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

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PRELIMINARY VERSION

International trade creates aggregate welfare gains in the long run. During the process of adjustment to trade, however, workers employed in import-competing industries might face costs in the form of temporary unemployment or depressed wages. We examine the period of adjustment of the German economy to the increase of trade with China and former Soviet Union countries and focus on the following question: Can redistribution of gains and losses from trade between partners mitigate adverse effects on workers in import-competing sectors? We find that due to the high level of assortative mating the trade shock affects partners similarly and this restricts the potential for redistribution. Nevertheless, couples can compensate on average 10% of the earnings losses of adversely affected workers by redistribution between partners. We then turn to the distributional consequences and find that the trade shock had a considerable inequality-increasing effect. Intra-household redistribution, however, did not help to dampen this effect.

JEL-Classification: F16, J12, J31

Keywords: Trade Adjustment, Intra-Household Redistribution, Earnings Inequality, IV-Fixed Effects

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1. Introduction

Trade liberalization creates aggregate welfare gains in the long run. However, before the full gains can be reaped, the economy has to undergo an adjustment process which involves reallocation of parts of the workforce either across or within industries.¹ If the process of moving workers between industries is subject to frictions, workers employed in import-competing sectors might be confronted with adjustment costs in the form of unemployment spells or temporarily depressed wages.² It is crucial to understand exactly which group of workers is hit the hardest by the adverse effects of import competition in order to design well-targeted policies to mitigate these effects.

Two basic findings emerge from previous empirical research: Adjustment to trade liberalization goes along with substantial costs for workers in terms of earnings losses and these costs are highly unevenly distributed across the workforce. In a seminal study, Autor et al. (2014) show that Chinese import competition in US manufacturing forced many workers to switch to less exposed industries inside or outside the manufacturing sector. This triggered earnings losses over the medium run, especially for less skilled workers. Dauth et al. (2016) portray the same mechanism in the context of Germany's increase in trade with China and Eastern Europe. In the light of growing inequality in many countries (ILO 2015), these results call for redistributive policies that serve to stabilize income streams of the most vulnerable workers at the bottom of the earnings distribution. It is therefore no surprise that the US government has introduced the *Trade Adjustment Assistance Program* which aims at mitigating the adverse effects on workers and firms during the process of adjustment to trade.³

In this paper, we study intra-household redistribution of gains and losses from trade as an alternative mechanism which has the potential to act as a stabilizer during the period of adjustment. We thus deviate from the conventional individualistic view in the literature about trade-adjustment by shifting the focus on the household level and portray how this

¹Classical trade theories like the Ricardo model or the Heckscher-Ohlin model suggest reallocation across industries, more recent models emphasize intra-industry reallocation to more productive firms (e.g. Melitz 2003).

²See section 2 for a more detailed discussion of potential theoretical mechanisms.

³See <https://www.dol.gov/general/topic/training/tradeact> for more information on this policy.

could alter the conclusions about the effects of international trade on individual workers. More specifically, we examine the large and sudden increase of Germany's trade with China and former Soviet Union countries between 1993 and 2008 and portray the degree to which this trade shock affected partners differentially both within married and within unmarried couples. In our empirical setting, industries differ in the degree to which they are exposed to import competition on the one hand and benefit from export opportunities on the other hand. Additionally, the impact of a given trade shock on a worker depends on her educational level. Consequently, the shock affects partners differentially as soon as they are employed in different industries and/or do not belong to the same skill-group. We then conduct the following thought experiment: 'to what extent could adverse effects on workers be mitigated if partners redistributed gains and losses from trade?'. Suppose that a worker employed in an import-competing industry loses his job and experiences a period of unemployment. His wife might be employed in an industry that benefits from increased export opportunities and this is why she gains from higher job-stability or gets promoted. If this is the case, she can redistribute gains from trade to her partner and mitigate the adverse effects of temporary unemployment.⁴

Our main result is that partners can compensate about 10% of the earnings losses of adversely affected individuals by redistribution of gains from trade. Room for compensation differs considerably across couples as some couples can compensate all of the earnings losses, whereas others have no room for compensation since partners are subject to similar trade shocks. Our main contribution to the literature therefore is to illustrate that a look at the household-level impact of trade shocks can deliver additional insights on how trade liberalization affects individual workers. Existing studies ignore this dimension and thereby focus on individual labor market outcomes as the only driver of individual welfare during the adjustment process.⁵ The policy implications that emerge from these studies

⁴The general idea of consumption smoothing via redistribution within households is well known in family economics since Becker (1974). See the section 2 for a more detailed explanation of this mechanism. Our dataset does not allow us to directly observe the act of redistribution between partners and this is why we conduct the thought experiment of asking what would be the effect of the trade shock on individuals if partners redistributed gains and losses from trade. However, as almost 70% of all couples report some kind of income pooling we are confident that a substantial degree of redistribution is present in our sample.

⁵Note that we do not aim to quantify the exact welfare consequences of the trade shock but rather focus

thereby are based implicitly on the assumption that partners are completely independent from each other and do not redistribute money. A large literature in family economics however suggests that this is not necessarily the case. We take this as a motivation to complement the existing literature by an analysis that takes redistribution between partners into account. Our results suggest that this perspective is extremely relevant as some workers who incur adjustment costs can be compensated by their partners whereas other cannot.

In a first step, we estimate the impact of Germany's trade liberalization with China and Eastern Europe on individual labor market outcomes with the help of fixed effects and instrumental variable fixed effects regressions that carefully control for unobserved heterogeneity.⁶ In line with previous studies (e.g. Autor et al. 2014; Dauth et al. 2014; Dauth et al. 2016) we find that workers employed in industries that benefit from increasing export opportunities experience higher earnings, whereas workers employed in import-competing industries suffer from lower earnings. We find that the negative effects of import competition are stronger for low-skilled workers. In a next step, we exploit the extensive household dimension of our dataset and provide evidence on the degree to which this trade shock affected partners differentially. We observe a high degree of assortative mating, both in terms of industry affiliation and education. 70% of workers have the same educational level and 15% work in the same 2-digit industry as the partner and this is why the trade shock affects partners to a similar extent on average. We then focus on workers who suffer from the trade shock and find that redistribution of gains and losses from trade within couples can compensate on average about 10% of their earnings losses. We also detect a large variation: In some couples, all of the earnings losses can be compensated, whereas in other couples there is no room for compensation. This result is robust across different assumptions about how couples redistribute gains and losses.

In a last step, we turn to the potential quantitative implication of the mechanism for

on the costs and benefits that arise in terms of individuals' labor market outcomes and how these can be redistributed. Structural empirical approaches (e.g. Caliendo et al. 2015) are more suitable for a welfare analysis that takes into account price changes as well.

⁶Our identification strategy is most closely related to Dauth et al. (2016) who build on Autor et al. (2013) and Autor et al. (2014).

inequality. We estimate the impact of the trade shock on inequality under two scenarios: one scenario in which redistribution of gains and losses from trade between partners takes place and one scenario in which no redistribution takes place. If we impose no redistribution between partners, we find that the trade shock on average increased the differential between the 75th and the 25th earnings percentile by 110-130 Euros per year which corresponds to 13-16% of the average yearly increase of this measure. Interestingly, our analysis suggests that intra-household redistribution does not serve to mitigate the inequality-increasing effect of the trade shock. This mainly has two reasons. One reason is that due to the high degree of assortative mating the trade shock affects partners similarly and this curbs the potential for intra-household redistribution. Another reason is that a substantial fraction of low-earnings (high-earnings) workers who win (lose) in terms of earnings compensate (are compensated by) their partner and this reinforces the inequality-increasing effect of the trade shock.

The policy implication that emerges from our results is straightforward: Policies that aim to mitigate adjustment costs to workers should take into account the joint impact of the trade shock on the household. This helps to design the right policies in order to dampen the adverse effects on some workers during trade-adjustment. The basic mechanism we illustrate carries over to any kind of policy or shock that has heterogeneous effects across individuals.

The rest of this paper is structured as follows. In section 2 we give a more detailed illustration of the nature of adjustment costs during trade liberalization and explain under which conditions these costs can be mitigated at the household level. Section 3 outlines the data. In section 4 we estimate the individual-levels effects. Section 5 presents evidence on the mechanism at hand. Section 6 provides robustness checks. Section 7 concludes.

2. Adjustment Costs and why the Partner Could Matter

2.1. Adjustment Costs: Theoretical Reasoning

The adjustment costs we aim to capture empirically can be rationalized in a specific factor model as studied by Feenstra (2004). Suppose that an economy consists of two industries that employ labor and capital and consider capital to be immobile between industries. Further suppose that labor is mobile in the long run and this is why wages between both industries are equalized. If one sector experiences a decrease in product demand (e.g. because the rest of the world becomes more productive in this industry), this will cause wages in this industry to fall below wages in the other industry. In a frictionless economy with perfect labor mobility, workers would immediately switch to the other industry until wages again are equilibrated. In the presence of frictions of moving workers between industries, however, the process of adjustment might be sluggish and some workers remain stuck for some time in the import-competing industry and face depressed wages until they manage to reallocate. Workers initially employed in the import-competing industry thus experience lower cumulative earnings than workers employed in the unaffected industry and the period of adjustment drives the difference.⁷ These are the kind of adjustment costs that we aim to capture empirically. Product demand for import-competing industries falls due to the rise of China and Eastern European countries as exporters on the world market and this forces many of the workers in these industries to switch to less exposed firms.⁸ Note, however, that in our empirical setting, there are also benefits of trade as workers employed in export-oriented industries benefit from higher job stability or higher wages.

Turning to the nature of the frictions that impede immediate reallocation of workers, the literature has put forward different possibilities. One can for example think of search and matching frictions as modeled by Davidson and Matusz (2006) or Helpman et al. (2010). In the presence of search and matching frictions, workers whose wages are depressed due

⁷Autor et al. (2014) provide a formal illustration of this mechanism. In contrast to Autor et al. (2014), our dependent variable is not cumulative earnings over several years but yearly earnings. The basic mechanism, however, remains unchanged.

