Adjusting to Globalization in Germany*

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Abstract

We study the impact of trade exposure in the job biographies, measured with daily accuracy, of 2.4 million workers in Germany. To profit from export opportunities, workers adjust through increased employer switching. Highly skilled workers benefit the most, consistent with an increase in skill demand. The incidence of import shocks falls mostly on low-skilled workers, as they are not able to adjust as well as medium- and high-skilled workers. Imports also destroy rents by workers at high-wage plants who separate from their original firm. We connect our results to the growing theoretical literature on the labor market effects of trade.

JEL-Classification: F16, J31, R11

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1 Introduction

What are the distributional effects of globalization and trade? This is one of the classical questions in economics that dates back, at least, to the work by Stolper and Samuelson (1941). In the public and academic debate, there is a particular focus on the labor market. Does increased foreign competition lead to job losses at home? Which workers are the winners and losers of increased international trade – and are the gains and losses of economic significance? A recent and influential literature has indeed unmarked large discrepancies between local labor markets and a very unequal distribution in particular of the costs of trade. Examples of this literature include Autor, Dorn, and Hanson (2013) for the US, Topalova (2010) for India, Dix-Carneiro and Kovak (2017b) for Brazil, and Dauth, Findeisen, and Suedekum (2014) for Germany.[1] Another recent and theoretical literature has analyzed the interaction between labor market imperfections and international trade in models, in which firms of different productivity self-select into exporting.[2] Examples of this literature include Helpman, Itskhoki, and Redding (2010) and Sampson (2014).[3] Models in this literature typically make predictions how new opportunities to export affect wage inequality and how exposed workers are expected to adjust to industry export shocks.

In this article, we investigate how workers in the labor market adjust to the substantial shocks in labor demand caused by trade, as documented in the previous empirical literature. We analyze the reallocation process – how workers move across firms within and across industries, and sectors – in response to both export and import shocks. It is important to understand empirically how individual workers adjust – not only to foreign competition – but also to positive labor demand shocks caused by the self-selection of domestic firms into exporting. Focusing on exports has the advantage that it connects the empirical to the growing theoretical literature on the interaction of trade and labor market adjustments (in the presence of frictions).

Our paper focuses on the effect of exports and imports on the German labor market. Germany is regularly portrayed as a manufacturing powerhouse in the media.[4] In addition, the country consistently ranks among the most open economies in the world and has held the unofficial title of the "export world champion", making it one of the most interesting countries to look at when searching for the labor market effects of export and import shocks.

[1] Autor, Dorn, Hanson, and Song (2014) and Dix-Carneiro and Kovak (2017a) study the impact of trade competition on the careers of individual workers including adjustment mechanisms. Exhaustive surveys of the literature are provided by Autor, Dorn, and Hanson (2016) and Muendler (2017).

[2] In the original Melitz (2003) model, which most papers build on, all workers are paid the same wage. Frictions or other deviations from a purely neoclassical labor market are needed to generate an effect of trade on inequality in this class of models.

[3] See Helpman (2016) for a survey.

[4] See e.g., among many other examples, Steven Rattner "The Secrets of Germany's Success", *Foreign Affairs*, July 2011, Richard Anderson "German economic strength: The secrets of success", *BBC News*, August 2012, or Noah Smith "Workers Made Germany Into the World's Best Economy", *Bloomberg*, April 2017.

We consider two trade shock episodes which hit the German economy in the aftermath of important political events in the early 1990's. The first is the fall of the iron curtain and the rapid transformation of the former socialist countries in Eastern Europe, and the second is the rise of China and its integration into the world economy.[5] The pace of those changes was much faster than with respect to any other trading partner in the world, making them the major globalization shocks that hit the German economy in those two decades.[6] We will use a big administrative data set, which covers a large part of all private sector employment in Germany and allows to follow workers over time and across firms, industries, and regions, to investigate the adjustment process in detail.

