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All we need is love? Trade-adjustment, inequality, and the role of the partner

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Katrin Huber and Erwin Winkler

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All We Need is Love? Trade-Adjustment, Inequality, and the Role of the Partner*

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October 10, 2016

We examine the distributional effect of Germany's trade integration with China and Eastern Europe and show that there are considerable differences between the household level and the individual level impact. The trade shock increased inequality of individual earnings. At the household level, however, about 40% of this distributional effect is reduced by a simple insurance effect that occurs if partners within married and unmarried couples are differently affected by the trade shock. The insurance effect is substantial since the trade shock had a large variation across industries and 80% of individuals within couples are employed in different industries. Our analysis also reveals that many workers who individually benefit from the trade shock turn into 'losers' at the household level because they have a partner who experiences a strong negative impact. All in all, this paper suggests that a household level perspective is essential in order to understand the exact distributional consequences of globalization.

JEL-Classification: J31, F16

Keywords: Earnings Inequality, International Trade, Household, Insurance

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1. Introduction

International trade creates aggregate welfare gains in the long run. But are these gains equally distributed across the whole population? The usual answer to this question that can be found in every international economics textbook is 'no'. International trade creates winners and losers and thereby influences the earnings distribution in a country. During times of increasing earnings inequality within many countries (*OECD* 2008a) and discussions about further trade liberalization, understanding the distributional consequences of trade is of large interest not only for the public but also for policymakers who need to design redistributive policies which ensure that gains from trade accrue to the whole population.

Recent empirical evidence suggests that the distributional impact of trade is especially large during the adjustment process when workers have to switch between industries and sectors. Autor et al. (2014) for example show that US manufacturing workers employed in industries exposed to Chinese import competition suffered from lower cumulative earnings. Earnings losses have been larger for less educated workers who churned within import competing industries and repeatedly have been exposed to adverse trade shocks. In contrast, high-skilled workers experienced smaller earnings losses as they were better able to switch to less exposed industries outside manufacturing.¹ On the other hand, workers employed in export-oriented industries experience an immediate positive effect that comes from higher wages and higher job stability (Dauth et al. 2014; Dauth et al. 2016). There is thus evidence that during the adjustment process a trade shock triggers earnings inequality because its impact strongly varies across industries and workers' characteristics such as their skill level.

Previous literature on trade and inequality has in common a focus on individual level outcomes such as individual earnings and inequality. We contribute to this literature with a household (=married and unmarried couples) level analysis of the impact of international trade on earnings and argue that this is essential in order to understand the exact distributional consequences of globalization for two broad reasons. First, if we are interested in who is better and who is worse off after a trade shock and we base our judgment exclusively on individual level outcomes, we implicitly assume that individuals within households are completely independent agents who have separable budgets. However, this assumption is at odds with empirical evidence and theoretical reasoning in family economics. For example, in our sample 70% of couples report income pooling and this suggests that within the household redistribution of money takes place.² A related

¹Similar results have been documented for other countries. See e.g. Balsvik et al. (2015) for evidence from Norway, Utar (2015) from Denmark, and Nilsson Hakkala and Huttunen (2016) from Finland.

²Heimdal and Houseknecht (2003) report similarly high numbers for the USA (80.6%) and Sweden (65.6%). Even though income pooling does not necessarily mean equal sharing (e.g. Browning et al. 1994), it is hard to argue that partners who pool their income have completely independent budgets.

theoretical point dates back to Becker (1974) who argues that household members redistribute money because they care for each other and this is why the household constitutes an insurance in case of a negative shock to individuals. Therefore, as individual welfare is partly determined at the household level, a look at the household level impact of a trade shock can contribute to the understanding of who benefits and who loses from international trade. Second, a pure individual level analysis hides an important insurance effect at the household level. If partners have different characteristics (e.g. work in different industries), they might be subject to opposing shocks and negative effects on one individual might be (partly) offset by positive effects on her partner. At the aggregate level, this can translate into distributional effects that are different at the household than at the individual level. In this paper, we contribute to the existing literature by emphasizing this insurance effect and its implications for the distributional consequences of trade shocks.

More specifically, we analyze a major trade shock on the German economy, namely the large increase in trade with China and Eastern Europe, and show that its household level impact on earnings and earnings inequality indeed substantially differs from its individual level impact. We start with a conventional *individual level* analysis and show that this trade shock generated winners and losers and thereby had a strong inequality-increasing impact. However, when we assume that partners share the gains and losses from trade equally, the distributional effect becomes about 40% smaller. Additionally, the share of individuals who incur a negative impact ('losers') is larger at the household level. The reason is that a fraction of workers who experience a small positive impact have a partner with a far larger negative impact. These results remain very robust when we allow for incomplete sharing of the gains and losses from trade. They also hold regardless of whether we include single households into the analysis or not.

We detect sizable heterogeneities along several dimensions: First, the mitigating impact on inequality at the household level is exclusively driven by the lower tail of the earnings distribution. At the upper tail, the inequality-increasing effect is even slightly stronger at the household level and this might be one of the reasons why household earnings inequality in Germany increased predominantly at the upper tail (Grabka et al. 2015). Second, we find that sectoral affiliation plays a large role. Adversely affected manufacturing workers at the bottom of the earnings distribution disproportionately benefit from the insurance effect, whereas non-manufacturing workers on average serve as an insurance for their partners who tend to be more negatively affected. Third, there are considerable differences between males and females. The trade shock tends to be positively biased towards males and this is why at the household level the insurance effect on average comes from males being more positively affected than females.

All these results are surprising in the light of significant assortative mating among couples in several respects.³ Indeed, we also find high levels of assortative mating for

³See e.g. Eika et al. (2014) for evidence on assortative mating from the USA and Norway.

example in terms of education and this is why the trade shock on average affected partners similarly. However, since the trade shock had a large heterogeneity across industries and about 80% of individuals work in a different 2-digit industry as their partner, there is considerable scope for an insurance effect and that makes the household level perspective very relevant.

The main contribution of this paper is to show that a pure individual level analysis of the effect of trade on earnings might give an incomplete picture of who is affected in which way by a trade shock. Some workers who individually benefit from the trade shock turn out to be losers at the household level since their partners are strongly negatively affected. Most importantly, the distributional effect can be very different at the household level. Our results therefore indicate that a household level perspective on trade and inequality is worthwhile for anyone who is concerned with the distributional effects of globalization. Given that trade-induced increases in inequality might erode a substantial part of the overall gains from trade (Antras et al. 2016), this paper also contributes to a larger discussion about the size of gains from trade liberalization.

The rest of this paper is structured as follows. The next section briefly discusses how this paper fits into previous literature. Section 3 outlines the data and section 4 presents the individual level results. In section 5, we discuss the difference between the individual and the household level effects. Section 6 presents robustness checks and section 7 concludes.

2. Related Literature

Our paper is related to a strand of literature which analyzes the impact of increasing trade with China (and in some cases Eastern Europe) on individual earnings and implicitly also on earnings inequality. Autor et al. (2014) examine the impact of Chinese import competition in US manufacturing on workers' earnings and find that workers employed in industries that are strongly exposed to import competition suffer from earnings losses.⁴ However, the effects differ strongly across groups of workers. Whereas high-skilled workers manage to switch to less exposed industries mainly outside manufacturing without major earnings losses, low-skilled workers churn among import-competing industries and are subsequently exposed to adverse trade shocks which significantly reduce their earnings. Several following studies find the same results for other countries, e.g. Utar (2015) for Denmark and Nilsson Hakkala and Huttunen (2016) for Finland. Dauth et al. (2014) and Dauth et al. (2016) perform a similar analysis for Germany, a country which was exposed to substantial import competition from China and Eastern Europe since the 1990s but also benefited from increasing export opportunities to those countries. They also detect a negative labor market impact of import competition but find that this is overcompensated

⁴In terms of methodology, this is an extension of the region level approach by Autor et al. (2013). Other studies that use this approach are Balsvik et al. (2015) or Dauth et al. (2014).

by the positive effect of exports. Our paper is similar to those studies in the sense that it also exploits the differential exposure of industries to increasing trade with China and Eastern Europe in order to estimate the impact of a large and sudden trade shock on earnings. In contrast to the previous literature, however, we extend our analysis beyond the individual level and consider the insurance effect at the household level that emerges if partners are differently affected by a trade shock. By looking at the family dimension, our paper is also related to Autor et al. (2015) who analyze how import competition affects the structure of marriage in the USA and find that import shocks concentrated on male employment reduce marriage rates and increase the prevalence of single-headed households. In contrast to them, we do not analyze how trade affects mating behavior but rather highlight the difference between the individual and the household level impact of a trade shock for the existing mating pattern throughout our sample period.

We also contribute to the literature on the drivers of increasing earnings inequality within countries. Most OECD countries have experienced a sharp increase in earnings inequality between households during the last decades (*OECD* 2008a). In Germany, earnings inequality increased stronger than in most other OECD countries and labor market changes have been identified as the main driver of this development (*OECD* 2008b). Previous research has identified a variety of channels through which international trade can have an impact on inequality. See e.g. Harrison et al. (2011) for an overview of theoretical mechanisms and empirical evidence. In terms of increasing wage inequality (see e.g. Dustmann et al. 2009), there is evidence that growing international trade has contributed, e.g. via the exporter wage premium (Baumgarten 2013). In terms of increasing earnings inequality (including lower earnings from unemployment spells), trade theory has proposed different mechanisms (e.g. Helpman et al. 2010; Egger and Kreickemeier 2009). However, as Harrison et al. (2011) point out, empirical evidence on international trade and unemployment is still scarce. Studies that implicitly touch the issue of trade, unemployment and earnings inequality come for example from Autor et al. (2014) and Dauth et al. (2014), and Dauth et al. (2016). We thus aim to contribute to the literature by providing an analysis of trade and inequality under explicit consideration of unemployment spells and their role for earnings inequality. Additionally, to the best of our knowledge, we are the first to empirically take into account the household level impact of a trade shock. In particular, we are the first to consider the insurance mechanism at the household level that is present if both partners are active in the labor market and are subject to opposing or different trade shocks.