⁸As Dauth et al. (2016) illustrate, workers adjust by switching to different firms inside or outside their initial industry.

to the trade shock have to incur costly and time-consuming search for a job in the other industry. The same applies to a worker who has been laid off after the trade shock. Dix-Carneiro (2014) incorporates switching costs into his model by assuming that workers have comparative advantage across sectors. Additionally, following the idea by Neal (1995), he assumes that workers accumulate sector-specific human capital which is imperfectly transferable across sectors. Artuc et al. (2010) in contrast simply assume that moving between industries is subject to idiosyncratic moving costs for workers and is more agnostic about the exact nature of these costs.

2.2. Adjustment Costs: Empirical Evidence

The adjustment process of economies during trade shocks has been subject of several reduced form empirical studies as well as structural empirical studies. The following results emerge: Adjustment to trade is a process that takes several years, it creates substantial costs to workers in terms of lower earnings, and these costs are highly dispersed across the workforce, i.e. some workers manage to adjust without major earnings losses whereas others experience heavy losses during the adjustment process.

During the last two decades, the rise of China on the world market has induced a drastic change in the pattern of world trade and this provides an ideal setting to study the adjustment process of industrialized economies to a major trade shock. China, a large labor-abundant country, emerged as a major exporter of labor-intensive manufacturing goods such as textiles and apparel. Naturally, this trade shock created considerable pressure on labor-intensive industries in industrialized countries and induced a reallocation of factors of production from these industries to high-tech manufacturing or non-manufacturing industries. In an influential study, Autor et al. (2014) investigate adjustment of workers in US manufacturing industries to Chinese import competition and find that workers who in 1991 worked in manufacturing industries that experienced high import competition from China experienced lower cumulative earnings, spend less time working for their initial employer in their initial 2-digit industry, and more time working in a non-manufacturing

sector during the following 16 years.⁹ Interestingly, earnings losses are larger for workers with low education, low labor force attachment and low tenure. High-skilled workers in contrast are better able to cushion the adverse effects of Chinese import competition by switching to less exposed industries inside or outside the manufacturing sector.¹⁰ Utar (2015) confirms these results for Chinese import competition in Denmark. Dauth et al. (2016) study the adjustment behavior of German manufacturing workers during a period of strongly increasing trade with China and Eastern European countries which formerly belonged to the Soviet Union and confirm the large scale and heterogeneity of adjustment costs.¹¹

Recent structural empirical studies largely confirm these findings. Artuc et al. (2010) use data from the US Current Population survey and find that costs of switching between sectors are high and have a large variance and this is why the economy adjusts only slowly to trade shocks and why wages in import-competing industries fall sharply. Dix-Carneiro (2014) comes to the same conclusion in the context of Brazil. Several other studies document the sluggish adjustment behavior during a trade shock but do not explicitly focus on adjustment costs which arise for the individual worker (e.g. Kambourov 2009; Caliendo et al. 2015).

2.3. How could Adjustment Costs be Mitigated at the Household Level?

Our main interest now lies in the question of whether and how partners could mitigate these adjustment costs for individual workers at the household level. To put it simply, taking the household perspective would not add any value to the classic individual-level view if partners were not willing to redistribute or pool income at the household level and

⁹In terms of methodology, this study is an extension to the worker-level of the regional-level approach pioneered by Autor et al. (2013).

¹⁰See Autor et al. (2016) for a comprehensive overview about the 'China Shock' and the empirical literature that examined the resulting adjustment process of the US labor market.

¹¹In contrast to for example the USA, Germany benefits from better export opportunities to these countries and this on aggregate overcompensates the short term negative effect of import competition.

thus managed their income completely independently of each other.¹²

Based on the *common preferences* model of Samuelson (1956), Becker (1974) argues that partners do not act as fully independent agents but that each family has a household head who redistributes income within the household. He points out that the redistribution mechanism within a family serves as an insurance against income shocks: if any kind of disaster reduces one family member's income the household head would increase the contribution to this family member by lowering own consumption and the transfers to the other family members.

It is important to keep in mind that this kind of income pooling does not necessarily mean that income is equally shared between partners and does consequently not imply that each household member's income is just the average of overall household income. Elsas (2013) for example uses SOEP data to show that one can reject the equal sharing hypothesis. Moreover, models on (cooperative or non-cooperative) household bargaining suggest that the use of household resources could depend on each household member's relative bargaining power (e.g. Manser and Brown 1980; Chen and Woolley 2001).

Provided that partners are willing to redistribute money, the partnership could serve as a kind of risk sharing mechanism if partners have offsetting trade shocks. As partners are not necessarily employed in the same industry they are also not always exposed to the same trade shock. Exemplary, three scenarios are possible¹³:

- (A) The husband works in an industry with increasing import competition and gets unemployed. His wife benefits from better export opportunities and has a more stable job. Thus, a negative shock hits one partner but the other partner experiences a positive shock.
- (B) The husband works in an industry with increasing import competition and gets unemployed. His wife also works in an industry that suffers from import competition and gets a wage cut. Thus, both partners suffer from a negative shock.
- (C) The husband works in an industry with increasing export opportunities and benefits

¹²Keep in mind that we are not interested in how partners pool income in general but only in the redistribution of gains and losses from the trade shock.

¹³The terms *husband* and *wife* are of course exchangeable.

from higher job stability. His wife also works in an industry with a positive export shock and gets a wage increase. Thus, both partners experience a positive shock.

Depending on which scenario prevails, partners' correlations of trade shocks will on average be negative (scenario (A)) or positive (scenarios (B) and (C)). The stronger the negative correlation, the larger the resulting portfolio-effects and the more households are able to mitigate a negative shock through intra-household redistribution. Note that, even if the average correlation is positive, this does not imply that intra-household shock coping is impossible for all households. As long as the correlation is not perfectly positive, some couples still have offsetting trade shocks and are able to compensate each other.

Moreover, previous literature (e.g. Dauth et al. 2016; Autor et al. 2014) found that workers with lower education level, shorter tenure and weaker labor force attachment suffer more from negative trade shocks as they are not able to switch to less exposed industries so easily. Thus, the potential of the household to deal with a given trade shock also depends on the distribution of such characteristics within and between households. For instance, compare a couple where both partners have high education level with a couple where both partners have low education and assume that a negative trade shock hits both partners of each couple. The likelihood that at least one partner is able to switch to a less exposed or even positively affected industry is much larger for the high-skilled couple than for the low-skilled couple. Thus, the potential for intra-household shock coping increases if at least one partner is highly educated and can react more flexibly to labor market changes.¹⁴

Both the correlation of partners' trade shocks and the potential to deal with a given shock heavily depends on sorting of partners with respect to industry affiliation but also concerning education. Becker (1973) points out that individuals mate depending on financial, psychological or genetical traits and thus have a certain taste for similarity. This

¹⁴In line with models in the spirit of Melitz (2003), recent empirical evidence for Germany pronounces the rising importance of firm-component of wages (Card et al. 2013). We therefore also estimated heterogeneity in the effects along firm size. However, it turned out that the individual education level plays a larger role for the heterogeneity of the effect. This can be due to the high correlation between firm-size and workforce skills (see e.g. Bernard et al. 2007). Unfortunately, due to the small sample size, we cannot divide the dataset into infinitely many cells for the regression analysis. We therefore decided to focus on industry and education as the two dimensions across which the effect of the trade shock varies.

phenomenon is known as *assortative mating* in the family economics literature and plays an important role for our analysis: the stronger assortative mating with respect to industry affiliation, the more positive the correlation of partners' trade shocks and the lower the potential for intra-household compensation. The stronger assortative mating with respect to education level, the lower the possibilities to mitigate a given trade shock at the household level, especially for those who are already more vulnerable to the shock *per se*.

Unfortunately, we do not observe the act of redistribution between partners and this is why we have to make assumptions about how gains and losses from trade are redistributed. However, note that the results we obtain in section 5 are robust across different redistribution schemes.¹⁵

While we focus on this rather mechanical effect, intra-household shock coping could also work via behavioral responses of one partner to a trade shock of the second partner. Such effects are referred to as *added worker effects* (AWE) (e.g. Mincer 1962; Maloney 1987; Lundberg 1985). The main idea of this strand of literature is that women increase their labor supply if their husband gets unemployed in order to mitigate the resulting reduction of family income. Although empirical research¹⁶ remains inconclusive on whether the AWE really exists, we run different panel regressions in order to see whether a trade shock on one partner caused a behavioral responses of the other partner. We do not find any evidence for an added worker effect.¹⁷ Moreover, we agree with the previous literature (e.g. Bredtmann et al. 2014), that the AWE is hard to measure and that estimates could be confounded by unobserved partner characteristics or in our case assortative mating patterns that lead to a positive correlation of partners' shocks. We will therefore not include the regression results in section 5.

¹⁵We can obtain information on whether couples pool their income or not only for years 2004, 2005 and 2008. About 70% of all couples report some kind of income pooling and this is why we are confident that redistribution of money is present within the couples. However, as argued above, income pooling does not mean that partners split the household income equally.

¹⁶Recent empirical papers investigating the AWE are for example Triebe (2015), Ayhan (2015), Martinoty (2015), Goux et al. (2014), and Cullen and Gruber (2000).

¹⁷Results can be obtained upon request.

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)¹⁸ 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, NACE, 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.

We then construct an unbalanced panel of households from 1993 through 2008. As a balanced panel would artificially keep the mating structure of partners constant and as we are also interested in the change of this mating structure and the resulting potential for intra-household redistribution, an unbalanced panel is more suitable for our purpose.¹⁹ We keep all individuals which we can observe for at least 5 periods and for which we have all relevant information for both partners.²⁰ As the main focus of our analysis is on households, we drop all singles and only consider married and unmarried partners. We restrict our sample to the working population aged between 16 and 64. To be consistent with Dauth et al. (2016), we follow their restriction on individuals who were fulltime employed in the base year²¹. To capture adjustment costs, however, we allow for unemployment²²

¹⁸For more information on the SOEP see Wagner et al. (2007).

¹⁹Moreover, we do not estimate a classical Difference-in-Differences model but make use of yearly shocks and thus do not need a balanced panel structure. Balancing the panel would furthermore reduce our sample size considerably.