To preview the results, we find that workers who are initially employed in industries with more export exposure see robust and lasting earning gains (relative to less exposed workers). Importantly, these gains are mostly realized on *two different margins* with an equal contribution of each one: first, on-the-job with the original employer, and second, in a different firm but within the original industry. This means, in order to profit from globalization, many workers in Germany have adjusted by switching their employer, and make full use of their accumulated industry specific human capital. The firm switching channel for individual workers to realize earnings gains is a common mechanism in the mentioned theoretical literature and our paper show its empirical importance.

Our next contribution is to detect important heterogeneity in the export adjustment mechanisms. In line with the focus of the previous literature, on the worker side we focus on skill. We measure skill – flexibly and on a continuous scale – by pre-estimated (i.e. in a preceding period) two-way fixed-effects models with worker and plant effects (Abowd, Kramarz, and Margolis, 1999; Card, Heining, and Kline, 2013). We show that the firm switching channel is driven by the re-allocation of the highest skilled workers in Germany. Consequently, trade has increased skill demand in industries with greater trade exposure, and this led to a re-allocation of high-skilled workers across firms to profit from exporting opportunities. This is consistent with the theoretical results from Sampson (2014).

Import competition, in contrast to export exposure, has only muted total effects on worker earnings in Germany. We, moreover, find that the negative consequences of import competition on German workers are concentrated on workers starting out in high-wage plants, when we again rank workers and firms by their fixed-effects from pre-estimated models. Interestingly, import competition seems to mostly destroy worker rents at the highest paying companies, but workers

[5] In a related paper, we estimate the aggregate effects of these trade shock episodes on the German labor market and in particular on the composition of service versus manufacturing jobs (Dauth, Findeisen, and Suedekum, 2017).

[6] Please also see Figure 1 in Section 2.

at lower paying firms are sheltered from import competition.

Although the total effects of import competition on exposed workers are rather moderate, we consider one important group for which import competition has larger consequences. An influential literature, which is naturally related to the effects of import competition, has focused on the long-run consequences of job loss caused by mass-layoffs, following the pioneering work by Jacobson, LaLonde, and Sullivan (1993). We combine the two sources of variation – industry affiliation before the trade shocks and exploiting mass-layoff events – to ask how globalization in the form of import competition affects the cost of job displacement. We find large heterogeneity in the strength of scarring effects. Being subject to a mass-layoff in an import competing industry is associated with a slower recovery in earnings and employment prospects, compared to being laid-off in another industry.

Our article contributes to two literatures investigating the labor market effects of trade. A recent literature studies the worker-level effects of trade using administrative datasets with contributions by Autor, Dorn, Hanson, and Song (2014), Dix-Carneiro and Kovak (2017a), and Utar (2016). Our paper is different and complements these studies by our focus on exports which allows us to make an important and previously missing connection to a growing theoretical literature. Second, the German data allows us, moreover, to rank all firms and workers in the sample by a very flexible measure of quality (by the pre-estimated AKM model), which permits to study the effects among heterogenous employer-employee matches.

While the worker level literature has largely ignored adjustments to export opportunities, Verhoogen (2008) and Amiti and Davis (2012) study responses to export shocks from the firm side. They show that in Mexico and Indonesia, wage inequality has increased between exporting and nonexporting firms, which confirms another central prediction of the mentioned recent strand of theoretical models. Our longitudinal matched employer-employee dataset allows us to study the worker side and test another central theoretical prediction of most models, concerning the reallocation of workers in export industries. Krishna, Poole, and Senses (2014) argue that in Brazil, following trade liberalization, the (positive) sorting of workers to firms increases. Our results are consistent with this, as we find stronger mobility responses by high-skilled workers after export shocks.

In Section 2, we start by describing the data. Section 3 provides baseline estimates on the effects of export and import shocks on workers' careers over a ten-year horizon. Section 4 contains our first set of main results and illustrates the adjustment dynamics. Section 5 considers heterogeneity with respect to worker skills and firm specific wage premia. Section 6 shows how the scarring effects of layoffs are affected by import competition, and Section 7 concludes.