3. Data

Data on individuals and households. For the individual and household level data, we use the German Socio-Economic-Panel (SOEP), a longitudinal and representative survey

of approximately 11,000 private households in Germany. Interviews take place on a yearly basis since 1984 (East Germany since 1990) and provide a large battery of information on each individual’s socio-economic characteristics (e.g. gender, age, migration background, education level), on labor market outcomes (e.g. type of occupation, industry, tenure, wages), but also on more general household-level characteristics (e.g. number of household members, identifier for partner, region of residence). Most importantly for our purpose the SOEP offers the possibility to match individuals with their partners and to thus exactly determine which individuals live in a shared household. For more information on the SOEP see Wagner et al. (2007).

We construct an unbalanced panel of married and unmarried couples from 1993 through 2008. As a robustness check, we repeat the whole analysis with a sample of both couples and singles. We keep all couples for which we can observe the relevant variables like industry, education, tenure or earnings for at least 5 periods. We restrict our sample to the working population aged between 16 and 64 being in dependent employment. Consistent with Dauth et al. (2016) we use a sample of fulltime employed in the base year but allow for unemployment⁵ or parttime work in subsequent years.

Combining the information on the average monthly amount of income in each year and the information on the number of months the individual received this average amount, we compute gross yearly labor income and thereby construct the outcome variable. Furthermore, we convert income from DM to EUR for years prior to 2001 and deflate it according to the consumer price index (base year 2010) provided by the German Federal Statistical Office. Table A1 in the Appendix contains summary statistics on annual earnings.

Data on international trade flows. Based on the 2-digit industry information in the SOEP, we merge individual level data with data on exports and imports from the United Nations Commodity Trade Statistics Database (Comtrade). This database contains annual statistics on commodity trade of more than 170 countries. We 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, we then aggregate the product-level trade flows to trade flows at the 2-digit industry level.

We compute the degree to which an industry j is directly exposed to import competition and export opportunities with respect to China and Eastern Europe in year t :

$$IM_{jt}^{Direct} = \frac{Imports_{jt}^{E+C \rightarrow G}}{Imports_{jt}^{World \rightarrow G}} \times 100$$

$$EX_{jt}^{Direct} = \frac{Exports_{jt}^{G \rightarrow E+C}}{Exports_{jt}^{G \rightarrow World}} \times 100$$

⁵In case of unemployment, we follow Dauth et al. (2016) and assign the last observed industry affiliation to this individual.

where $Imports_{jt}^{E+C \rightarrow G}$ and $Exports_{jt}^{G \rightarrow E+C}$ denote industry j 's imports from and exports to China and Eastern Europe⁶ in year t . $Imports_{jt}^{World \rightarrow G}$ and $Exports_{jt}^{G \rightarrow World}$ are the corresponding trade flows with the rest of the world and account for considerable size differences between industries. In addition to this specification which is for example used by Bloom et al. (2016), we also compute import and export exposure using lagged industry wage sums in the denominator (see Dauth et al. 2016) as a robustness check.⁷ During our sample period, trade with China and Eastern European countries as a share of total trade increased from roughly 5% in 1993 to 24% in 2008, absolute trade volumes rose by even 700-800%. This trade shock thus constituted the main globalization shock for Germany in the last decades. Figure A1 in the Appendix shows that variation in trade exposure stems mainly from variation in the numerator.

As the trade shock is arguably a shock to the German manufacturing sector (Dauth et al. 2014), we obtain the direct trade exposure measures for 22 2-digit manufacturing industries. To capture the extent to which export and import shocks are transmitted along the value chain between both manufacturing and non-manufacturing sectors we compute indirect export and import exposure using the method of Acemoglu et al. (2016), i.e. the trade exposures for (non-manufacturing) firms that supply intermediates are a weighted average of the trade shocks that are faced by the (manufacturing) purchasers of these intermediate inputs.⁸ The only additional information we need for this is coming from input-output tables of the German Federal Statistical office.⁹ Total export and import exposure results as the sum of the direct and indirect exposure measures and will be used as explanatory variables IM_{jt} and EX_{jt} in our regression framework. We end up with trade exposure measures for 22 manufacturing industries (computed as direct plus indirect trade exposure) and 34 non-manufacturing industries (consisting only of the indirect trade exposure). As our sample contains a considerable share of partners who are not employed in the same sector (about 20%), taking the effect of the trade shock on the non-manufacturing sector into account is necessary for our further analysis.

Table A1 gives a descriptive overview of the total trade shocks ΔIM_{jt} and ΔEX_{jt} , where we refer to the shock as being the change in trade exposure between t and $t + 1$. On average, workers experienced a yearly increase of import exposure through China and Eastern Europe relative to total imports of 0.50%-points and an annual increase of export exposure of 0.40%-points during the entire 16-years-period. However, we find substantial variation across industries.

⁶Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, and the former USSR or its succession states Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

⁷We are grateful to Wolfgang Dauth for providing this data to us.

⁸As Acemoglu et al. (2016) show that linkages to suppliers are much more relevant than linkages to purchasers, we only include supply-linkages in our analysis.

⁹We take the input-output table from the earliest possible year (1994).

4. Individual-level analysis

In the following section we identify the causal effect of the trade shock from China and Eastern Europe on individual earnings. However, one has to keep in mind that this section only serves as a starting point for our main analysis and that we therefore build on the identification strategy of Dauth et al. (2016).

4.1. Identification

Regression. In a first step we investigate the effect of contemporaneous changes in trade exposure on workers' annual earnings and thereby extend the analysis of Dauth et al. (2016) also to the non-manufacturing sector that is affected by indirect trade exposure.

We make use of the panel structure in our data and estimate the following empirical specification:

$$Y_{ijrt} = \beta_1 \times IM_{jt} + \beta_2 \times EX_{jt} + \alpha \times X'_{it} + \gamma_i + \delta_{t,r} + \delta_J + \epsilon_{ijrt} \quad (1)$$

Y_{ijrt} denotes annual earnings of individual i , working in 2-digit industry j in federal state r in period t relative to i 's earnings in the base year, i.e. the first year the individual is observed in our dataset. We multiply the dependent variable by 100. We include the two main explanatory variables IM_{jt} and EX_{jt} as levels but due to our fixed effects framework we only exploit the changes in industry j 's total export and import exposure from year t to $t+1$ in our identification strategy. X'_{it} controls for age and age squared of the worker. We include individual fixed effects γ_i and thereby control for time-constant differences between workers. Moreover, German federal states differ in many labor market related aspects. Although East Germany started to catch up with the West, West German regions for example still have lower unemployment rates than East German regions. Also, regions are specialized in different industries and these specialization patterns might change over time. To control for such time-specific differences between German regions, we add year \times region fixed effects ($\delta_{t,r}$). Lastly, to account for time-constant sectoral heterogeneity, we additionally include 1-digit-industry fixed effects (δ_J) and only compare individuals employed in the same 1-digit industry. The approach thus exploits the variation in person i 's earnings and trade exposure over time. This variation might result either from changes in the exposure of i 's original industry or from changes due to movements to other industries. We estimate equation (1) separately for low-skilled workers (ISCED 1-4) and high-skilled workers (ISCED 5-6).

Although the fixed effects can control for unobserved time-constant confounding factors, the estimation might still give rise to bias due to sector-level time-varying demand and productivity shocks that are correlated with the trade measures and have an impact on individual earnings. We thus apply the IV-strategy used by Dauth et al. (2016) and

instrument the trade exposures by the respective exposures of a group of other countries, namely Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom.

Predicted Impact on Individual Earnings. Next, we compute the estimated change in earnings of individual i between period t and $t + 1$ that is induced by the trade shock (ΔIM_j and ΔEX_j) on i between t and $t + 1$. Note that for this purpose we can only use individuals that are observed in two subsequent periods and that this reduces our initial sample size. Remember that the regression coefficients of the trade shocks reflect the estimated change in normalized earnings of individual i (in percentage points) that is induced by a change in trade exposure by one percentage point. First consider the expression for the estimated change in normalized earnings:

$$\left(\frac{\widehat{E_{ijr,t+1}}}{E_{ijr,0}} - \frac{E_{ijr,t}}{E_{ijr,0}} \right) \times 100 \quad (2)$$

where $E_{ijr,t}$ denotes individual i 's earnings in period t and $E_{ijr,0}$ denotes her base year earnings. $\widehat{E_{ijr,t+1}}$ reflects hypothetical earnings of individual i in period $t + 1$ if the trade shock between t and $t + 1$ had occurred as observed in the data and *everything else had stayed constant* between t and $t + 1$.¹⁰ The estimated change in normalized earnings is a function of individual i 's trade shock and of the impact of a given trade shock:

$$\left(\frac{\widehat{E_{ijr,t+1}}}{E_{ijr,0}} - \frac{E_{ijr,t}}{E_{ijr,0}} \right) \times 100 = \Delta IM_j \times \hat{\beta}_{1s} + \Delta EX_j \times \hat{\beta}_{2s} \quad (3)$$

where $\hat{\beta}_{1s}$ and $\hat{\beta}_{2s}$ are the estimated coefficients from equation (1) that are different for high-skilled and low-skilled workers (skill level s) and ΔIM_j and ΔEX_j reflect the trade shock on individual i between period t and $t + 1$. Note that $\widehat{E_{ijr,t+1}}$ is the only unknown in this equation. We can rearrange and solve for $\widehat{E_{ijr,t+1}} - E_{ijr,t}$, which reflects the predicted change in earnings due to the trade shock. We call this difference $\widehat{Impact_{ijrs,t}}$:

$$\widehat{Impact_{ijrs,t}} = (\Delta IM_j \times \hat{\beta}_{1s} + \Delta EX_j \times \hat{\beta}_{2s}) \times E_0 \times \frac{1}{100} \quad (4)$$

Put simply, the predicted impact on earnings is a function of the worker's trade shock as well as his education-level.

