	-0.0054*** (0.0006)	-0.0055*** (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 table shows the results of a regression of the estimated worker component 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 an explanation of the data preparation and wage decomposition. Levels of significance: *10%, **5%, ***1%.

Table A5: Reallocation into non-manufacturing and sorting - by initial firm type

Manufacturing in t	Non-manufacturing in $t + 10$ (%)			
	Firm type:			
	All firms (1)	High-wage (2)	Medium-wage (3)	Low-wage (4)
(a) High-wage firms				
High-wage workers (N=784,836)	12.7	9.4	2.4	0.9
Medium-wage workers (N=905,964)	12.6	6.5	3.8	2.3
Low-wage workers (N=797,306)	15.1	5.6	5.1	4.4
(b) Medium-wage firms				
High-wage workers (N=184,136)	13.0	6.4	4.5	2.1
Medium-wage workers (N=263,843)	16.9	6.2	6.8	3.9
Low-wage workers (N=282,667)	19.7	5.3	7.3	7.1
(c) Low-wage firms				
High-wage workers (N=50,344)	16.9	5.8	6.9	4.2
Medium-wage workers (N=48,625)	23.4	6.7	9.5	7.2
Low-wage workers (N=51,752)	24.8	5.4	8.8	10.6

Notes: Column (1) shows the share of workers who are employed in the non-manufacturing sector in $t + 10$. Columns (2)-(4) split up the share from column (1) into employment by high-wage, medium-wage, and low-wage firms. See section 2 for a more detailed explanation of the data preparation and wage decomposition.

Table A6: Top net importing and exporting industries

3-digit industry	Change 1990-2010
(a) Increase in net imports	
Office machinery	10.81
Ships	5.27
Electronic components	5.27
Sound and video recording apparatus	4.74
Furniture	3.66
(b) Increase in net exports	
Motor vehicles	9.23
Other special purpose machinery	6.09
Parts and accesoires for motor vehicles	4.25
Machinery for production of mechanical power	4.09
Pharmaceuticals	3.11

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

Table A7: Alternative outcome variables

Dependent variable (dummy):	(1) Same firm in $t + 10$	(2) Manuf. in $t + 10$	(3) Out of sample in $t + 10$
Δ NetImp	-0.17*** (0.03)	-0.16*** (0.03)	0.06*** (0.02)
Δ NetImp*Medium-wage worker	0.00 (0.00)	0.00 (0.00)	-0.02*** (0.01)
Δ NetImp*High-wage worker	0.00 (0.01)	-0.01 (0.02)	-0.01* (0.01)
R2	0.05	0.04	0.03

Notes: N=3,369,473. In column (1), the dependent variable is 1 if the worker is full-time employed in the same manufacturing firm in $t+10$ as in t . In column (2), the dependent variable is 1 if the worker is full-time employed in manufacturing in $t+10$. In column (3), the dependent variable is 1 if the worker is out of the sample in $t+10$. Workers are out of the sample if they are unemployed, self-employed, part-time employed, are in early retirement employed in the public sector as civil servants in $t+10$ or have passed away between t and $t+10$. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 2 and 5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

Table A8: Upward and downward mobility

Dependent variable:	(1)	(2)	(3)	(4)	(5)
	Dummy: Non-manufacturing in $t + 10$				Premium
	All	High-wage	Medium-wage	Low-wage	in $t + 10$
[2SLS]	(a) Workers employed by high-wage firms in t				
	N=2,488,106				
Δ NetImp	0.11*** (0.03)	0.05*** (0.02)	0.03*** (0.01)	0.03*** (0.01)	-0.07*** (0.02)
Δ NetImp*Medium-wage worker	0.01 (0.02)	0.03* (0.02)	-0.00 (0.00)	-0.02*** (0.00)	0.04*** (0.01)
Δ NetImp*High-wage worker	0.01 (0.03)	0.06 (0.04)	-0.02*** (0.01)	-0.03*** (0.01)	0.06*** (0.02)
R2	0.05	0.03	0.02	0.02	0.43
[2SLS]	(b) Workers employed by medium-wage firms in t				
	N=730,646				
Δ NetImp	0.06*** (0.02)	0.02*** (0.01)	0.03*** (0.01)	0.01*** (0.01)	-0.02** (0.01)
Δ NetImp*Medium-wage worker	0.03*** (0.01)	0.02 (0.01)	0.01* (0.01)	0.01 (0.01)	-0.00 (0.01)
Δ NetImp*High-wage worker	0.03* (0.02)	0.04** (0.02)	-0.00 (0.01)	-0.01 (0.01)	0.01 (0.01)
R2	0.04	0.02	0.02	0.02	0.40
[2SLS]	(c) Workers employed by low-wage firms in t				
	N=150,721				
Δ NetImp	0.02 (0.03)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	-0.02 (0.02)
Δ NetImp*Medium-wage worker	0.02 (0.02)	-0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
Δ NetImp*High-wage worker	0.04 (0.03)	0.04** (0.02)	0.01 (0.01)	-0.00 (0.01)	0.02 (0.02)
R2	0.04	0.02	0.01	0.02	0.32