2 Data and Measurement

2.1 Labor Market Side

Our data source is the Integrated Labor Market Biographies (IEB V12.00.00 - 2015.05.15) from the German Institute for Employment Research. This data set stems from the mandatory notifications to the social security insurance, which essentially covers the universe of all individuals in the German labor market who were either employed in a job liable to contributions in the social security or were unemployed and received benefits from the unemployment insurance.[7] Our data set consists of all spells that belong to a 30 percent random sample of all individuals from the full data. This results in an individual-level spell data set that is highly accurate – even on a daily basis – due to its original purpose of calculating retirement pensions. In this administrative data, we can observe the location and industry of the workplace establishment along with individual characteristics such as age, gender, nationality, educational attainment, and the daily wage. This allows us to follow single workers over time, and keep track of all their on-the-job earnings changes, employer changes at the establishment level within and across industries and regions, as well as non-employment spells.

Our main observation period spans the time period from 1990 to 2010, which we split into two separate 10-year time windows. To construct our sample, we identify all individuals in either 1990 or 2000, who were between 22 and 54 years old, and were full-time employed in manufacturing with a tenure of at least two years and had a mean daily wage above the marginal-job threshold on June 30th of the respective base year. This results in a dataset that comprises the full employment biographies of more than 2.4 million individuals. For any given day during the observation period, we know if a person held a job or was registered as unemployed. People may drop out of the dataset for several reasons. We can observe if people died or if they moved to another country while being registered as unemployed. Other reasons are retirement, withdrawal from the labor market, taking up a job as a sworn civil servant or self-employed. We drop the full biographies of people who die during the observation window or emigrate. Since we cannot observe the nature of the other cases, we assume that all other people who drop out of the dataset are non-employed with zero earnings.[8]

As the wage information is subject to right-censoring at the social security contribution ceiling, we apply the imputation procedure by Card, Heining, and Kline (2013). Moreover, we convert

[7] See Oberschachtsiek, Scioch, Seysen, and Heining (2009) for an extensive introduction to this dataset.

[8] This will underestimate employment and earnings in cases of civil servants and self-employed. However, this problem may be small in practice since we are only interested in high tenured manufacturing workers who, even if they find employment in the public sector, are not likely to be rewarded the sworn status that would exempt them from the social security insurance. As for self-employment, Germany ranks among the countries with the lowest entrepreneurship rates in the world (Global Entrepreneurship Monitor, 2017).

all earnings into constant 2010- € using the consumer price index of the *Bundesbank*. Finally, we express annual incomes in multiples of the individual's earnings in the base year (1990 or 2000).[9] Panels A and B of Table 1 report informative descriptive statistics on the outcome variables and individual and workplace characteristics.

2.2 Trade Exposure

Information on international manufacturing trade comes from the United Nations Commodity Trade Statistics Database (Comtrade). This data contains annual trade statistics of over 170 reporter countries detailed by commodities and partner countries. We also convert trade flows into 2010-€. To merge them with our labor market data, we harmonize industry classifications by a correspondence between 1031 SITC rev. 2/3 product codes and the employment data at the 3-digit industry level (equivalent to NACE) as provided by the UN Statistics Division.[10] This yields information on international trade at the level of 93 3-digit manufacturing industries.

Figure 1 illustrates the evolution of German industry-level trade, both with respect to the East and the world as a whole.[11] Trade volumes are depicted on a log scale and normalized to one in 1990, and the graphs capture the evolution across the industry distribution for the 25^{th}, 50^{th}, and 75^{th} percentile. The solid lines show that, at the median of the distribution, German trade volumes with the East increased by a factor of ten between 1990 to 2010, both on the import and on the export side. This substantially out-paces the growth of trade with the world as a whole, which only doubled over the same period. The rise of trade exposure from the East started in the late 1980s, while the trends were flat before. It was particularly strong in the years immediately after the fall of the iron curtain in 1990/91, flattened out over the 1990s, and then received another boost in 2001 which coincides with the Chinese entry into the WTO.