Note that in our setting the mating structure of individuals can change during the observation period, possibly also due to the trade shock (see Autor et al. 2015). Nevertheless, we do not control for the effect of trade on the mating structure as this is simply

¹⁰One could for example think about i 's educational level changing between t and $t + 1$ which might have an effect on i 's earnings. In order to isolate the impact of the trade shock, we let the trade shock between t and $t + 1$ happen but assume that characteristics like education as well as returns to those characteristics remain constant. This is inspired by the decomposition literature in labor economics. See Fortin et al. (2010) for an extensive overview of this literature.

part of the effect that drives the difference between the household and the individual level. Holding the mating structure constant in our setting would be equivalent to a bad control problem (see Angrist and Pischke 2009).

4.2. Results

Regression. Both the fixed effects and the IV-fixed effects estimates in table 1 show that there is a significant relation between industry-level trade exposure and individual annual earnings. We find that workers employed in industries that benefit from rising export opportunities experience significantly higher earnings and workers employed in import-competing industries experience earnings losses.¹¹ The large positive effect of export exposure on annual earnings is consistent with the existence of an exporter wage premium in Germany (Schank et al. 2007; Baumgarten 2013) and can also be due to higher job stability in export-oriented industries (Dauth et al. 2014). The positive effect of export exposure is stronger for high-skilled individuals whereas the negative effect of import exposure is only significant for low-skilled workers. The first stage F-statistics of the IV are large and show that the IV does not suffer from weak instrument problems. First stage regressions can be found in table A3 in the Appendix. Our findings are in line with the results of Dauth et al. (2016). We also estimate the regression using their alternative definition of import and export exposure (see Appendix table A4) and thereby confirm our previous estimates.

Predicted Impact on Individual Earnings. To get a better impression of the size of the estimated effects and to investigate whether the effects differ along the earnings distribution, we compute the predicted impact of the shock for each individual. We order all observations according to yearly earnings and divide the sample into ten intervals where each interval comprises ten percentiles. Interval number 10 captures the top ten percent in terms of yearly earnings and number 1 comprises the bottom ten percent.¹²

¹¹Results where both skill groups are pooled can be found in Appendix table A2.

¹²In our sample, yearly earnings range from 0 to 185,352 EUR.

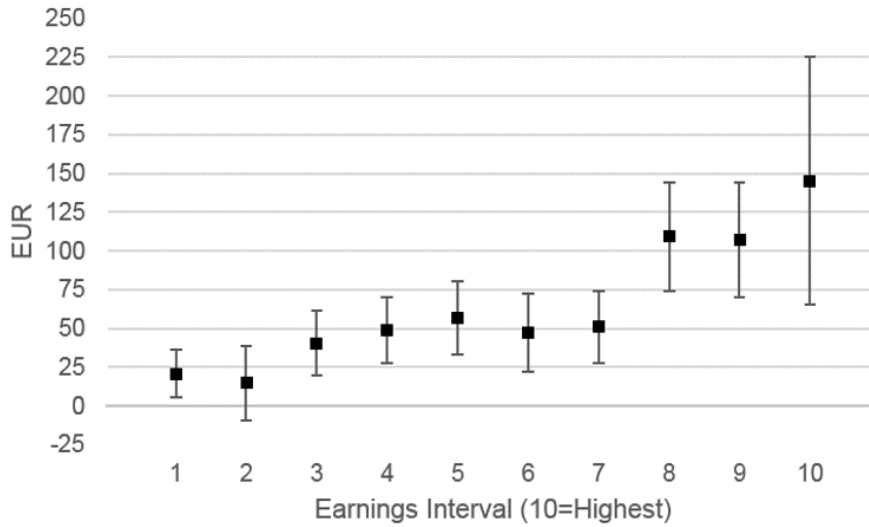
Table 1: Effect of Trade Shock on Individual Earnings

Norm. annual earnings $\times 100$	Low-skilled		High-skilled	
	FE	IV-FE	FE	IV-FE
Export Exposure (EX)	0.6283*** (0.1427)	1.1150*** (0.2239)	1.0718*** (0.3625)	1.1747*** (0.5034)
Import Exposure (IM)	-0.1480* (0.0863)	-0.5251*** (0.1249)	-0.1877 (0.1802)	-0.2027 (0.3405)
R2	0.75	0.75	0.86	0.86
1st stage F (EX)	-	348.64	-	452.86
1st stage F (IM)	-	152.044	-	193.79
Observations	28,293	28,293	12,805	12,805
Worker FE	x	x	x	x
Region x Year FE	x	x	x	x
1-Digit Industry FE	x	x	x	x

Notes: Column (1) and (3) show results of estimating equation (1). In column (2) and (4) we additionally instrument trade flows with trade flows to other countries (instrument group: Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom). Further controls include age and age squared. Standard errors clustered by 2-digit industry \times year in parentheses. Low-skilled refers to individuals with ISCED level 0-4 (e.g. General Elementary, Middle Vocational, Vocational Plus Abi). High-skilled individuals have ISCED 5 or 6 (Higher Vocational or Higher Education). Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

In Figure 1 we depict the average predicted impact for each interval, using the coefficients of the fixed effects specification for β_{1s} and β_{2s} in equation (4). The average impact of the trade shock is positive (64 EUR), however, the effects varies considerably across the different earnings intervals. Low-earnings individuals benefit on average only slightly (20 EUR), whereas workers in the highest earnings interval experience large gains of almost 150 EUR. As section 5 will show, this difference is significant. The first column in table 4 in section 5.2 shows that not everybody gains from the trade shock. About 23% of observations have a predicted impact that is smaller than zero. The share tends to be larger at the bottom half of the earnings distribution. Figure A2 and A3 in the Appendix show the predicted impact along the earnings distribution using the IV-FE coefficients and the alternative definition of trade exposures. The implications do not change.

Figure 1: Impact on Individual Earnings



Notes: All observations are ordered according to yearly earnings (ascending order) and divided into ten intervals where each interval comprises ten percentiles. Interval number 10 thus captures the top ten percent in terms of yearly earnings and number 1 comprises the bottom ten percent. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table 1 and the respective 95% confidence intervals result from 1,000 bootstrap replications clustered at the household level.

5. The Role of the Partner

We now ask whether there is an insurance effect at the household level that changes the conclusions about the impact of the trade shock on earnings and earnings inequality. More specifically, we ask two questions. First, do workers at the bottom of the earnings distribution benefit from partners who are more positively affected by the trade shock than themselves? Second, if yes, does this reduce the inequality-increasing impact of the trade shock?

5.1. Descriptives

The insurance effect at the household level is high if partners are subject to opposing effects. In our empirical setting, the predicted impact on earnings depends on industry affiliation and education. The trade shock thus affects partners differently if they are employed in different industries or if they have a different education level. In our sample, about 71% of workers have the same education level and 18% (29%) work in the same 2-digit (1-digit) industry as their partner. It is therefore not surprising that table 2 shows a highly significant positive correlation of predicted impacts between partners. Rows 2 and 3 indicate that the correlation is considerably smaller for couples where partners are employed in a different 2-digit industries or have different education levels. The estimates

in row 4 show that the correlation becomes negligible and turns insignificant for couples where partners have different education levels and work in a different 2-digit industry. The same applies to couples where both partners are employed in a different sector (rows 5 and 6). The insurance effect therefore should be especially large for these couples.

Table 2: Correlation of Partners' Affectedness

	Correlation pred. impact	Same pred. impact (%) (positive or negative)	Obs
All	0.0686*** (0.0077)	79.15	16,604
Different 2-Digit Industry	0.0258*** (0.0085)	75.92	13,624
Different Education	0.0500*** (0.0141)	77.02	4,857
Different 2-Digit Industry and Education	0.0085 (0.0152)	74.96	4,186
Different Sector	0.0070 (0.0129)	69.8	5,742
Different Sector and Education	0.0011 (0.0230)	69.64	1,726

Notes: Correlations result from simple OLS regression of the predicted impact on the partner's predicted impact. Column (2) shows the percentage of partners having the same predicted impact in terms of a negative or positive impact. Sector is either Manufacturing or Non-Manufacturing, Education is either high (ISCED 5-6) or low (ISCED 0-4).

In column 2 we ask whether partners have the same predicted impact (larger or smaller than zero) and the pattern is similar. Almost 80% of workers have the same predicted impact as their partner. The share decreases to 75% for workers who are employed in a different 2-digit industry and have a different education level as their partner. It further decreases to about 70% for couples where partners are employed in different sectors and have a different education level.

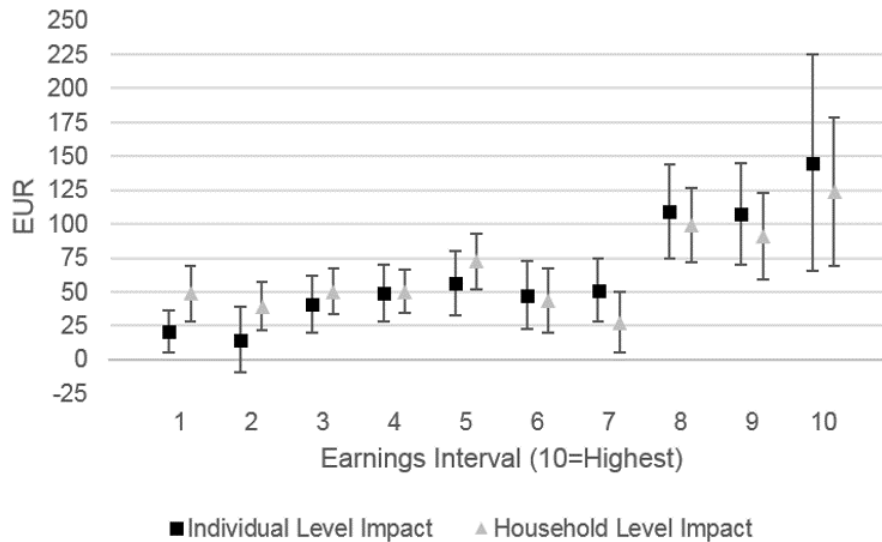
All in all, the descriptives show considerable levels of assortative mating and this is in line with findings from other countries (e.g Eika et al. 2014; Greenwood et al. 2014; Frémeaux and Lefranc 2015). It is therefore not surprising that the trade shock on average affected partners similarly. However, there is no perfect assortative mating in our sample - especially for couples where partners are employed in different industries or sectors and have a different education level, there is considerable scope for an insurance effect.