²⁰We drop individuals employed in an industry with NACE code 95 or larger because we do not have trade shocks for these industries. We also drop households with missing information for relevant variables like industry, education, tenure,...

²¹Consequently, we exclude by construction that workers switch from parttime to fulltime employment in the first observed period. Nevertheless, to make our result comparable to the Dauth et al. (2016) study, we keep the fulltime restriction. Moreover, we can justify this restriction because parttime workers might have a weaker attachment to their respective industry and are consequently not the most affected group.

²²In case of unemployment, we follow Dauth et al. (2014) and assign the last observed industry-affiliation to this individual.

or parttime work in subsequent years. We do not impose the same fulltime restriction on these individuals' partners because they are not relevant for the individual-level results²³.

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 income²⁴ and thereby construct the dependent variable. As the trade shock should not affect self-employed individuals, civil servants, individuals who are still in education, workers in military or community service and pensioners, we drop these groups from the sample. Furthermore, we convert income from DM to EUR for years prior to 2001 and deflate income according to the consumer price index provided by the German Federal Statistical Office. Table 1 contains summary statistics on annual earnings.

Data on international trade flows. Data on exports and imports come from the United Nations Commodity Trade Statistics Database (Comtrade). To ensure comparability of our results and the estimates by Dauth et al. (2014) and Dauth et al. (2016) we follow their preparation of the trade data quite closely. The Comtrade 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 the German Bundesbank supplies. Using 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.²⁵

The two main explanatory variables in our empirical analysis are industry j 's total export and import exposure from China and Eastern Europe in year t . They reflect the degree to which a given industry is exposed to import competition and export opportunities with respect to China and former Soviet Union countries. We start by computing industry j 's direct export and import exposure in a given year t :

²³The only restriction we need in order to determine the partner's trade shock is that she is not unemployed in the first observed year.

²⁴Includes income from wages and second jobs.

²⁵Since the SOEP only provides individuals' industry affiliation at the 2-digit level, we deviate from Dauth et al. (2016) and do not use 3-digit level industry codes.

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

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

where $Imports_{jt}^{E+C \rightarrow G}$ and $Exports_{jt}^{G \rightarrow E+C}$ denote industry j 's exports to and import from China and Eastern Europe²⁶ in year t and $Imports_{jt}^{World \rightarrow G}$ and $Exports_{jt}^{G \rightarrow World}$ are the corresponding trade flows with the rest of the world. During our sample period, trade with China and former Soviet Union countries as a share of total trade increased from roughly 5% in 1993 to 24% in 2008. Figure A1 in the Appendix further shows that the higher growth of trade with China and Eastern Europe as compared to trade with the rest of the world drove this effect. Therefore, increasing trade with China and Eastern Europe is the main globalization shock from Germany's point of view and variation in trade exposure stems mainly from variation in the numerator. Due to considerable size differences between industries it is however important to normalize with trade flows from the world as a whole.

As the trade shock is arguably a shock to the German manufacturing sector (Dauth et al. 2014), we obtain the direct trade exposure measures only for 22 manufacturing industries. However, even if the direct shock only concerns the manufacturing sector, the non-manufacturing sector is also affected. As Acemoglu et al. (2014) argue, service sectors which supply intermediate goods to the manufacturing sector might suffer from lower demand for these goods if the respective manufacturing sectors are adversely affected by import competition. The same logic holds for linkages between manufacturing sectors. Consider for example an industry a which supplies intermediate inputs to industry b . If industry b benefits from increasing export opportunities to China and Eastern Europe it will demand more intermediate inputs from industry a and industry a will benefit as well. Conversely, if industry b suffers from import competition it will demand less intermediates from a . To capture the extent to which export and import shocks are transmitted along the value chain we compute indirect export and import exposure using

²⁶Following Dauth et al. (2016), we define Eastern Europe as the group of the following countries: Bulgaria, 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.

the method of Acemoglu et al. (2014), 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.²⁷ The only additional information we need for this is coming from input-output tables of the German Federal Statistical office.²⁸ Total export and import exposure results as the sum of the direct and indirect exposure measures.²⁹ We end up with trade 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 (about 20%) who are not employed in the same sector, taking the effect of the trade shock on the non-manufacturing sector into account is necessary for our further analysis.

Table 1 gives a descriptive overview of the 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.³⁰

To determine the extent to which the trade shock affected each individual or household we merge the trade data to the SOEP data on the basis of the 2-digit NACE information in each year.³¹

²⁷As Acemoglu et al. (2014) show that linkages to suppliers are much more relevant than linkages to purchasers, we only include supply-linkages in our analysis.

²⁸We take the input-output table from the earliest possible year (1994) and keep the input-output structure constant in order to mitigate the problem that the trade shock influences the input-output structure.

²⁹Since the trade shock arguably affected the manufacturing sector, direct trade exposure in all non-manufacturing sectors is equal to zero (Acemoglu et al. 2014).

³⁰Descriptives for 1993-2000 and 2001-2008 separately can be found in the Appendix table A1.

³¹In case of unemployment in period t we use the last observed industry affiliation prior to t .

Table 1: Descriptives on trade flows and earnings 1993-2008

	Mean	SD	Min	Max	Obs
yearly earnings (EUR)	30,351.18	21,277.93	0.00	400,920.00	41,392
100 x rel. earnings	105.57	99.60	0.00	3,532.20	41,392
Δ Import Exposure (%)	0.20	7.76	-54.86	40.96	11,160
Δ Export Exposure (%)	0.24	4.71	-33.30	22.72	11,160
Δ Import Exposure (%) + linkages	0.50	5.62	-54.86	51.12	33,524
Δ Export Exposure (%) + linkages	0.40	3.58	-33.30	34.85	33,524

Notes: Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

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. (2014) and Dauth et al. (2016). Moreover, we do not yet take any potential intra-household compensation mechanisms into account.

4.1. Identification

In contrast to Autor et al. (2014) and Dauth et al. (2014) who highlight the effect on cumulative earnings over a full decade, we investigate the effect of contemporaneous changes in trade exposure on workers' annual earnings. Considering yearly changes is more appropriate for our purpose for two reasons: first, the annual changes in the mating structure play an important role for our analysis and second, because we are interested in the change in income inequality over time. Consequently, we borrow the short-run approach by Dauth et al. (2016) but extend the analysis also to the non-manufacturing sector that is affected by indirect trade exposure (see section 3).

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. Changes in IM_{jt} and EX_{jt} capture the rise of the relative importance of China and Eastern Europe as trading partners for Germany in a given industry. We make then use of the panel structure in our data and estimate the following empirical specification where we observe individuals on an annual basis and gradually introduce individual fixed effects, region \times year fixed effects and 1-digit-industry-level fixed effects:

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

Y_{ijrt} ³² 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 year³³. As a robustness check we will use earnings normalized with logs instead of base year earnings. The worker's contemporaneous industry affiliation determines IM_{jt} and EX_{jt} . X'_{ijt} controls for age and age squared of the worker.

As worker-specific characteristics like school degree, ability and skills can simultaneously influence annual earnings and might be correlated with industry affiliation (and thus her trade exposure) OLS estimation would lead to biased results. Therefore, we include γ_i in our first specification and thereby control for such differences between workers as long as these differences are constant over time.

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 ($\delta_{t,r}$) in a second specification.

Lastly, general sectoral trends could likewise influence an individual's trade exposure and her annual earnings. To account for time-constant sectoral heterogeneity, we addi-

³²Referred to as 'normalized earnings' in the following.

³³We define the base year as the first year the individual is observed in our dataset.

tionally include 1-digit-industry fixed effects (δ_J) in our main specification. The most conservative estimate (equation (1)) thus controls for general sectoral trends, for year-specific differences between federal states and for all time-constant differences between workers. The approach 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 industries³⁴On the one hand, one might want to control for such endogenous industry-switching by including industry \times worker fixed effects. On the other hand, by doing so, we might miss one important channel by which the trade shock influences individuals' earnings, because the size of the effect also depends on how easily workers can switch to less exposed sectors.

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 pioneered by Autor et al. (2013) and adapted to the German context by Dauth et al. (2014) and Dauth et al. (2016) and instrument the trade shocks by the respective shock on a group of other countries.

In the course of its transition to a market economy, China experienced large-scale rural-to-urban migration (Chen et al. 2010), gained access to foreign technologies, capital goods, and intermediate inputs (Hsieh and Klenow 2009) and multinational firms entered the economy (Naughton 2007). These factors have been responsible for large productivity gains in the country. These productivity gains, paired with China's accession to the WTO in 2001, which amplified the effect, are the source of the large increase of China's exports and imports. Most importantly, in the light of the factors explained above, China's rise on the world market can be considered to be an exogenous shock to the rest of the world, i.e. the increase of Chinese exports and imports has reasons that are internal to China and are not driven by factors coming from other countries like for example growing demand for Chinese goods. In the context of Germany, Dauth et al. (2014) extend the argument to German trade with Eastern Europe after the fall of the Iron Curtain. In a similar way

³⁴.

as in China, the fall of the Iron Curtain that went along with a transition to a market-oriented system triggered large productivity gains in Eastern European countries (Burda and Severgnini 2009). Moreover, some countries (e.g. Poland and the Czech Republic) joined the WTO and this amplified the effect coming from institutional change. The rise of German exports to and imports from China and Eastern Europe thus can be considered to be an exogenous shock to the German manufacturing sector.

The use of other countries' trade flows with China and Eastern Europe as an instrument removes the bias due to demand and productivity shocks if the following conditions are fulfilled. First, the instruments need to have explanatory power in order to circumvent a weak instruments problem (relevance). The instrument group should thus comprise high-income countries which are affected by the trade shock in a similar way as Germany. Second, demand shocks in the instrument countries should be uncorrelated with those in Germany and should have no direct effect on the labor market outcomes of German workers (validity). The instrument group should thus not include any direct neighbors of Germany and members of the Euro zone. The USA should not be part of the instrument group because of its large importance for world trade. Following Dauth et al. (2014) we end up with the following instrument group: Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom.

In section 5 we will make use of the regression estimates and alternatively employ the estimates from the full fixed effects and the instrumental variable fixed effects strategy. The basic findings are very robust across both specifications.