As those events were sudden and largely unexpected, we may thus suspect that much of this observed increase in German trade stems from developments that originate in those countries, namely the vastly rising productivity and market access of China and the Eastern European countries as they were transformed into market economies (Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2016). This rising trade exposure then constitutes the major globalization "shock" that hit the German labor market in that period. But it does not only accrue in the form of rising import

[9] This is a standard approach in the labor economics literature to take into account ex-ante earnings differences across workers. Notice that this normalized earnings approach is robust to observations with zero earnings in a year, which would not be the case if we had used (non-normalized) log annual earnings as the outcome variable. Instead of normalizing with base year earnings of a single year, we can also take an average over a few years. Results would not change.

[10] Ambivalent cases were partitioned according to national employment shares in 1978.

[11] The East is composed of China and 21 Eastern European countries, namely 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.

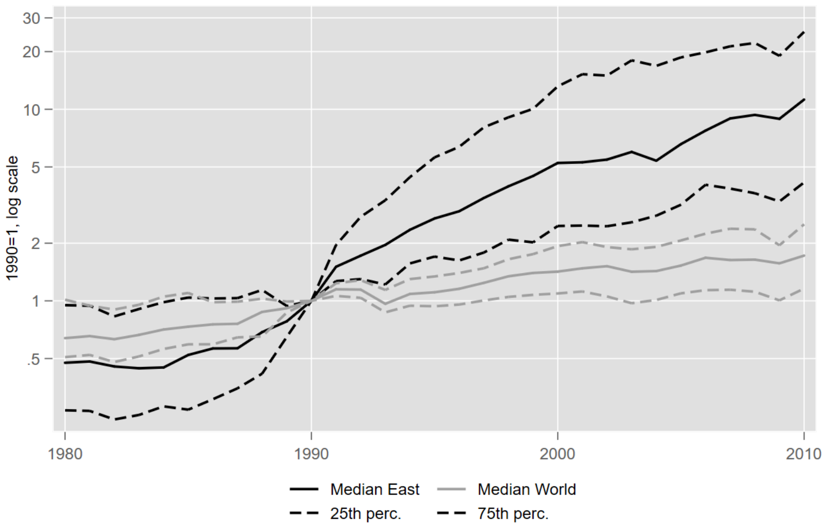
Table 1: **Descriptive overview**

	1990-2000		**2000-2010**	
observations	1,230,897		1,207,948	
	mean	(sd)	mean	(sd)
[A] Outcomes, cumulated over 10 years following base year				
100 x earnings / base year earnings	873.6	(414.7)	906.2	(372.1)
days employed	2925	(1032)	3179	(881)
average daily wage	121.6	(65.0)	124.3	(77.3)
[B] control variables, measured in base year				
base year earnings	42870	(24442)	47266	(44449)
dummy, 1=female	0.227	(0.419)	0.215	(0.411)
dummy, 1=foreign national	0.124	(0.330)	0.095	(0.294)
dummy, 1= age $\leq$34 yrs	0.372	(0.483)	0.310	(0.463)
dummy, 1= age 35-44 yrs	0.285	(0.451)	0.387	(0.487)
dummy, 1= age $\geq$45 yrs	0.333	(0.471)	0.287	(0.452)
dummy, 1=unskilled	0.215	(0.411)	0.139	(0.346)
dummy, 1=vocational training	0.710	(0.454)	0.759	(0.428)
dummy, 1=college degree	0.075	(0.263)	0.102	(0.303)
dummy, 1=tenure 2-4 yrs	0.248	(0.432)	0.276	(0.447)
dummy, 1=tenure 5-9 yrs	0.264	(0.441)	0.304	(0.460)
dummy, 1=tenure $\geq$10 yrs	0.444	(0.497)	0.364	(0.481)
dummy, 1=plant size $\leq$9	0.043	(0.203)	0.046	(0.210)
dummy, 1=plant size 10-99	0.181	(0.385)	0.245	(0.430)
dummy, 1=plant size 100-499	0.263	(0.440)	0.313	(0.464)
dummy, 1=plant size 500-999	0.125	(0.330)	0.118	(0.323)
dummy, 1=plant size 1,000-9,999	0.276	(0.447)	0.201	(0.401)
dummy, 1=plant size $\geq$10,000	0.112	(0.315)	0.074	(0.262)
dummy, 1=food products	0.074	(0.261)	0.089	(0.285)
dummy, 1=consumer goods	0.085	(0.280)	0.070	(0.255)
dummy, 1=industrial goods	0.369	(0.482)	0.391	(0.488)
dummy, 1=capital goods	0.472	(0.499)	0.450	(0.497)
[C] Trade exposure				
Δ export exposure	20.211	(16.874)	34.933	(28.079)
p10-p90 interval	[3.479 ; 44.136]		[5.436 ; 68.933]	
p25-p75 interval	[9.185 ; 26.997]		[17.989 ; 50.216]	
Δ import exposure	22.806	(26.198)	28.169	(54.724)
p10-p90 interval	[1.867 ; 47.600]		[1.878 ; 68.323]	
p25-p75 interval	[7.018 ; 32.341]		[4.999 ; 30.522]	