5.2. The Distributional Effect: Individual Level vs. Household Level

In the following, we contrast the individual level impact from section 4 to what we call the *household level impact*. Under the assumption of equal sharing of total household income, we compute the household level impact as the *mean of the individual's impact and the partner's impact*. As a robustness check, we allow for incomplete redistribution within households by simply shifting the weights from 50%-50% to 75% (own impact) - 25% (partner's impact).

Figure 2 shows the average individual level impact for every earnings interval as in section 4 and the average household level impact for the individuals in the respective interval.

Figure 2: Individual Level Impact versus Household Level Impact



Notes: All observations are ordered according to yearly earnings (ascending order) and divided into ten intervals where each interval comprises ten percentiles. Interval number 10 thus captures the top ten percent in terms of yearly earnings and number 1 comprises the bottom ten percent. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table 1. For each individual, we compute the household level impact as the average of the individual's impact and her partner's impact. Partners thus can be in different intervals but have the same household level impact. The respective 95% confidence intervals obtained from 1,000 bootstrap replications clustered at the household level.

The figure shows that the household level impact on average is larger than the individual level effect for individuals in the bottom half of the earnings distribution, whereas it is smaller for individuals at the upper half of the earnings distribution. The differences are sizable, especially at the lower half of the earnings distribution where the household impact on average is 71% higher. At the upper half, it is on average 19% lower. As the confidence bands are overlapping in all intervals, we perform a bootstrap exercise for the difference between the household and the individual level impact. It turns out that the differences are highly statistically significant in intervals 1,2 and 7 and marginally insignificant in interval

5 (see Appendix Table A5). There is thus evidence for a considerable insurance mechanism at the household, especially at the bottom of the earnings distribution. What about the distributional impact of the trade shock? Does the insurance mechanism mitigate the inequality-increasing effect? We test this in a bootstrap exercise where we measure the predicted impact of the trade shock on earnings inequality as the difference in predicted impact between e.g. the tenth and the first interval. We compare the differences at the individual level with those at the household level in order to see whether the insurance mechanism dampens the inequality-increasing effect of the trade shock.

Table 3 shows that this is the case. According to rows 1 and 2, the trade shock leads to a significant increase in the difference in earnings between the 10th and the 1st interval as well as the 9th and the 2nd interval. The respective inequality-increasing impact is smaller at the household level. The difference is highly statistically significant and amounts to 39% (44%) in case of the 10-1 (9-2) interval-difference. The insurance mechanism thus significantly reduces the individual level impact on earnings inequality. However, there are considerable differences along the earnings distribution. Columns 3 and 4 show that the bulk of the increase in individual earnings inequality occurs at the upper tail of the earnings distribution. The insurance effect, in contrast, only plays out at the lower tail (4-1) where the whole inequality-increasing impact vanishes at the household level. At the upper tail (10-7), the impact is even slightly reinforced at the household level. The difference, however, is not statistically significant. Results using the IV-FE estimates instead of the FE estimates can be found in Appendix table A6.

Table 3: Impact on Inequality using the FE-estimates

Difference between intervals	10-1	9-2	10-7	4-1
Individual level impact	124.36*** (42.45)	92.30*** (22.96)	94.14** (43.34)	28.00** (12.99)
Household level impact	75.28*** (29.64)	51.60*** (18.89)	96.51*** (29.17)	1.57 (12.94)
Difference	49.08** (23.66)	40.70** (17.37)	-2.38 (22.95)	26.43* (14.52)

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Column (1) shows the difference in the average predicted impact (as calculated by equation (4) using the FE-estimates of table 1) in earnings interval 10 minus the average predicted impact in interval 1, both for the individual and the household level. For each individual, we compute the household level impact as the average of the individual's impact and her partner's impact. Columns (2) to (4) compare further intervals respectively. Standard errors are obtained from 1,000 bootstrap replications clustered at the household level.

Table 4 indicates what drives the difference between the individual and the household level impact. In column 2 we depict for every earnings interval the share of workers who

have a partner who is more positively affected by the trade shock than himself/herself. It turns out that in the bottom half of the earnings distribution, the majority of workers have a partner who is more positively affected (e.g. 58.7% in the second interval). This is mirrored in the upper half of the earnings distribution, where the majority of workers have a partner who is more negatively affected. These numbers also take into account for example couples where both partners are negatively affected, with one partner being more negatively affected than the other one. In order to see the degree to which partners benefit from opposing effects (different sign), we restrict the sample to workers with a negative predicted impact and compute the share of the worker's loss that can be compensated by a positive impact on the partner. The resulting number can either be zero if the partner also experiences a negative impact or can be between zero and 100% if the partner benefits from the trade shock. Column 3 shows that on average about 22% of the losses are offset by partner's gains. Compensation is larger at the lower half of the earnings distribution. Workers at the very bottom of the earnings distribution experience the strongest compensation (30.7%).

Table 4: The Role of the Partner

Earnings Interval	Share of Workers (%)		Loss compensated (%)		Share of workers (%)
	Negative Impact Individual Level	Partner More Positively Affected	All Losers	Extreme Losers	Negative Impact Household Level
1	23.1	57.0	30.7	21.5	25.3
2	25.0	58.7	24.1	11.4	27.1
3	25.3	56.4	24.6	9.6	26.4
4	24.3	50.5	20.9	9.3	27.0
5	23.2	49.4	22.9	9.1	24.8
6	26.6	49.0	22.6	6.3	27.0
7	23.0	46.3	20.1	10.0	25.8
8	20.1	46.0	20.0	6.7	23.3
9	20.9	43.5	16.1	7.7	23.9
10	18.9	38.4	16.8	4.3	20.3

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Losers are workers that experience a non-positive predicted impact as calculated by equation (4), using the FE estimates from table 1. Extreme losers have a loss of at least 500 EUR. The household level impact is computed as the average of the individual's impact and her partner's impact.

When we restrict the sample to workers who lose at least 500 EUR, the compensation shares become smaller (on average: 9.6%) but the pattern remains unchanged. Consequently, individual losses from the trade shock can be partly compensated at the household

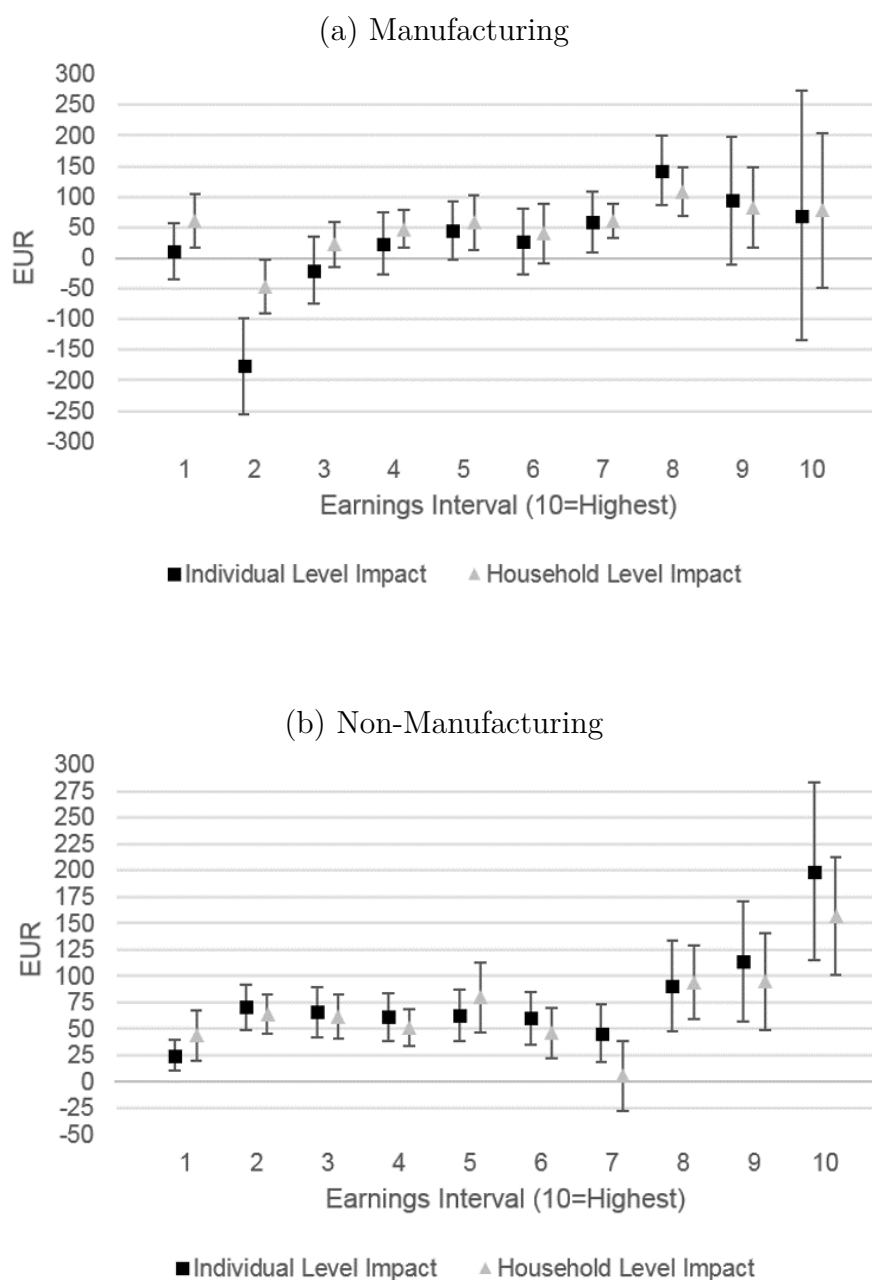
level. A comparison between columns 1 and 5 yields the direct consequence of the fact that losses on average can only be partially compensated: For every earnings interval, the share of 'losers' is about 2%-points larger at the household level than at the individual level.