Notes: See equation 5. Panel (a) restricts the sample on workers employed in high-wage manufacturing firms in base year t . Analogously, panels (b) and (c) restrict the sample on worker employed in medium-wage and low-wage manufacturing firms in t . Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 2 and 5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

Table A9: Drop workers affected by domestic outsourcing

Dependent variable:	(1)	(2)	(3)	(4)	(5)
	All	High-wage	Medium-wage	Low-wage	Premium in $t + 10$
Δ NetImp	0.10*** (0.02)	0.04*** (0.01)	0.03*** (0.01)	0.02*** (0.01)	-0.06*** (0.02)
Δ NetImp*Medium-wage worker	0.02 (0.01)	0.03** (0.01)	0.00 (0.00)	-0.01*** (0.01)	0.02*** (0.01)
Δ NetImp*High-wage worker	0.02 (0.03)	0.05** (0.03)	-0.01** (0.01)	-0.02*** (0.01)	0.05*** (0.01)
R2	0.05	0.03	0.02	0.02	0.47

Notes: N=3,147,481. See equation 5. Workers in food, cleaning, security and catering occupations are dropped. In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t + 10$. In column (2), the dependent variable is 1 if the worker is full-time employed in a high-wage non-manufacturing firm in $t + 10$. Analogously for columns (3) and (4). Column (5) shows the results with the estimated firm wage premium in $t + 10$ as a dependent variable. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 2 and 5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

Table A10: Drop 10% of least skilled workers

Dependent variable:	(1)	(2)	(3)	(4)	(5)
	All	High-wage	Medium-wage	Low-wage	Premium in $t + 10$
Δ NetImp	0.11*** (0.02)	0.05*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	-0.06*** (0.02)
Δ NetImp*Medium-wage worker	0.01 (0.01)	0.02* (0.01)	-0.00 (0.00)	-0.01*** (0.00)	0.02*** (0.01)
Δ NetImp*High-wage worker	0.01 (0.03)	0.05* (0.03)	-0.02*** (0.01)	-0.02*** (0.01)	0.05*** (0.01)
R2	0.05	0.03	0.02	0.02	0.47

Notes: N=2,526,031. See equation 5. Workers in bottom decile of estimated worker components are dropped. In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t + 10$. In column (2), the dependent variable is 1 if the worker is full-time employed in a high-wage non-manufacturing firm in $t + 10$. Analogously for columns (3) and (4). Column (5) shows the results with the estimated firm wage premium in $t + 10$ as a dependent variable. Additional controls (held constant at year t): dummies for worker types and initial firm types, the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 2 and 5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

Table A11: Export and import exposure separately

Dependent variable:	(1)	(2)	(3)	(4)	(5)
	Dummy: Non-manufacturing in $t + 10$				Premium in $t + 10$
	All	High-wage	Medium-wage	Low-wage	
Δ Imp	0.10*** (0.02)	0.04*** (0.01)	0.03*** (0.06)	0.03*** (0.01)	-0.06*** (0.02)
Δ Imp*Medium-wage worker	0.01 (0.01)	0.03** (0.01)	0.00 (0.00)	-0.01*** (0.00)	0.02*** (0.01)
Δ Imp*High-wage worker	0.02 (0.03)	0.06** (0.03)	-0.01*** (0.00)	-0.02*** (0.01)	0.05*** (0.01)
Δ Exp	-0.21*** (0.07)	-0.10** (0.04)	-0.06** (0.03)	-0.05** (0.02)	0.12** (0.05)
Δ Exp*Medium-wage worker	0.02 (0.06)	0.00 (0.06)	0.01 (0.01)	0.01 (0.02)	-0.02 (0.03)
Δ Exp*High-wage worker	0.14 (0.10)	0.00 (0.09)	0.08** (0.03)	0.05** (0.02)	-0.12*** (0.04)
R2	0.05	0.03	0.02	0.02	0.47

Notes: N=3,369,473. See equation 5. In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t + 10$. In column (2), the dependent variable is 1 if the worker is full-time employed in a high-wage non-manufacturing firm in $t + 10$. Analogously for columns (3) and (4). Column (5) shows the results with the estimated firm wage premium in $t + 10$ as a dependent variable. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 2 and 5 for more details. Levels of statistical significance: *10%, **5%, ***1%.