4.2. Results

The fixed effects estimates in table 2 show that there is a significant relation between industry-level trade exposure and individual annual earnings. When we control only for time-constant differences between workers (column (1)), 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. The large positive effect of export exposure on annual earnings is consistent with the ex-

istence of an exporter wage premium in Germany (Schank et al. 2007; Baumgarten 2013). Adding $\text{region} \times \text{year}$ (column (2)) and industry fixed effects (column (3)) slightly increases the size of the coefficients. The instrumental variable approach outlined in section 4.1 indicates an even stronger effect of the trade shock on individual earnings (column (4)). The first stage F-statistics are large and show that the IV does not suffer from weak instrument problems. First stage regressions for specification (4) can be found in the Appendix tables A2 (or A3 and A4 separately for low- and high skilled workers.). For the analysis in section 5 we will rely on both FE and IV-FE-estimates and we can show that the results are not influenced by the specification we choose. In our preferred specification (3) with the full range of fixed effects, a worker with mean change of export and import exposure ($\Delta EX = 0.40\% - \text{points}$, $\Delta IM = 0.50\% - \text{points}$), experiences an increase in annual earnings of $0.7614 \times 0.40 - 0.50 \times 0.2375 = 0.19\%$ -points, which corresponds to about 88 EUR (see section 5) . The impact of the trade shock on individual earnings thus is small on average. Variation in trade exposure across industries, however, leads to significant distributional consequences of the trade shock.

The heterogeneity of the trade shock becomes even more pronounced when we estimate the effect separately for different skill groups. Table 3 shows that 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. Dauth et al. (2016) have a closer look at the underlying adjustment mechanisms and show that high-skilled workers who are employed in negatively affected industries are better able to switch to less affected industries than low-skilled workers. Overall, the results suggest that the trade shock had a small positive impact on individual earnings biographies on average and that the gains and losses from the shock are not evenly distributed across the population.

Table 2: Pooled (IV-) Fixed Effects estimates

Dep.Var.: Norm. annual earnings	FE	FE	FE	IV-FE
	(1)	(2)	(3)	(4)
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*** (0.1462)
R2	0.78	0.78	0.78	0.78
Worker FE	x	x	x	x
Region x Year FE	-	x	x	x
1-Digit Industry FE	-	-	x	x
1st Stage F (EX)	-	-	-	426.38
1st Stage F (IM)	-	-	-	181.83
Observations	41,197	41,197	41,197	41,197

Notes: 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.

These findings are in line with previous literature on the impact of this trade shock on individual labor market outcomes (Dauth et al. 2014; Dauth et al. 2016). Our estimated effects are larger than the estimates of Dauth et al. (2016) and this could have two possible reasons: first, their wage variable is censored and has to be imputed for the top-earners which might lead to an underestimation of the highest wages and thus the resulting effects. Second, we do not only consider manufacturing but also non-manufacturing industries.

Table 3: (IV-) Fixed Effects estimates by skill level

Dep.Var.: Norm. annual earnings	FE (1)	FE (2)	FE (3)	IV-FE (4)
Low-skilled				
Export Exposure (EX)	0.4209*** (0.1347)	0.4407*** (0.1361)	0.6283*** (0.1427)	1.1150*** (0.2239)
Import Exposure (IM)	-0.1181 (0.0811)	-0.1345 (0.0835)	-0.1480* (0.0863)	-0.5251*** (0.1249)
R2	0.75	0.75	0.75	0.75
1st Stage F (EX)	-	-	-	348.64
1st Stage F (IM)	-	-	-	152.04
Observations	28,293	28,293	28,293	28,293
High-skilled				
Export Exposure (EX)	0.7374*** (0.2863)	0.8588*** (0.3066)	1.0718*** (0.3625)	1.1747*** (0.5034)
Import Exposure (IM)	-0.1246 (0.1648)	-0.1817 (0.1781)	-0.1877 (0.1802)	-0.2027 (0.3405)
R2	0.86	0.86	0.86	0.86
1st Stage F (EX)	-	-	-	452.86
1st Stage F (IM)	-	-	-	193.79
Observations	12,806	12,805	12,805	12,805
Worker FE	x	x	x	x
Region x Year FE	-	x	x	x
1-Digit Industry FE	-	-	x	x

Notes: 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.

5. Why the Partner Matters

The results from section 4 suggest that the large increase in trade with China and Eastern Europe created ‘winners and losers’ in terms of changes of annual earnings, depending on industry affiliation and educational level. In this section, we focus on two main questions: First, can intra-household redistribution of gains and losses from trade serve as a stabilizer to the most vulnerable group of workers, namely low-skilled individuals employed in import-competing sectors? The answer depends on how many of them have a partner who benefits from the trade shock. This leads to the second (and closely related) question: Is this mechanism capable of reducing the inequality-increasing effect of the trade shock?

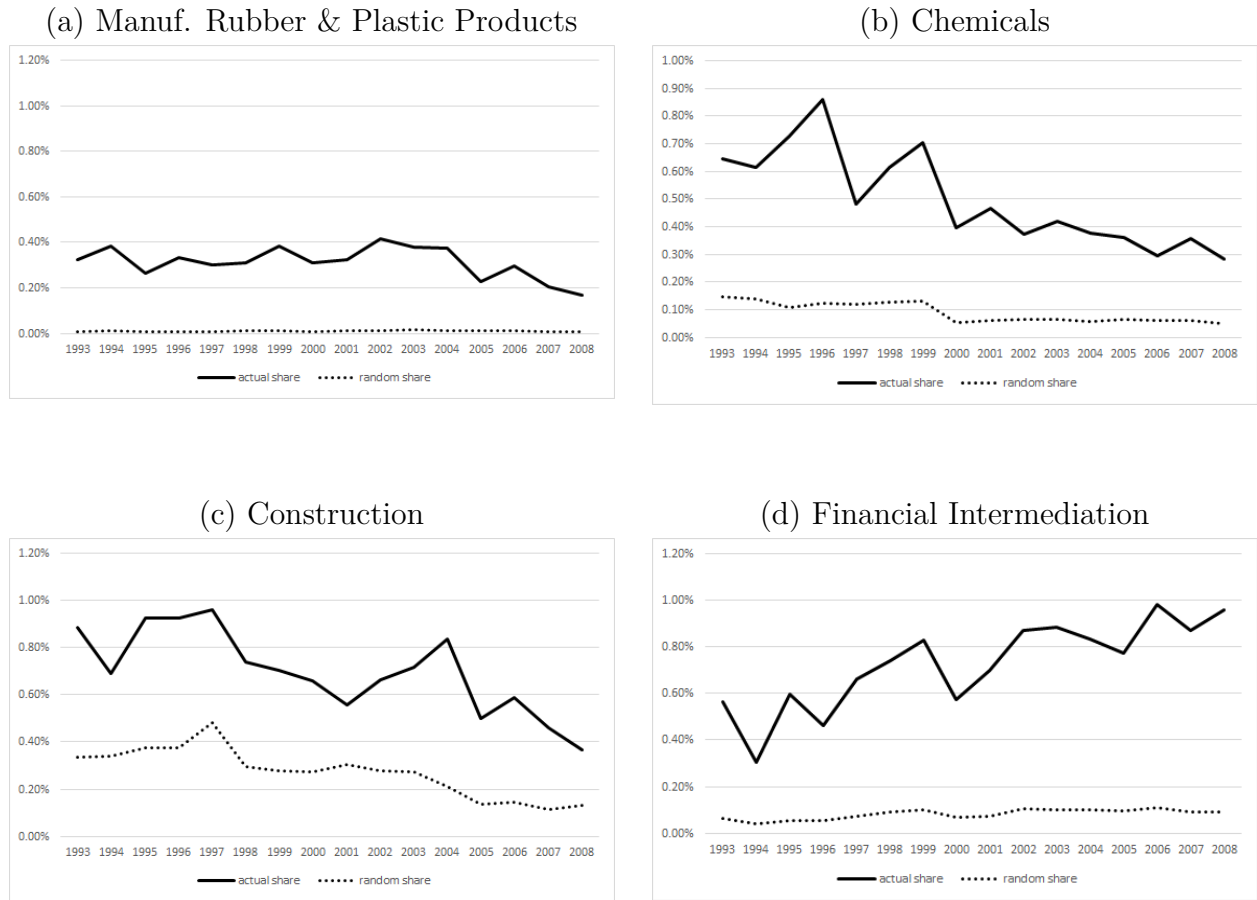
5.1. Potential for Redistribution

Industry Affiliation. As the impact of the trade shock on workers varies strongly across industries, it is worthwhile to first look at whether spouses are employed in similarly affected industries or not. In figure 1, we exemplary choose four 2-digit industries and depict the share of couples where both spouses are employed in the respective industry (bold line). We contrast the share with the respective share that one would expect if couples were matched randomly (dotted line).³⁵ The graphs suggest that workers tend to mate non-randomly with partners that are employed in the same industry. We also calculate the sorting parameters in the spirit of Eika et al. (2014): the ratio of the actual share and the share under random mating indicates how much more often individuals mate their alike than one would expect without assortative mating.³⁶ The parameters for all industries suggest non-randomness of mating, i.e. all sorting parameter are larger than 1, and we can observe substantial heterogeneity between industries: For instance, an individual who is employed in manufacturing of rubber and plastic has a partner in the same industry on average 29 times as often as one would expect with a random mating structure. For the construction sector, this value amounts only to 2.7.

³⁵Following Eika et al. (2014), we compute this as females in the respective industry as a share of all females times males in the same industry as a share of all males in our data.

³⁶See figure A2 Appendix.

Figure 1: Assortative Mating in selected 2-digit industries



Notes: The actual share represents the true share of partners in the sample who work in the same respective industry. The random share emerges from a hypothetical situation in which males and females in our sample are matched randomly without any assortative mating. Data sources: *SOEP v28*.

Overall, 14.46% of all individuals in our sample are employed in the same 2-digit industry as their partner. This share would only be 0.07% under random mating. It is therefore no surprise that table 4 shows a significant correlation of import and export exposure between partners. In this table we first regress export (import) exposure on the partner's export (import) exposure and find that an increase in one spouse's export (import) exposure by one percentage point is associated with a 0.04%-point (0.046%-point) increase in the other spouse's export (import) exposure. As the effect vanishes in row 2 we can show that this correlation is exclusively driven by couples where both partners are employed in the same industry. Conditional on employment in a different sector (manufacturing vs. non-manufacturing), the correlation is even slightly negative. The last row shows that

the correlation of trade exposures is strongest within the manufacturing sector.