5.3. Heterogeneities

Manufacturing vs. Non-Manufacturing. We now perform the whole analysis separately for workers in the manufacturing and the non-manufacturing sector. Figure 3 shows that the unfavorable effects at the lower tail of the earnings distribution are largely driven by adversely affected manufacturing workers at the lower part of the earnings distribution. These workers however benefit especially strongly from the insurance effect at the household level. Their household impact is on average 157% larger than their individual impact. The difference is highly statistically significant. This is mirrored by the results for non-manufacturing workers. They are more positively affected by the trade shock, especially at the lower part of the earnings distribution. Additionally, it turns out that non-manufacturing workers have a large insurance effect on their partners as in most intervals their household level impact is smaller than their individual level impact. The difference is statistically significant in intervals 7 and 10 (see Tables A7 and A8 Appendix). Therefore, a large part of the insurance effect that we detect on average seems to be driven by the differences between manufacturing and non-manufacturing workers.

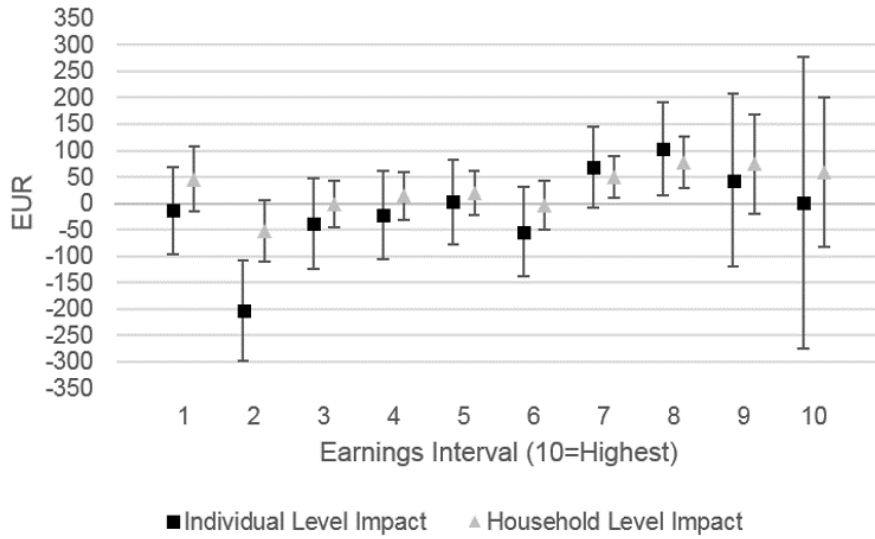
In order to explore this in more detail, we further restrict the sample to workers in manufacturing whose partners are employed in non-manufacturing. According to the descriptives, the insurance effect should be largest for these couples and figure 4 illustrates exactly this. Low-earnings workers in manufacturing especially benefit from the insurance effect at the household level if their partner is employed in non-manufacturing as their household level impact on average is almost 6 times larger than their individual level impact.

Figure 3: Impact on Manufacturing versus Non-Manufacturing Workers



Notes: Sample is divided into the same 10 earnings intervals as in figure 1. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table 1. The household level impact is computed as the average of the individual's impact and her partner's impact. Individual and household level impact only for manufacturing workers (partner can be manufacturing or non-manufacturing) in panel (a), only for non-manufacturing workers in panel (b). The respective 95% confidence intervals obtained from 1,000 bootstrap replications clustered at the household level.

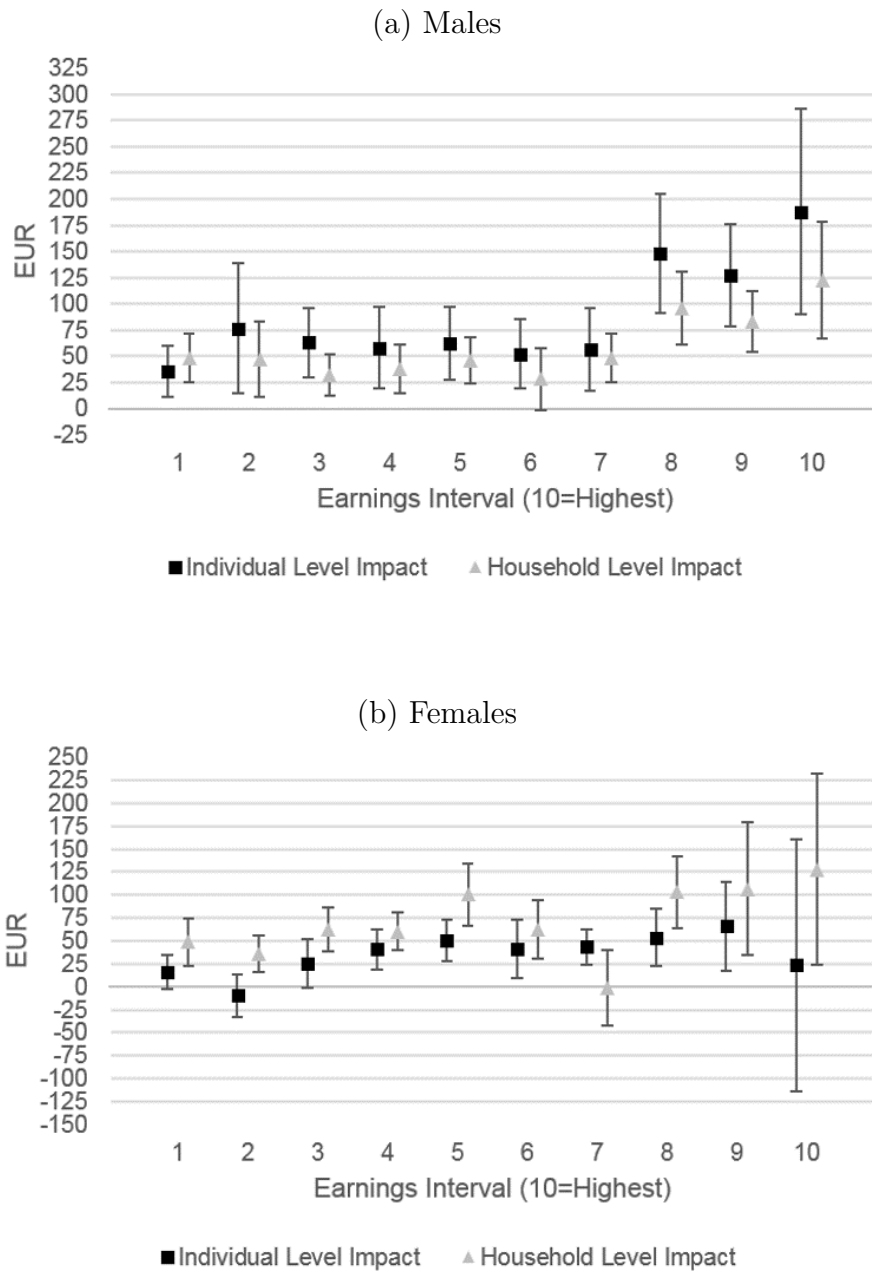
Figure 4: Inequality: Manufacturing versus Non-Manufacturing Workers



Notes: Sample is divided into the same 10 earnings intervals as in figure 1. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table 1 and the respective 95% confidence intervals obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact. Individual and household level impact only for manufacturing workers with a partner in non-manufacturing.

Males vs. Females. A separate analysis by gender shows that there are considerable differences between males and females. Figure 5 shows that males are on average more positively affected by the trade shock than females. This result stand in contrast to the findings in Autor et al. (2015) who show that Chinese import competition in US manufacturing was slightly negatively biased against males. Moreover, panel (a) shows that for males the household level impact is smaller than the individual level impact in almost all intervals. Tables A9 and A10 in the appendix show that these differences are mostly statistically significant. Therefore, the insurance effect we observe on average comes from males who are more positively affected than their partners and can consequently partly compensate their wives. Additionally, the figure shows that the inequality-increasing effect of the trade shock is driven mostly by males and not by females.

Figure 5: Impact on Male versus Female Workers

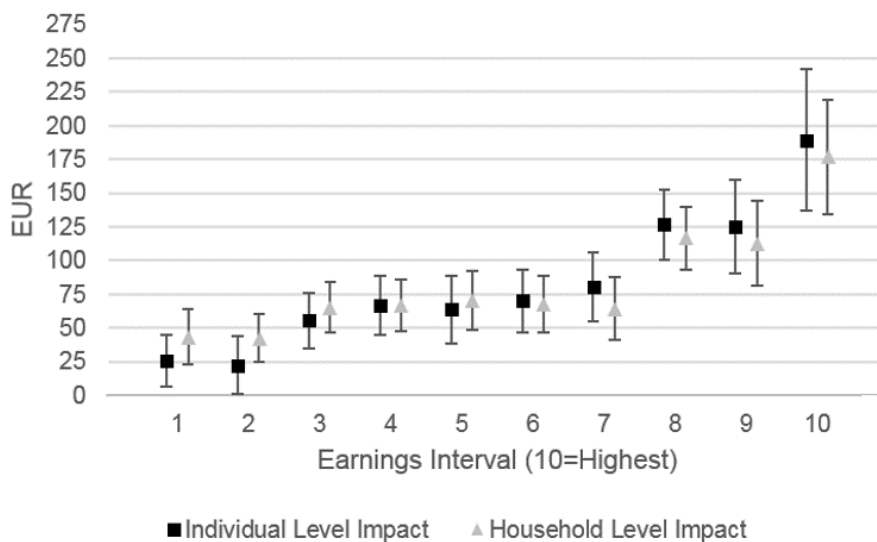


Notes: Sample is divided into the same 10 earnings intervals as in figure 1. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table 1 and the respective 95% confidence intervals obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact. Individual and household level impact only for male workers in panel (a), only for female workers in panel (b).