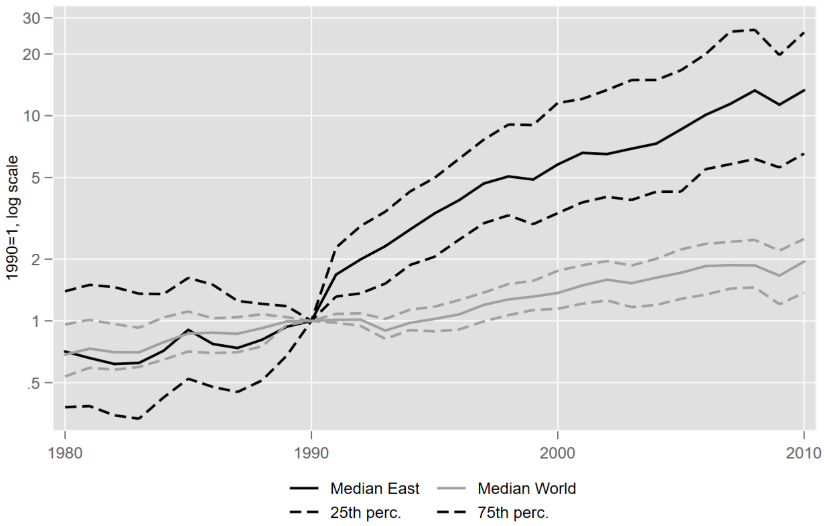
Notes: Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year.

penetration from labor-abundant countries with substantially lower wages. It also involves the surging export opportunities which reflects the rising demand for German products from those areas.

Figure 1 also highlights the strong differences in industry-level trade exposure. The broken lines depict the evolution of the trade volumes of the industry at the upper and lower quartile of the respective distribution of tradeflows. With respect to the East, imports and exports have increased across the whole industry distribution relative to 1990. However, there is considerable variation.



(a) Imports



(b) Exports

Figure 1: Rising German trade volumes

Notes: The figures display the quartiles of German industry level import and export volumes, normalized to one in 1990 (log scale).

In Table A.1 in the appendix, we report the industries with the highest export and import volumes in 2010, and the evolution of their trade over time. As can be seen, the automotive industry has by far the highest export volume (and also the strongest increase over time), followed by other German export sectors such as special purpose machinery or chemicals. On the import side, the car industry also shows up high on that list as there is substantial intra-industry trade within that particular manufacturing branch. But we also see very different industries among those with the highest import penetration, in particular relatively labor-intensive industries like wearing apparel, furniture, or office machinery in which China and Eastern European countries have developed a comparative advantage.