Table 4: Correlation of partners' trade shocks

	Export Exposure	Import Exposure
ALL	0.0399*** (0.0059)	0.0464*** (0.0062)
Different 2-Digit Industry	-0.0012 (0.0065)	0.0006 (0.0069)
Different Sector	-0.0254** (0.0102)	-0.0234** (0.0110)
Both Manufacturing	0.1659*** (0.0137)	0.1608*** (0.0152)

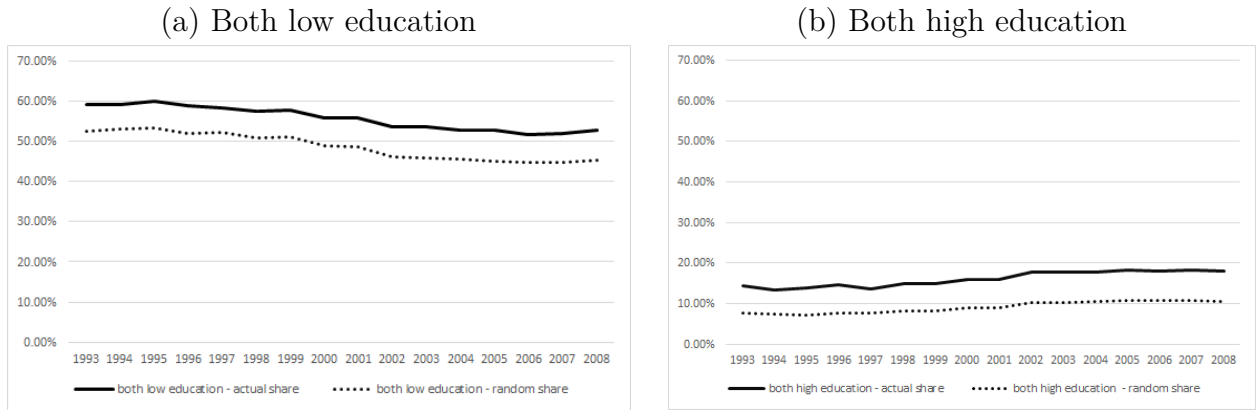
Notes: Simple OLS regression without additional controls. Standard errors are neither robust nor clustered. Sector refers to either manufacturing or non-manufacturing. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

To sum up, spouses tend to experience similar export and import exposures, mainly because a substantial fraction of partners are employed in the same industry. However, as the correlation is not perfect we have first evidence for potential for intra-household redistribution of gains and losses from trade.

Education. The impact of the trade shock on individuals does not only vary across industry but also across the worker's skill-level. The empirical analysis in section 4 shows that a given import exposure has a larger impact on low-skilled workers, whereas high-skilled workers benefit slightly more from export exposure. Figure 2 shows for every year the share of couples where both partners have low education or high education, respectively, and again depicts the respective share that one would expect under random mating. It turns out that in most couples both partners have the same level of education. A comparison to random mating suggests that individuals in our sample mate assortatively in terms of skills to a high degree which is in line with the empirical literature

on assortative mating based on skills (e.g. Grave and Schmidt 2012; Eika et al. 2014). The sorting parameters as explained above indicate that high-skilled individuals have a partner who is high-skilled as well about 1.8 times as often as expected under random mating. The sorting parameter for low-skilled partners is lower (1.15 on average), but also differs clearly from a random mating scenario.^{37 38}

Figure 2: Assortative mating in education



Notes: The actual share represents the true share of partners in the sample who have the same education level. The random share emerges from a hypothetical situation in which males and females in our sample are matched randomly without any assortative mating. Low education are individuals with ISCED 0-4, high education refers to ISCED 5-6. Data sources: *SOEP v28*.

Winners and Losers. The results in this section so far showed that both industry affiliation and education level are positively correlated and this might restrict the room for intra-household redistribution. We now combine these two dimensions in order to get an impression of the quantitative magnitude of both the individual gains and losses from trade and of the scope for intra-household redistribution.

Our goal is to obtain 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 $t + 1$. Remember that the regression coefficients of the trade shocks in section 4 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

³⁷see figure A3 Appendix

³⁸If education level is divided into three different categories, the sorting parameter for individuals with ISCED 0-2 amounts to about 3.1, for individuals with ISCED 3-4 to about 1.17 and for individuals with ISCED 5-6 to 1.8. Results can be obtained upon request.

expression for the estimated change in normalized earnings:

$$\left(\frac{\widehat{Y}_{ijs,t+1}}{E_0} - \frac{Y_{ijs,t}}{E_0}\right) \times 100 \quad (2)$$

where $Y_{ijs,t}$ denotes individual i 's earnings in period t and E_0 denotes her base year earnings. Note that $\widehat{Y}_{ijs,t+1}$ results from a *ceteris paribus* interpretation that is standard in regression analysis. It 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 $t+1$.³⁹ The estimated change in normalized earnings is a function of individual i 's trade shock and of the impact of a given trade shock:

$$\left(\frac{\widehat{Y}_{ijs,t+1}}{E_0} - \frac{Y_{ijs,t}}{E_0}\right) \times 100 = \Delta IM_j \times \hat{\beta}_{1s} + \Delta EX_j \times \hat{\beta}_{2s} \quad (3)$$

where $\hat{\beta}_{1s}$ and $\hat{\beta}_{2s}$ are the estimated coefficients from table 3 specification (3) 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 $\widehat{Y}_{ijs,t+1}$ is the only unknown in this equation. We can rearrange and solve for $\widehat{Y}_{ijs,t+1} - Y_{ijs,t}$, which reflects the predicted change in earnings due to the trade shock. We call this difference \widehat{Change}_{ijst} :

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

Put simply, the predicted impact on earnings is a function of the worker's trade shock

³⁹One 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.

as well as his education-level. In every period, we restrict \widehat{Change}_{ijst} such that $\widehat{Y}_{ijs,t+1}$ remains non-negative.

Table A5 in the Appendix shows that the mean predicted impact on individuals is positive and amounts to 87.82 EUR (94.23 EUR for the IV-FE estimates). We observe however a large dispersion of this measure and find that the trade shock did not only create winners. The maximum predicted loss is 34,848.75 EUR, whereas the maximum predicted gain in earnings is 34,825.46 EUR. In total, we predict that 82% of individuals experience a positive impact, whereas 18% of workers suffer from a negative impact. Strikingly, the percentage of winners is slightly below the average among low-skilled individuals and slightly above the average for high-skilled.

How about the distribution of gains and losses within households? We find that 83.56% of all couples experience predicted earnings changes that go into the same direction and only 16% of couples experience opposing predicted earnings changes. It is therefore no surprise that table 5 shows a positive correlation of predicted earnings changes between partners and it turns out that partners who work in the same 2-digit industry and have the same educational level are responsible for this positive relationship. Conditional on working in different industries, the correlations turn insignificant in the second row. Conditional on working in a different industry and having a different educational level, the correlation even becomes negative (but not significant). This shows that assortative mating might restrict the potential for redistribution within households. Finally, the positive correlation is stronger for couples who are both employed in the manufacturing sector. Note that the correlations are slightly higher if we use the IV-FE estimates, but the overall pattern is robust across both specifications.

A closer look at the losers. Does the positive correlation between partners imply that we have no room for intra-household redistribution of gains and losses from trade? As the correlation is not perfect and 16% of all couples experience opposing effects the answer is certainly ,no‘ . In the following, we portray the extent to which workers who lose from Germany’s trade integration with China and Eastern Europe have a partner

who can compensate these losses by redistributing gains from trade.

Table 5: Correlation of partners' predicted income changes

	FE	IV-FE
ALL	0.0044** (0.0019)	0.0066*** (0.0021)
Different 2-Digit Industry	0.0024 (0.0021)	0.0032 (0.0023)
Different 2-Digit Industry & Different Education	-0.0033 (0.0044)	-0.0041 (0.0048)
Different Sector	0.0044 (0.0035)	0.0051 (0.0040)
Both Manufacturing	0.0100** (0.0050)	0.0197*** (0.0062)

Notes: Simple OLS regression without additional controls. Sector refers to either manufacturing or non-manufacturing. Education is either low (ISCED 0-4) or high (ISCED 5-6). Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

We focus on workers whose predicted negative change of earnings is at least 500 EUR in order to make sure that very small predicted changes do not affect our results. Table 6 shows that over the whole sample period, 936 worker-observations experience a predicted impact of at least -500 EUR. Panel (a) shows that the average loss is sizable and amounts to 2,075.71 EUR which on average corresponds to 8.71% of annual earnings. We also detect a large dispersion of predicted losses. They range up to 34,848.75 EUR or 100% of total earnings. However, 64.74% of the losers have a partner who wins in terms of earnings.

But to what extent are winners able to compensate losers within the household? We consider a redistribution mechanism in which partners redistribute gains and losses in case of opposing effects. Imagine a couple where partner 1 loses 1000 EUR and partner 2 wins 1500 EUR. In this case we assume that partner 2 redistributes 1000 EUR to partner

1 in order to compensate her shock. If partner 2 wins 800 EUR, he redistributes the whole sum and thereby does not fully compensate the shock on partner 1. If partner 2 loses 200 EUR, we assume that no redistribution takes place. In row 4 of each panel we assume that partners redistribute gains and losses from trade in this manner and it turns out that partners can compensate on average almost 10% of the losses. That compensation is virtually zero in some cases whereas in other cases the partner is able to compensate the whole predicted earnings loss implies again a large variation between couples. In a robustness check in section 6 we assume that gains and losses are shared equally between partners and the basic result remains unchanged.

Panels (b) and (c) show the same analysis separately for low- and high-skilled workers. First, the majority of losers are low-skilled workers (583 or 62%). Whereas the average loss as well as the loss as a share of total earnings is higher for high-skilled workers, it turns out that there is more room for intra-household redistribution for low-skilled workers. 68.44% of low-skilled losers have a partner who wins in terms of earnings (as compared to 58.64% for high-skilled losers). The average compensation amounts to 11.92% for low-skilled losers (as compared to 6.07% for high-skilled losers).