6. Robustness Checks

Including singles in the analysis. In our main analysis, we focus on married and unmarried couples and therefore exclude singles. We now repeat the whole analysis of section 4 and 5 including singles in our sample. This makes our estimates for the distributional effect more representative for the whole population as we capture a larger and more representative share of the population, including e.g. low-earnings single mothers who are especially important for inequality-reducing policies. However, including singles into the analysis also comes at a cost. When we focus exclusively on couples, we are able to answer the question whether the insurance effect makes a difference between the household and the individual level outcomes for individuals within couples. When we include singles, we mix up this question with the question whether there can be an insurance effect in the first place as there is naturally no such insurance effect for singles.

Figure 6: Impact on Individuals versus Households including Singles



Notes: Sample includes singles and is divided into the same 10 earnings intervals as in figure 1. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table 1 and the respective 95% confidence intervals obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact. For singles, the household level impact equals the individual level impact.

Figure 6 shows that the basic conclusions remain unchanged. The household level impact on average is larger than the individual level effect for individuals in the bottom half of the earnings distribution, whereas it is smaller for individuals at the upper half of the earnings distribution. As expected, the differences are smaller than without singles because of the lack of compensation for single households. At the lower tail of the earnings distribution, the household impact is on average 38 % higher, at the upper half on average 9 % lower. The difference between the individual and household level impact is again

significant in interval 1,2 and 7.

We also check whether the implications for inequality change after including singles in the analysis. Table 5 shows results analogous to table 3.

Table 5: Impact on Inequality including Singles

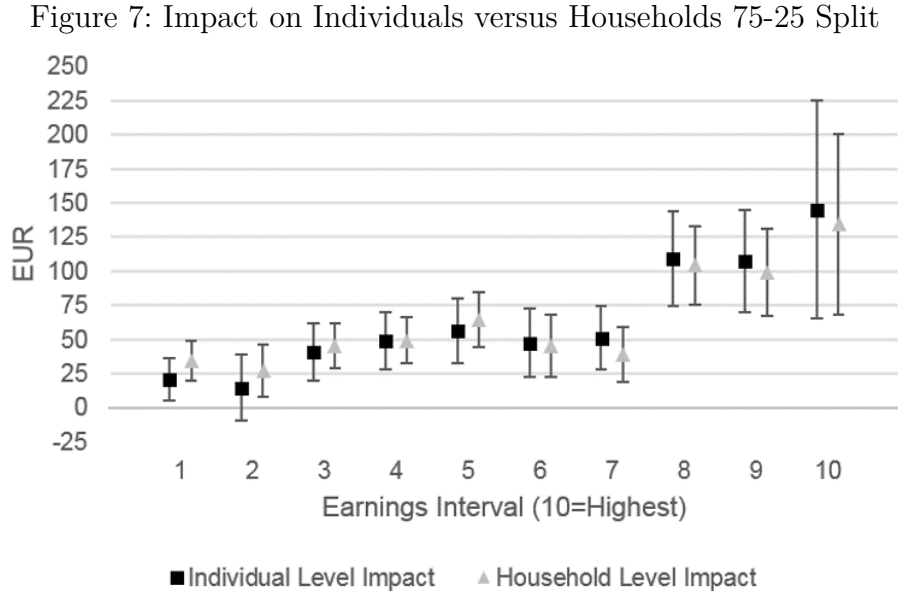
difference between intervals	10-1	9-2	10-7	4-1
Individual level impact	163.69*** (29.41)	102.62*** (21.66)	109.25*** (31.32)	40.98*** (14.88)
Household level impact	133.40*** (24.10)	70.21*** (18.8)	112.27*** (24.73)	23.61* (14.27)
Difference	30.29** (14.41)	32.42*** (10.93)	-3.02 (14.30)	17.37* (9.91)

Notes: Sample includes singles and is divided into the same 10 earnings intervals as in figure 1. Column (1) shows the difference in the average predicted impact (as calculated by equation (4) using the FE-estimates of table 1) in earnings interval 10 minus the average predicted impact in interval 1, both for the individual and the household level. Columns (2) to (4) compare further intervals respectively. Standard errors are obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact. For singles, the household level impact equals the individual level impact.

We still find a significant reduction of the inequality-increasing effect due to intra-household insurance for interval 10-1 and 9-2. Naturally, the reduction is somewhat smaller than without singles (about 30% compared to 40%). Taken together, though the effects naturally are less pronounced, our implications for inequality still hold when we include singles in our analysis.

Changing the sharing rule. Second, even though equal sharing seems to be a quite reasonable approximation, we also check whether incomplete sharing changes our results. To this end, we assume that individuals do not just split up the gains or losses equally, but that individual i 's own impact gets a weight of 75 % whereas the partner's impact only a weight of 25%. For instance, consider a couple where the wife gains 500 EUR due to the trade shock whereas the husband loses 200 EUR. Under the assumption of equal sharing, they would just split up the net gain of 300 EUR and end up with a gain of 150 EUR for each of them. If we apply the 75-25 sharing rule however, the wife, after partly offsetting the negative effect on her husband, would gain $(500 \times 0.75 - 200 \times 0.25) = 325$ EUR and the husband would still lose $(500 \times 0.25 - 200 \times 0.75) = -25$ EUR. Note that, what we for simplicity continue to call *household level impact*, is actually an individual level impact taking into account imperfect redistribution at the household level. This *household level impact* is now different for each partner within a couple as soon as partners are not exposed to exactly the same shock. Figure 7 compares the average predicted impact for individuals

and households in the different earning intervals. Again, the difference between individual and *household level impact* is smaller than in the main analysis (household level impact is 35% larger in the lower half of the earnings intervals, 9% smaller in the upper half) and the differences are still significant in intervals 1,2 and 7.



Notes: Sample is divided into the same 10 earnings intervals as in figure 1. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table 1 and the respective 95% confidence intervals obtained from 1,000 bootstrap replications clustered at the household level. The *household level impact* is calculated as $(0.75 \times \text{own impact} + 0.25 \times \text{partner's impact})$.

Table 6 shows the results for the impact on inequality.

Table 6: Impact on Inequality 75-25 split

difference between intervals	10-1	9-2	10-7	4-1
Individual level impact	124.36*** (42.45)	92.30*** (22.96)	94.14** (43.34)	28.00** (12.99)
Household level impact	99.82*** (36.65)	71.95*** (19.14)	95.32*** (35.12)	14.79 (10.74)
Difference	24.54** (11.83)	20.35** (8,69)	-1.19 (11.47)	13.22* (7.26)

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Column (1) shows the difference in the average predicted impact (as calculated by equation (4) using the FE-estimates of table 1) in earnings interval 10 minus the average predicted impact in interval 1, both for the individual and the *household level*. Columns (2) to (4) compare further intervals respectively. Standard errors are obtained from 1,000 bootstrap replications clustered at the household level. The *household level impact* is calculated as $(0.75 \times \text{own impact} + 0.25 \times \text{partner's impact})$.

The inequality-reducing effect of intra-household insurance is naturally somewhat lower under the assumption of incomplete sharing. However, we still find a significant positive effect for the lower end of the earnings distribution (20-22%). Consequently, the results in Section 5 are very robust to choosing an alternative sample or implying a different sharing rule.

7. Conclusion

To the best of our knowledge, this is the first study which investigates the difference between the household and the individual level in terms of the distributional impact of a trade shock. We exploit a large trade shock on the German labor market and the results reveal substantial differences between the household and the individual level, both in terms of who benefits and who loses from the trade shock as well as in terms of the distributional impact. Even though our results do not overturn everything we know about trade and inequality, they suggest that a household level analysis is essential in order to get the full picture about the distributional effects of globalization. We show that the difference between the household and the individual level can be heterogeneous along the earnings distribution and this makes the household perspective especially relevant. We therefore aim to encourage further research on the micro-level consequences of globalization to take into account the household level.

By showing that the inequality-increasing effect of international trade is reduced by the insurance mechanism, we also contribute to a discussion about the size of gains from trade. Antras et al. (2016) show that trade-induced inequality reduces the gains from trade since redistribution is costly. Our results suggest that some degree of 'automatic redistribution' of gains from trade takes place at the household level and this is why a pure individual level analysis might underestimate aggregate gains from trade. The mechanism we illustrate carries over to any kind of policy or shock that has heterogeneous effects across different dimensions and therefore our paper is relevant not only for future research in international trade but also for a broader strand of research questions.

What about the role of insurance effects in case of future trade shocks? The extent to which adverse effects can be mitigated by the partner will depend on whether assortative mating in terms of relevant characteristics increases or decreases. It will also depend on the heterogeneity of the trade shock along several dimensions as this governs the extent to which there is potential for an insurance effect in the first place. We leave these questions for further research.