Rising Eastern trade exposure, hence, affects workers very differently, depending on industry affiliation. To reflect this variation, we construct our main exposure measures for import penetration and export opportunities in industry j as follows:

$$ImE_{jt} = \frac{IM_{jt}^{EAST \to D}}{\overline{w}_{j(t-1)} L_{j(t-1)}} \qquad \text{and} \qquad ExE_{jt} = \frac{EX_{jt}^{D \to EAST}}{\overline{w}_{j(t-1)} L_{j(t-1)}} \tag{1}$$

where $IM_{jt}^{EAST \to D}$ and $EX_{jt}^{EAST \to D}$ are aggregate national import/export volumes with the East in industry j and year t. We normalize them with a measure for sector j's overall size in the German economy, more specifically with the total domestic wage bill lagged by one year.[12] Panel C of Table 1 reports descriptive statistics for the individual trade exposure measures (1). We there report the changes of ImE_{jt} and ExE_{jt} over ten years and find a notable heterogeneity across workers. For example, during the first decade, the worker at the 75^{th} percentile experienced an almost five times stronger increase in import penetration than the the worker at the 25^{th} percentile, and a six times stronger increase during the second decade. Similarly, for exports we also find that rising opportunities in the East affected some workers much stronger than others.

3 Estimating the Effects of Trade Exposure on Worker Careers

We begin by studying the effects of trade on the earnings trajectories of German manufacturing workers. Our estimates identify relative effects between industries. In essence, we compare the labor-market trajectories of – ex ante – observationally similar workers who differ in their initial industry of employment at the onset of the trade shocks. In our baseline model, for each worker i starting out in a manufacturing industry, we add up all labor earnings over the next 10 years, irrespective of where they accrued, and divide them by the respective base-year labor income.

[12] This approach follows Autor, Dorn, Hanson, and Song (2014), who normalize trade flows with total domestic consumption. Directly replicating their normalization is not feasible in our context because the required data for Germany are only available from surveys of larger firms and at a different level of aggregation.

We use data from the two decades $t = 1990 - 2000$ and $t = 2000 - 2010$. For the first decade, we construct the dependent variable as $Y_{ijt} = \frac{\sum_{k=1991}^{2000} E_{ijk}}{E_{ij1990}}$, where i is the worker index, j is a worker's initial industry at the beginning of the decade t, and E are yearly earnings in k. For the second decade 2000-2010, the dependent variable is constructed analogously. This approach – normalizing cumulative earnings by a pre-treatment base year[13] – allows us to decompose the total effects of export and imports into different channels of adjusting (Autor, Dorn, Hanson, and Song, 2014), because it permits the inclusion of all observations even when a worker's earnings from some source are zero.

We regress the (normalized) cumulated individual earnings Y_{ijt} on the increases in import and export exposure of the worker's *original* 3-digit industry j during the respective time period:

$$Y_{ijt} = \boldsymbol{\alpha} \cdot \mathbf{x}'_{ijt} + \beta_1 \cdot \Delta ImE_j + \beta_2 \cdot \Delta ExE_j + \phi_{REG(i)} + \phi_{J(j)} + \phi_t + \epsilon_{ijt} \tag{2}$$

In the vector $\mathbf{x}_{ij}$ we include a rich set of worker-level variables and firm size, with dummies for gender, foreign nationality, 3 skill categories, 3 tenure categories, 3 age groups, and 6 plant size groups. We add dummies for 141 commuting zones denoted by $\phi_{REG(i)}$. This means we identify effects within local labor markets. This is potentially important because of the German reunification shock – but as we show more directly below, the inclusion or exclusion of East Germany does not affect our estimates.

We include dummy variables for four broad manufacturing industry-groups $\phi_{J(j)}$.[14] ϕ_t is a time dummy to differentiate the two cross-sections (1990-2000 and 2000-2010).

The two main coefficients, β_1 and β_2, capture causal effects when there are no parallel unobservable shocks that simultaneously affect trade and labor market outcomes. To address this concern, we follow common practice and instrument the exposure variables with trade flows of other countries vis-a-vis the East.[15]

In Table 2 in Panel A, we first estimate model (2) by ordinary least squares (OLS). In all columns, there are statistically significant relationships between the change in trade exposure and cumulative earnings. Standard errors are clustered by industry x commuting zone x base year. Working in an industry with higher export (import) growth to Eastern Europe and China is associated with higher (lower) total earnings. Columns 1 and 2 control for worker demographics.