The results essentially stay the same if we use the coefficients from the IV-fixed effects estimates instead (see table A6 Appendix). All in all, we conclude from these findings that assortative mating in terms of industry affiliation and education level clearly restricts the potential for intra-household redistribution after the trade shock. However, partners are not perfectly similar in all households and this leaves room for compensation within a number of partnerships. Low-skilled workers have a higher probability to have a partner who can mitigate this loss. The results thus suggest that failing to account for this mechanism would yield an incomplete picture of who benefits and who loses during Germany's trade integration with China and former Soviet Union countries. Whether this finding could affect the distributional consequences of the trade shock will be discussed in section 6.

Table 6: A closer look at the losers

	Mean	Median	Min	Max	N
(a) ALL					
Average Loss (EUR)	2,075.71	1,311.10	500.81	34,848.75	936
Average Loss (% of Earnings)	8.71	4.67	0.50	100	936
Is partner a "winner"? (%)	64.74	-	-	-	936
Compensation by Partner (% of Loss)	9.93	0.3	0	100	599
(b) Low-skilled					
Average Loss (EUR)	1,474.28	1,228.34	500.81	5,747.20	583
Average Loss (% of Earnings)	8.64	4.90	0.64	100	583
Is partner a "winner"? (%)	68.44	-	-	-	583
Compensation by Partner (% of Loss)	11.92	0.37	0	100	395
(c) High-skilled					
Average Loss (EUR)	3,069.00	1,638.35	502.62	34,848.75	353
Average Loss (% of Earnings)	8.82	4.26	0.50	100	353
Is partner a "winner"? (%)	58.64	-	-	-	353
Compensation by Partner (% of Loss)	6.07	0.20	0	100	204

Notes: Sample restricted to workers whose predicted loss of earnings is at least 500 EUR. Low-skilled individuals have ISCED 0-4, high-skilled ISCED 5-6. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

5.2. Intra-Household Redistribution and Inequality

The results in the section 5.1 point to potential for intra-household redistribution of gains and losses from trade. In the following, we want to answer two questions: First, what is the impact of Germany's trade integration on earnings inequality during the adjustment process if we ignore the household dimension? Second, does intra-household redistribution change the conclusion about the distributional effect of the trade shock? To this end, we compute the estimated impact on inequality without compensation by the partner

and contrast the results with the estimated impact under the assumption that partners redistribute gains and losses from trade as explained in section 5.1.

Method. We can estimate the distributional impact in a straightforward way from the results in section 5.1. Consider actual earnings of worker i in period t ($Y_{ijs,t}$). Predicted earnings of individual i after the trade shock between periods t and $t + 1$ had occurred ($\widehat{Y}_{ijs,t+1}$) can be computed using \widehat{Change}_{ijst} :

$$\widehat{Y}_{ijs,t+1} = Y_{ijs,t} + \widehat{Change}_{ijst} \quad (5)$$

As already argued in section 5.1, we interpret $\widehat{Y}_{ijs,t+1}$ as individual i 's earnings in $t + 1$ if the trade shock between t and $t + 1$ had occurred as observed in the data and all other worker characteristics as well as returns to those characteristics had stayed at their period- t -level. Having this in mind, we can compute inequality of $Y_{ijs,t}$ and $\widehat{Y}_{ijs,t+1}$ and interpret the difference as the impact of the trade shock on earnings inequality between periods t and $t + 1$. We can contrast this result with the respective estimates that we obtain imposing the redistribution schedule explained in section 5.1. In this case, $\widehat{Y}_{ijs,t+1}$ can be interpreted as individual i 's predicted income after redistribution of gains and losses between partners took place. Our preferred measure of inequality is the difference between the 75th and the 25th percentile of earnings. This mainly has two reasons. First, we want to obtain estimates on the impact on inequality that are not influenced by outliers at the top or the bottom of the earnings distribution. Second, we do not use conventional measure like the Gini index or the standard deviation of logs since we have observations with zero earnings in our data.⁴⁰ In contrast, as only about 5-10% of observations per year report zero earnings, they do not affect the 25th percentile in any of the years.

For the sake of space and clarity we do not report the estimated effects separately for every year t . Instead, we combine all years and compute inequality of actual and pre-

⁴⁰Results remain unchanged if we set zero earnings to one and use the Gini index or the standard deviation of logs.

dicted earnings for the whole sample period at once in order to obtain an average impact on earnings inequality.⁴¹ We obtain standard errors via 1,000 bootstrap replications with clustering at the household-year level.

Results. Figure A4 in the Appendix shows that income inequality between the 25th and the 75th earnings percentile is substantial and increasing over time. To check whether the trade shock had a significant influence on this development, table 7 depicts the result of the computation of the effect on inequality just described. We compute predicted earnings changes using the Fixed effects estimates and alternatively using the IV-Fixed effects estimates of table 3. A look at column 1 and 2 shows that Germany's trade integration had a statistically significant inequality-increasing effect. According to the estimates in columns 1 and 2, the differential between the 75th and the 25th percentile increased by 110-130 Euros on average per year. This corresponds to 13-16% of the average yearly increase of this measure. This result is in line with many models that predict trade integration to have a substantial impact on inequality (e.g. Helpman et al. 2010; Egger and Kreckemeier 2012) and is consistent with recent empirical evidence Baumgarten (2013). Strikingly, intra-household redistribution of gains and losses from trade cannot mitigate this effect. The second row shows that the inequality-increasing effect even becomes slightly larger in case of the FE-estimates if we impose the compensation mechanism. The difference, however, is not statistically significant. How can the inequality-increasing effect be larger if partners redistribute gains and losses from trade? The following example illustrates that the relationship between redistribution and the inequality-increasing effect is ambiguous: Consider a couple that consists of a low-earnings husband and a high-earnings wife. Suppose that the husband gains and the wife loses in terms of earnings due to the trade shock. In the individualistic view without compensation, these two observations work towards a decrease of earnings inequality. If we impose compensation, however, the husband redistributes (a part) of his gains from trade to her wife and this prohibits the trade shock to be inequality-decreasing for this couple.

⁴¹The point estimates do not vary greatly over the years. However, due to the low number of observations in a given year, some estimates are statistically insignificant. Estimates are available upon request.

Table 7: Impact on Inequality

Dep.Var.: Estimated Impact on 75-25 Interval	Unrestricted Sample		Restricted Sample	
	FE	IV-FE	FE	IV-FE
w/o Compensation by Partner	109.54** (49.59)	130.45** (50.08)	109.54** (53.00)	130.45** (51.59)
with Compensation by Partner	116.07** (51.03)	119.46** (50.53)	109.51** (54.03)	113.75** (52.04)
Difference	-6.53 (8.72)	10.99 (11.56)	0.03 (5.69)	16.70 (12.52)
Difference (in %)	-5.63	9.20	0.03	14.68
Observations	28,903	28,903	28,903	28,903

Notes: Impact of trade shock on earnings difference between 25th and 75th earnings percentile. In the restricted sample we set compensation to zero for couples where one spouse has earnings below the sample mean who gains in terms of earnings and the other one has earnings above the sample mean and loses in terms of earnings. Standard errors are clustered at the household \times year level and are obtained by 1.000 bootstrap replications. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

In columns 3 and 4 of table 7 we set compensation to zero for couples where one spouse has earnings below the sample mean and gains in terms of earnings and the other one has earnings above the sample mean and loses in terms of earnings. The results indicate that these couples drove the negative difference in case of the FE-estimates. Consistently, the positive difference in case of the IV-FE estimates becomes even larger. However, the difference is never statistically significant. Again, we perform the same exercise in section 6 assuming the partners share gains and losses from trade equally. This does not change the basic results.

To sum up, the estimates provide first evidence that the large increase in trade of Germany with China and former Soviet Union countries has contributed to the overall increase in inequality (see also Dustmann et al. 2009). In contrast, intra-household compensation does not play a major role in terms of the impact of the trade shock on earnings inequality.

6. Robustness checks

6.1. Individual level regressions

To check the validity of our individual-level regression in section 4, we conduct several robustness checks. First, we normalize the dependent variable using the logarithm instead of dividing by base year earnings. This approach is more common in the labor economics literature, the disadvantage however is that we cannot take the logarithm for individuals who have earnings of zero in one or several periods. Consequently, we set all zero-earnings to one. Specifications (1)-(3) in table 8 show results of Fixed effects estimates, column (4) is the IV-FE estimate. The results are in favor of our identification strategy and do not change the main implications as the estimated mean impact on earnings (152 EUR) is even larger than in our baseline specifications (88 EUR).

Table 8: Robustness check: log normalized earnings

Dep.Var.: ln earnings	FE (1)	FE (2)	FE (3)	IV-FE (4)
Export Exposure (EX)	0.0226*** (0.0055)	0.0137*** (0.0052)	0.0207*** (0.0061)	0.0285*** (0.0088)
Import Exposure (IM)	-0.0127*** (0.0034)	-0.0069** (0.0034)	-0.0063* (0.0034)	-0.0168*** (0.0055)
R2	0.57	0.58	0.58	0.58
Worker FE	x	x	x	x
Region x Year FE	-	x	x	x
1-Digit Industry FE	-	-	x	x
1st Stage F (EX)	-	-	-	426.38
1st Stage F (IM)	-	-	-	181.83
Observations	41,197	41,197	41,197	41,197

Notes: Zero earnings are set to 1. The dependant variable is the logarithm of annual earnings. 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.