References

- Acemoglu D., Autor D. H., Dorn D., Hanson G. H., Price B. (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics* 34 (S1), 141–198.
- Angrist J.D., Pischke J.S. (2009). *Mostly harmless Econometrics-An empiricist's companion*. Princeton, Oxford: Princeton University Press.
- Antras P., Gortari A. de, Itskhoki O. (2016). Globalization, Inequality and Welfare. *NBER Working Paper* (22676).
- Autor D. H., Dorn D., Hanson G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review* 103 (6), 2121–2168.
- Autor D. H., Dorn D., Hanson G. H., Song J. (2014). Trade Adjustment: Worker Level Evidence. *Quarterly Journal of Economics* 129 (4), 1799–1860.
- Autor D. H., Dorn D., Hanson G. H. (2015). The Labor Market and the Marriage Market: How Adverse Employment Shocks Affect Marriage, Fertility, and Children's Living Circumstances. *MIT Working Paper*.
- Balsvik R., Jensen S., Salvanes K.G. (2015). Made in China, sold in Norway: Local labor market effects of an import shock. *Journal of Public Economics* 127, 127–136.
- Baumgarten D. (2013). Exporters and the rise in wage inequality: Evidence from German linked employer-employee data. *Journal of International Economics* 90, 201–217.
- Becker G.S. (1974). A Theory of Social Interactions. *Journal of Political Economy* 82 (2).
- Bloom N., Draca M., Van Reenen J. (2016). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *Review of Economic Studies* 83 (1), 87–117.
- Browning M., Bourguignon F., Chiappori P.-A., Lechene V. (1994). Income and Outcomes: A Structural Model of Intrahousehold Allocation. *Journal of Political Economy* 102 (6), 1067–1096.
- Dauth W., Findeisen S., Suedekum J. (2014). The Rise of the East and the Far East: German Labor Markets and Trade Integration. *Journal of the European Economic Association* 12 (6), 1–33.
- (2016). Adjusting to Globalization: Evidence from Worker-Establishment Matches in Germany. *CEPR Discussion Paper*.
- Dustmann C., Lundsteck J., Schoenberg U. (2009). Revisiting the German Wage Structure. *The Quarterly Journal of Economics* 124 (2), 843–881.
- Egger H., Kreickemeier U. (2009). Firm Heterogeneity and the Labor Market Effects of Trade Liberalization. *International Economic Review* 50, 187–216.
- Eika L., Mogstad M., Zafar B. (2014). Educational Assortative Mating and Household Income Inequality. *Federal Reserve Bank of New York Staff Reports*, no. 682.

- Fortin N., Lemieux T., Firpo S. (2010). Decomposition Methods in Economics. *NBER Working Paper*.
- Frémeaux N., Lefranc A. (2015). Assortative mating and earnings inequality in France.
- Grabka M.M., Goebel J., Schröder C. (2015). Income Inequality Remains High in Germany — Young Singles and Career Entrants Increasingly At Risk of Poverty. *DIW Economic Bulletin* 25, 325–339.
- Greenwood J., Guner N., Kocharkov G., Santos C. (2014). Marry Your Like: Assortative Mating and Income Inequality. *American Economic Review: Papers Proceedings* 104 (5), 348–353.
- Harrison A., McLaren J., McMillan M. (2011). Recent Perspectives on Trade and Inequality. *Annual Review of Economics* 3, 261–89.
- Heimdal K., Houseknecht S.K. (2003). Cohabiting and Married Couples' Income Organization: Approaches in Sweden and the United States. *Journal of Marriage and Family* 65, 525–538.
- Helpman E., Itskhoki O., Redding S. (2010). Inequality and Unemployment in a Global Economy. *Econometrica* 78 (4), 1239–1283.
- Nilsson Hakkala K., Huttunen K. (2016). Worker-Level Consequences of Import Shocks. *IZA Discussion Paper No. 10033*.
- OECD (2008a). *Growing Unequal? : Income Distribution and Poverty in OECD Countries, Country Summary*.
- OECD (2008b). *Growing Unequal? : Income Distribution and Poverty in OECD Countries, Country Note Germany*.
- Schank T., Schnabel C., Wagner J. (2007). Do exporters really pay higher wages? First evidence from German linked employer–employee data. *Journal of International Economics* 72 (1), 52–74.
- SOEP v28. *Socio-Economic Panel (SOEP), data for years 1984-2011, version 28, SOEP, 2012*. DOI: doi:10.5684/soep.v28.
- Utar H. (2015). Workers beneath the Floodgates: The Impact of Low-Wage Import Competition and Workers' Adjustment. *mimeo*.
- Wagner G. G., Frick J.R., Schupp J. (2007). The German Socio-Economic Panel Study (SOEP)-scope, evolution and enhancements. *Schmollers Jahrbuch* 127 (1), 139–169.

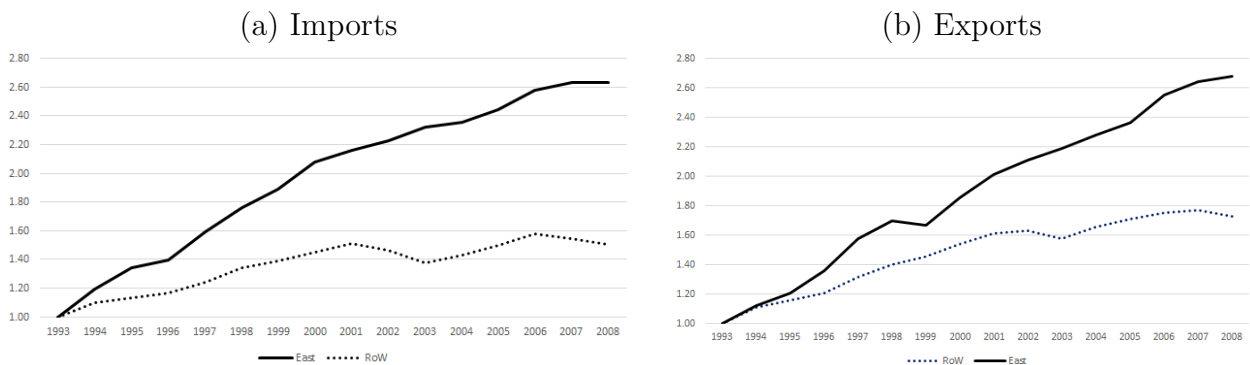
A. Appendix

Table A1: Descriptives on Trade Shocks and Earnings 1993-2008

	Mean	SD	25th	75th	Obs
Yearly Earnings (EUR)	30,351.18	21,277.93	18,156	39,204	41,392
100 x Norm. Earnings	105.57	99.60	0.00	3,532.20	41,392
Δ Import Exposure (%-points)	0.50	5.62	0.04	72.87	33,524
Δ Export Exposure (%-points)	0.40	3.58	0.05	61.05	33,524

Notes: Yearly earnings include wages and income from second jobs and are calculated using the information on average monthly income and the number of months an individual received this income. Norm. earnings are yearly earnings normalized by base year earnings. Δ Import Exposure and Δ Export Exposure is the change of trade exposures between t and $t + 1$. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Figure A1: German Trade Volumes



Notes: (a) Imports of manufacturing goods from Eastern Europe, China and the rest of the world to Germany. (b) Exports of German manufacturing goods to Eastern Europe, China and the rest of the world. Trade Flows in 1993 are normalized to 1, log scale. RoW = Rest of World, East = China and Eastern Europe. Data sources: COMTRADE, German Federal Statistical Office.

Table A2: Effect of Trade Shock on Individual Earnings - All Skill Levels

Norm. Earnings	FE	FE	FE	IV-FE
Export Exposure (EX)	0.6188*** (0.1479)	0.6656**** (0.1489)	0.7614*** (0.1588)	1.1553*** (0.2543)
Import Exposure (IM)	-0.1767** (0.0793)	-0.2176*** (0.0820)	-0.2375*** (0.0848)	-0.5463*** (0.0848)
R2	0.78	0.78	0.78	0.78
1st stage F (EX)	-	-	-	426.38
1st stage F (IM)	-	-	-	181.83
Observations	41,197	41,197	41,197	41,197
Worker FE	x	x	x	x
Region x Year FE		x	x	x
1-Digit Industry FE			x	x

Notes: Column (1) only controls for worker fixed effects, column (2) adds region \times year fixed effects and (3) show results of estimating equation (1). In column (4) we additionally instruments trade flows with trade flows to other countries (instrument group: Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom). Regressions include all skill levels from ISCED 0 to ISCED 6. Further controls include age and age squared. Standard errors clustered by 2-digit industry \times year in parentheses. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table A3: First stages of IV-FE estimates by Skill Level

Dep. Var.	Low-skilled		High-skilled	
	Export Exp.	Import Exp.	Export Exp.	Import Exp.
Export Exp. Instrument	0.6998*** (0.0348)	-0.1825** (0.0915)	0.7081*** (0.0387)	-0.0785 (0.0927)
Import Exp. Instrument	0.2860*** (0.0258)	0.9503*** (0.0461)	0.3185*** (0.0294)	1.0688*** (0.0535)
R2	0.98	0.95	0.96	0.96
F-statistic	348.64	152.04	452.86	193.79
Observations	28,293	28,293	12,805	12,805

Notes: First stage regression referring to table 2, columns (2) and (4). Export and Import Exposure as defined in Section 3, instruments are respective trade flows to Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. Standard errors clustered on 2-digit industry \times year in parentheses. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table A4: Effect of Trade Shock on Individual Earnings using Wage Sums