In addition, we conduct the medium-run approach in the spirit of Autor et al. (2014), Dauth et al. (2014), and Dauth et al. (2016). This medium-run regression is a cross-sectional analysis in which we do not investigate the contemporaneous changes of trade exposure on annual earnings but the effect of an 8-years-change on cumulated earnings. For this purpose we follow the previous literature and split our observation period into two eight-years intervals (1993-2000 and 2001-2008). Our dependent variable is then defined as worker i 's cumulated earnings over the respective period normalized with the annual earnings of the base year (1993 or 2001). We regress these normalized cumulated earnings on the change of import and export exposure during the 8 years in the industry j the worker was originally employed in the base year. We additionally control for standard individual-level controls (age, age squared, gender, migration background, tenure, education level, pre-shock income), for the respective time period, for firm size and for German federal states. Like Dauth et al. (2014) and Dauth et al. (2016), we instrument our trade exposure measures with trade flows of other countries to China and Eastern Europe to mitigate the problem of unobservable confounding shocks that simultaneously affect trade and labour market outcomes in the respective period. Table 9 shows the results of the medium-run approach. In line with Dauth et al. (2016) we observe large positive effects for export exposure on cumulated earnings and substantial negative effects of import exposure. The size of our estimated coefficients is also very close to their results. However, in comparison to the Dauth et al. (2016) study who can make use of roughly 217,000 observations, we do only have about 1,500 observations which we observe for all 8 years of either 1993-2000 or 2001-2008. This explains why our standard errors are too large to give us statistically reliable estimates and also justifies that we rely on the short-run panel approach in our main specification.

Table 9: Medium run approach

Dep. Var.: normalized cumulated earnings	IV (1)	IV (2)	IV (3)
Δ Export Exposure (EX)	3.2565 (3.6062)	2.6058 (3.5384)	1.7917 (3.5118)
Δ Import Exposure (IM)	-1.9885 (2.3467)	-2.2029 (2.5314)	-2.1078 (2.5794)
R2	0.0938	0.1163	0.1259
individual level controls	x	x	x
firm size controls	-	x	x
federal states controls	-	-	x
1st Stage F (EX)	636.99	479.9	267.1
1st Stage F (IM)	96.91	72.97	40.04
Observations	1,478	1,478	1,478

Notes: Annual earnings and trade exposures are cumulated over the respective period 1993-2000 or 2001-2008. All regressions control for the respective observation period. Individual level controls include gender, migration background, age and age squared, three tenure categories, three education levels (low: ISCED 0-2, medium: ISCED 3-4, high: ISCED 5-6) and logarithm of pre-earnings. Standard errors clustered by 2-digit industry \times year in parentheses. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

6.2. Intra-Household Redistribution and Inequality

We also carry out two robustness checks for the inequality-analysis. First, we assume that partners split up gains and losses from trade equally. For example, if partner 1 wins 200 EUR and partner 2 wins 300 EUR, partner 2 redistributes 50 EUR to partner 1 such that both end up with a gain of 250 EUR. Table 10 shows that the basic pattern of results remains largely unchanged as compared to our baseline specification. The estimated impact on inequality is larger with compensation and the picture reverses if we set redistribution to zero for couples where redistribution reinforces the inequality-increasing effect. The differences, however, are larger than in our baseline scenario.

Table 10: Robustness check: share gains and losses equally

Dep.Var.: Estimated Impact on 75-25 Interval	Unrestricted Sample		Restricted Sample	
	FE	IV-FE	FE	IV-FE
w/o Compensation by Partner	109.54** (53.00)	130.45** (51.59)	109.54** (53.00)	130.45** (51.59)
with Compensation by Partner	154.85*** (52.44)	143.77** (57.83)	32.80 (50.52)	10.43 (55.01)
Difference	-45.31 (39.78)	-13.32 (43.88)	76.73 (31.46)	120.02** (32.92)
Difference (in %)	-29.26	-9.26	233.96	1150.72
Observations	28,903	28,903	27,281	28,903

Notes: Impact of trade shock on earnings difference between 25th and 75th earnings percentile. In the restricted sample we set compensation to zero for couples where one spouse has earnings below the sample mean who gains in terms of earnings and the other one has earnings above the sample mean and loses in terms of earnings. Standard errors are clustered at the household \times year level and are obtained by 1,000 bootstrap replications. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

In a second robustness check, we test whether the changing trade exposures that occur because workers are switching industries drive the pattern we observe. In our baseline scenario, a worker's trade exposure can change in two ways: Either she stays in the same industry and trade exposure of this industry changes or she switches to an industry with a different trade exposure. In this robustness check, we compute the worker's trade exposure between t and $t+1$ exclusively based on her industry affiliation in t and therefore switch off one channel through which her trade exposure can change. Table 11 shows that this does not alter our overall conclusion in case of the IV-FE specification. In case of the pure FE specification, however, the results point to an inequality-decreasing effect of the trade shock, both with and without compensation. This illustrates the importance of endogenous industry-switching as Autor et al. (2014) and Dauth et al. (2016) argue. Not all workers are equally good in mitigating the effects of the trade shock by switching to unaffected industries and this induces a major distributional effect.

Table 11: Robustness check: only intra-industry variation

Dep.Var.: Estimated Impact on 75-25 Interval	Unrestricted Sample		Restricted Sample	
	FE	IV-FE	FE	IV-FE
w/o Compensation by Partner	-4.52 (45.69)	149.22*** (54.15)	-4.52 (45.69)	149.22*** (54.15)
with Compensation by Partner	-12.17 (45.31)	150.37*** (53.50)	-12.17 (45.31)	148.39*** (53.24)
Difference	7.64 (5.51)	-1.15 (9.33)	7.64 (5.51)	0.83 (8.53)
Difference (in %)	169.25	-0.76	169.25	0.56
Observations	33,488	33,488	33,488	33,488

Notes: Impact of trade shock on earnings difference between 25th and 75th earnings percentile. In the restricted sample we set compensation to zero for couples where one spouse has earnings below the sample mean who gains in terms of earnings and the other one has earnings above the sample mean and loses in terms of earnings. Standard errors are clustered at the household \times year level and are obtained by 1.000 bootstrap replications. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

7. Conclusion

In this paper, we analyze the large increase in Germany's trade with China and former Soviet Union countries and its impact on individual workers. However, in contrast to previous literature, we switch our focus from the individual level to the household level. This allows us to ask a novel question which has not received attention so far: Can the adverse effects of import competition during the period of trade-adjustment be mitigated at the household level by redistribution of gains and losses from trade between partners?

We can summarize our results as follows: First, we find strong and heterogeneous effects of the trade shock on individual labor market outcomes. These effects are highly positively correlated between partners due to the high level of assortative mating in terms of education and industry affiliation. Nevertheless, we can detect a non-negligible portfolio effect at the household level as the shocks are not perfectly correlated. We find that

partners who are positively affected by the trade shock can compensate about 10% of the earnings losses of adversely affected individuals. We then go on to analyze the distributional consequences. We estimate the impact of the trade shock on inequality under two scenarios: one scenario in which redistribution of gains and losses from trade between partners takes place and one scenario in which no redistribution takes place. We find that the trade shock is significantly inequality-increasing. However, a comparison between the two scenarios suggests that redistribution did not help to dampen this effect. All in all, our findings suggest that it is worthwhile to take the joint impact of shocks and policies on households into account. This perspective is especially relevant from a policymaker's perspective who relies on knowing the exact impact of a certain shock on individuals in order to be able to design well-targeted policies.

What about the role of the partner 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. Our results suggest that there will be counteracting effects as assortative mating decreased among high-skilled workers and many industries and increased among low-skilled workers. This question however is beyond the scope of this paper and this is why we leave it for further research.

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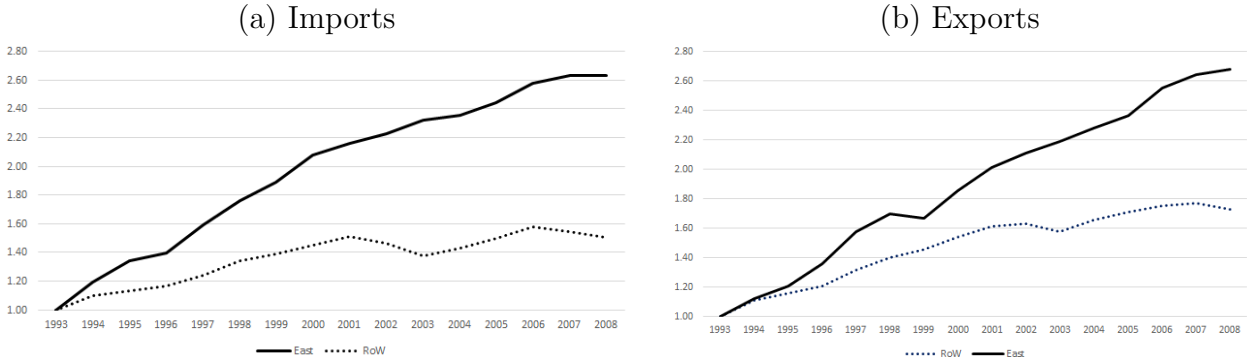
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A. Appendix

Figure A1: German trade volumes



Notes: 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 A1: Descriptives on trade flows and earnings 1993-2000 and 2001-2008

	Mean	SD	Min	Max	Obs
1993-2000					
yearly earnings (EUR)	27704.38	16916.58	0.00	400920.00	18,061
100 x rel. earnings	102.66	81.11	0.00	2250.57	18,061
Δ Import Exposure (%)	0.53	6.67	-43.02	33.05	5,377
Δ Export Exposure (%)	0.13	3.97	-29.25	18.62	5,377
Δ Import Exposure (%) + linkages	0.57	4.86	-43.02	46.91	15,699
Δ Export Exposure (%) + linkages	0.32	3.08	-29.25	27.73	15,699
2001-2008					
yearly earnings (EUR)	32400.12	23918.59	0.00	337140.00	23,331
100 x rel. earnings	107.83	111.79	0.00	3532.20	23,331
Δ Import Exposure (%)	-0.10	8.64	-54.86	40.96	5,783
Δ Export Exposure (%)	0.33	5.30	-33.30	22.72	5,783
Δ Import Exposure (%) + linkages	0.45	6.21	-54.86	51.12	17,825
Δ Export Exposure (%) + linkages	0.47	3.97	-33.30	34.85	17,825

Notes: Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table A2: First stage: pooled IV-FE estimates

Dep. Var.:	Export Exposure	Import Exposure
Export Exp. Instrument	0.7077*** (0.0340)	-0.1282 (0.0893)
Import Exp. Instrument	0.2947*** (0.0257)	0.9723*** (0.0458)
R2	0.98	0.95
F-statistic	426.38	181.83
Observations	41,197	41,197