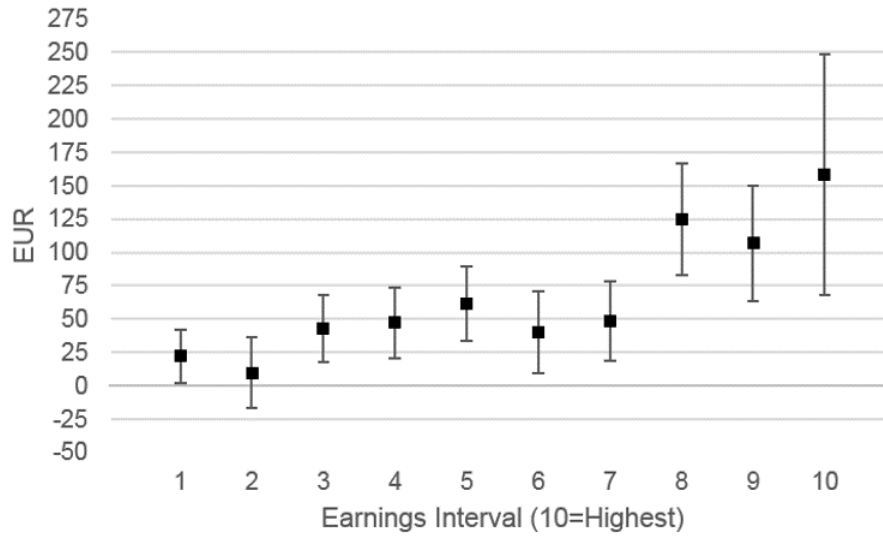
Norm. annual earnings	Low-skilled		High-skilled	
	FE	IV-FE	FE	IV-FE
Export Exposure (EX)	0.2119*** (0.0326)	0.1904*** (0.0450)	0.3108*** (0.0435)	0.3686*** (0.0805)
Import Exposure (IM)	-0.0800*** (0.0160)	-0.0778*** (0.0209)	-0.1217*** (0.0435)	-0.1573*** (0.0460)
R2	0.75	0.75	0.86	0.86
First stage F (EX)	-	234.52	-	169.68
First stage F (IM)	-	665.79	-	487.58
Observations	29,016	29,016	13,069	13,069
Worker FE	x	x	x	x
Region x Year FE	x	x	x	x
1-Digit Industry FE	x	x	x	x

Notes: Column (1) and (3) show results of estimating equation (1). In column (2) and (4) we additionally instruments trade flows with trade flows to other countries (instrument group: Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom).

Trade exposures are defined as: $IM_{jt} = \frac{Imports_{jt}^{E+C \rightarrow G}}{Wagesum_{j,(t-1)}}$, $EX_{jt} = \frac{Exports_{jt}^{G \rightarrow E+C}}{Wagesum_{j,(t-1)}}$.

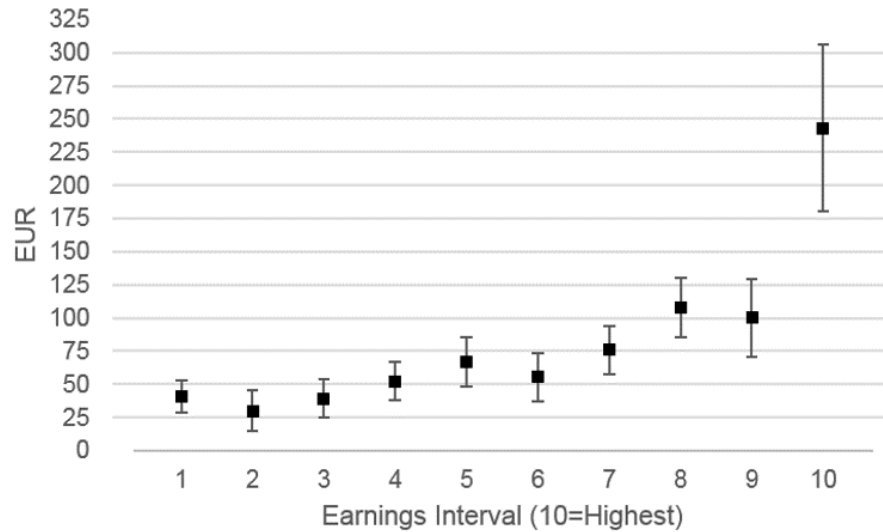
Further controls include age and age squared. Standard errors clustered by 2-digit industry \times year in parentheses. Low-skilled refers to individuals with ISCED level 0-4 (e.g. General Elementary, Middle Vocational, Vocational Plus Abi). High-skilled individuals have ISCED 5 or 6 (Higher Vocational or Higher Education). Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Figure A2: Impact on Individual Earnings: IV Estimates



Notes: Sample is divided into the same 10 earnings intervals as in figure 1. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the IV-FE-estimates of table 1 and the respective 95% confidence intervals obtained from 1,000 bootstrap replications clustered at the household level.

Figure A3: Impact on Individual Earnings: Wage Sums



Notes: Sample is divided into the same 10 earnings intervals as in figure 1. The figure depicts the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table A4 and the respective 95% confidence intervals obtained from 1,000 bootstrap replications clustered at the household level.

Trade exposures are defined as: $IM_{jt} = \frac{Imports_{jt}^{E+C+G}}{Wagesum_{j,(t-1)}}$, $EX_{jt} = \frac{Exports_{jt}^{G \rightarrow E+C}}{Wagesum_{j,(t-1)}}$.

Table A5: Predicted impact - Bootstrap Results for all Intervals, FE specification

Earnings Interval	Individual Level	Household Level	p-value Diff	Obs
1	20.79	48.73	0.012	1,661
2	14.87	39.46	0.006	1,661
3	40.56	50.44	0.257	1,689
4	48.79	50.31	0.841	1,639
5	56.73	72.42	0.101	1,656
6	47.55	43.85	0.657	1,668
7	51.01	27.51	0.036	1,661
8	109.40	99.33	0.42	1,651
9	107.18	91.06	0.28	1,658
10	145.15	124.02	0.25	1,659

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Numbers are the average predicted impact over all individuals in the respective earnings interval as calculated by equation (4), using the FE-estimates of table 1. The household level impact is calculated as the average of both partners' impact. P-values on the difference between individual and household level are obtained from 1,000 bootstrap replications clustered at the household level.

Table A6: Impact on Inequality: IV-FE Estimates

Difference between intervals	10-1	9-2	10-7	4-1
Individual level impact	136.54*** (48.12)	97.31*** (26.55)	109.88** (48.92)	25.04 (16.94)
household level impact	89.70*** (33.47)	50.23** (21.59)	113.65*** (32.63)	-1.93 (15.8)
difference	46.84* (27.21)	47.09** (20.34)	-3.77 (26.29)	26.97 (17.65)

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Column (1) shows the difference in the average predicted impact (as calculated by equation (4) using the IV-FE-estimates of table 1) in earnings interval 10 minus the average predicted impact in interval 1, both for the individual and the household level. Columns (2) to (4) compare further intervals respectively. Standard errors are obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact.

Table A7: Predicted impact - Bootstrap Results for all Intervals, Manufacturing

Earnings Interval	Individual Level	Household Level	p-value Diff	Obs
1	10.46	60.57	0.018	466
2	-176.90	-46.77	0	374
3	-20.74	22.20	0.021	493
4	23.64	47.72	0.125	548
5	45.36	57.86	0.446	560
6	26.34	39.84	0.327	622
7	58.53	60.41	0.894	661
8	143.04	109.22	0.045	582
9	93.69	83.35	0.704	557
10	69.04	77.75	0.852	687

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Column (1) shows the difference in the average predicted impact (as calculated by equation (4) using the FE-estimates of table 1) in earnings interval 10 minus the average predicted impact in interval 1, both for the individual and the household level. Columns (2) to (4) compare further intervals respectively. Individual and household level impact only for manufacturing workers (partner can be manufacturing or non-manufacturing). Standard errors are obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact.

Table A8: Predicted Impact - Bootstrap Results for all Intervals, Non-manufacturing

Earnings Interval	Individual Level	Household Level	p-value Diff	Obs
1	24.82	44.12	0.154	1,195
2	70.56	64.50	0.519	1,288
3	65.82	62.07	0.722	1,196
4	61.43	51.60	0.285	1,091
5	62.54	79.86	0.272	1,096
6	60.16	46.24	0.195	1,046
7	46.05	5.76	0.021	1,000
8	91.09	93.95	0.853	1,069
9	114.00	94.96	0.376	1,101
10	198.94	156.72	0.076	972

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Column (1) shows the difference in the average predicted impact (as calculated by equation (4) using the FE-estimates of table 1) in earnings interval 10 minus the average predicted impact in interval 1, both for the individual and the household level. Columns (2) to (4) compare further intervals respectively. Individual and household level impact only for non-manufacturing workers (partner can be manufacturing or non-manufacturing). Standard errors are obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact.

Table A9: Predicted impact - Bootstrap Results for all Intervals, Males

Earnings Interval	Individual Level	Household Level	p-value Diff	Obs
1	35.84	48.53	0.245	366
2	76.51	47.42	0.101	470
3	63.08	31.90	0.004	677
4	58.27	37.89	0.073	742
5	62.37	46.09	0.127	856
6	52.45	28.60	0.011	912
7	56.41	47.96	0.436	968
8	148.13	96.55	0.001	972
9	127.08	83.37	0.007	1,118
10	188.09	122.58	0.008	1,226

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Column (1) shows the difference in the average predicted impact (as calculated by equation (4) using the FE-estimates of table 1) in earnings interval 10 minus the average predicted impact in interval 1, both for the individual and the household level. Columns (2) to (4) compare further intervals respectively. Individual and household level impact only for male workers. Standard errors are obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact.

Table A10: Predicted Impact - Bootstrap Results for all Intervals, Females

Earnings Interval	Individual Level	Household Level	p-value Diff	Obs
1	16.53	48.79	0.021	1,295
2	-9.43	36.32	0	1,192
3	25.49	62.83	0.006	1,012
4	40.95	60.58	0.081	897
5	50.69	100.60	0.003	800
6	41.64	62.26	0.132	756
7	43.47	-1.06	0.032	693
8	53.96	103.31	0.023	679
9	65.97	106.99	0.202	540
10	23.56	128.09	0.015	433

Notes: Sample is divided into the same 10 earnings intervals as in figure 1. Column (1) shows the difference in the average predicted impact (as calculated by equation (4) using the FE-estimates of table 1) in earnings interval 10 minus the average predicted impact in interval 1, both for the individual and the household level. Columns (2) to (4) compare further intervals respectively. Individual and household level impact only for female workers. Standard errors are obtained from 1,000 bootstrap replications clustered at the household level. The household level impact is calculated as the average of both partners' impact.