Notes: First stage regression referring to table2, column (4). Standard errors clustered on 2-digit industry \times year in parentheses. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table A3: First stage: IV-FE estimates low-skilled

Dep. Var.:	Export Exposure	Import Exposure
Export Exp. Instrument	0.6998*** (0.0348)	-0.1825** (0.0915)
Import Exp. Instrument	0.2860*** (0.0258)	0.9503*** (0.0461)
R2	0.98	0.95
F-statistic	348.64	152.04
Observations	28,293	28,293

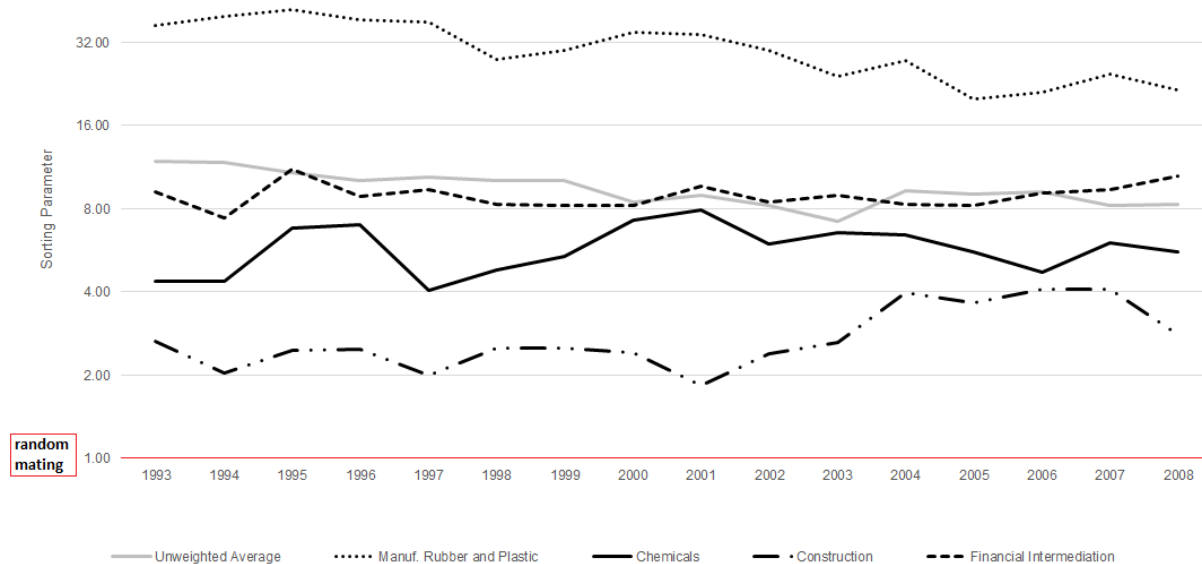
Notes: First stage regression referring to table3, panel (a), column (4). Standard errors clustered on 2-digit industry \times year in parentheses. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table A4: First stage: IV-FE estimates high-skilled

Dep. Var.:	Export Exposure	Import Exposure
Export Exp. Instrument	0.7081*** (0.0387)	-0.0785 (0.0927)
Import Exp. Instrument	0.3185*** (0.0294)	1.0688*** (0.0535)
R2	0.96	0.96
F-statistic	452.86	193.79
Observations	12,805	12,805

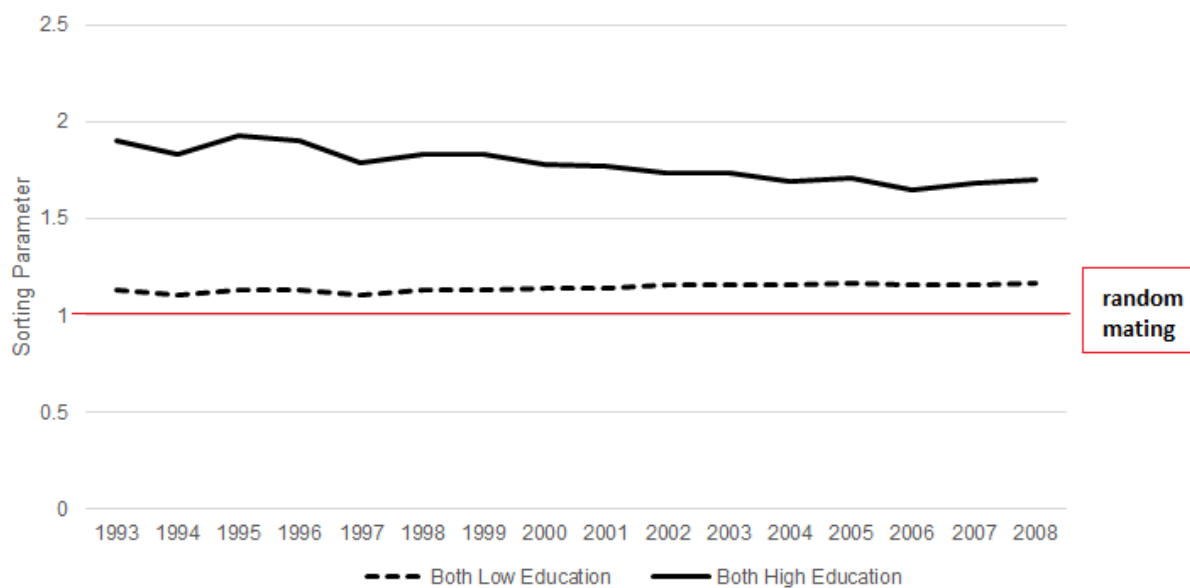
Notes: First stage regression referring to table3, panel (b), column (4). Standard errors clustered on 2-digit industry \times year in parentheses. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Figure A2: Sorting parameters of selected 2-digit industries



Notes: Sorting parameters in the spirit of Eika et al. (2014) as the ratio of the actual share of partners in the respective industry and the hypothetical share under random mating in terms of affiliation to the respective industry. A sorting parameter of 1 indicates no assortative mating. Data source: *SOEP v28*

Figure A3: Sorting parameters education levels



Notes: Sorting parameters in the spirit of Eika et al. (2014) as the ratio of the actual share of partners with respective education level and the hypothetical share under random mating. A sorting parameter of 1 indicates no assortative mating in terms of education. Data source: *SOEP v28*

Table A5: Descriptives on predicted earnings changes

	Mean	Median	Min	Max	Obs
(a) FE					
ALL	87.82	4.44	-34,848.75	34,825.46	28,903
Low Education	55.23	3.61	-5,747.20	6,465.80	19,889
High Education	159.74	6.59	-34,848.75	34,825.46	9,014
(b) IV-FE					
ALL	94.23	4.24	38,194.46	38,168.94	28,903
Low Education	57.55	3	13,628.34	13,378.99	19,899
High Education	175.16	7.22	38,194.46	38,168.94	9,014

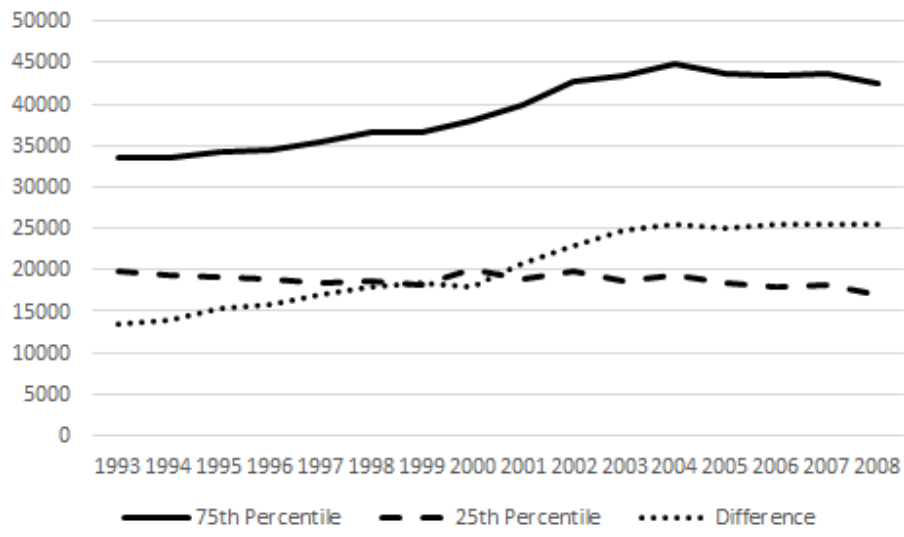
Notes: Panel (a) uses FE-estimates (specification (3)) of table 2 and 3 to estimate predicted earnings changes. Panel (b) uses IV-FE-estimates respectively. Data source: *SOEP v28*

Table A6: A closer look at the losers - IV-FE-estimates

	Mean	Median	Min	Max	Obs
(a) ALL					
Average Loss (EUR)	1,936.83	1,183.85	500.02	38,194.46	1,379
Average Loss (% of Earnings)	7.96	4.05	0.51	100	1,379
Is partner a "winner"? (%)	53.88	-	-	-	1,379
Compensation by Partner (% of Loss)	12.97	0.45	0	100	737
(b) Low-skilled					
Average Loss (EUR)	1,465.02	1,107.27	500.34	13,628.34	1,006
Average Loss (% of Earnings)	7.52	4.01	0.64	100	1,006
Is partner a "winner"? (%)	46.12	-	-	-	1,006
Compensation by Partner (% of Loss)	15.07	0.55	0	100	527
(c) High-skilled					
Average Loss (EUR)	3,209.33	1,571.43	500.02	38,194.46	373
Average Loss (% of Earnings)	9.17	4.35	0.51	100	373
Is partner a "winner"? (%)	57.1	-	-	-	373
Compensation by Partner (% of Loss)	7.72	0.27	0	100	210

Notes: Sample restricted to workers whose predicted loss of earnings is at least 500 EUR. Predicted earnings are computed with coefficients from tables 2 and 3, specification (4). Low-skilled individuals have ISCED 0-4, high-skilled ISCED 5-6. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Figure A4: Evolution of inequality



Notes: y-axis: annual earnings, Data source: *SOEP v28*