[13] Our results are robust to using more pre-treatment years to construct the denominator. I.e. if we normalize cumulative by 3 or 5 year averages our estimates of interest are almost unaffected.

[14] These are: food products, consumer goods, industrial goods, and capital goods.

[15] This instrumental variable approach has been developed by Autor, Dorn, and Hanson (2013) and applied to the German case by Dauth, Findeisen, and Suedekum (2014). We follow their approach, and use the trade flows of Australia, New Zealand, Japan, Singapore, Canada, Sweden, Norway, and the UK to construct the instrument by replacing the numerators of ImE_{jt} and ExE_{jt}, respectively. The rationale is that demand shocks in those "instrument countries" are largely uncorrelated with German ones, and have little direct effects on German workers. On the other hand, those countries are similarly affected by the rise of the East.

Table 2: **Trade Exposure and Individual Employment Outcomes**

[A] OLS	(1)	(2)	(3)	(4)
export exposure	0.9058***	1.0301***	0.6988***	0.4880***
	(0.057)	(0.061)	(0.056)	(0.047)
import exposure	-0.0940***	-0.1310***	-0.1540***	-0.0550**
	(0.031)	(0.033)	(0.029)	(0.027)
R^2	0.085	0.109	0.119	0.126
[B] 2SLS	(1)	(2)	(3)	(4)
export exposure	1.2215***	1.3328***	0.9515***	0.5245***
	(0.092)	(0.098)	(0.087)	(0.084)
import exposure	-0.2234***	-0.3052***	-0.2677***	-0.1038**
	(0.046)	(0.047)	(0.042)	(0.043)
R^2	0.085	0.108	0.118	0.126
Kleibergen-Paap weak ID F-statistic	32.8	32.5	31.8	44.0
[C] 1st Stage: import exposure	(1)	(2)	(3)	(4)
export exposure	0.1565***	0.1566***	0.1520***	0.1477***
	(0.026)	(0.026)	(0.027)	(0.023)
import exposure	0.2487***	0.2488***	0.2491***	0.2365***
	(0.018)	(0.018)	(0.018)	(0.020)
R^2	0.473	0.473	0.476	0.501
F-statistic of excl. instruments	120.423	120.013	118.254	115.465
[D] 1st Stage: export exposure	(1)	(2)	(3)	(4)
export exposure	0.2265***	0.2239***	0.2172***	0.2114***
	(0.018)	(0.018)	(0.018)	(0.014)
import exposure	0.0113*	0.0116*	0.0121**	0.0107**
	(0.006)	(0.006)	(0.006)	(0.005)
R^2	0.372	0.379	0.397	0.436
F-statistic of excl. instruments	141.193	140.585	136.269	198.303
age, gender, nationality dummies	Yes	Yes	Yes	Yes
education and tenure dummies	No	Yes	Yes	Yes
ln base yr earnings	No	Yes	Yes	Yes
plant size dummies	No	No	Yes	Yes
broad industry dummies	No	No	No	Yes
commuting zone dummies	No	No	No	Yes

Notes: Based on 2,438,845 workers. The outcome variable is 100 x earnings normalized by earnings in the base year and cumulated over the ten years following the base year. Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. In Panel B, this is instrumented by analogous measures constructed from tradeflows of other high-income countries. Age groups are ≤ 34 (reference), 35-44, ≥ 45 years of age in the base year. Tenure groups are < 2 (reference), 2-4, 5-9, ≥ 10 years. Plant size groups are ≤ 9 (reference), 10-99, 100-499, 500-999, 1,000-9,999, $\geq 10{,}000$ workers. Broad industries are food products (reference), consumer goods, industrial goods, and capital goods. Standard errors, clustered by industry x commuting zone x base year in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Adding plant size indicators in Column 3, reduces the export coefficient by about a third. This is in line with the interpretation that larger plants offer steeper wage trajectories and self-select more into exporting.

Panel B shows the second-stage results of the instrumental variable estimation. We again find statistically significant relationships in all models. Across all columns, compared to the OLS estimates, in absolute magnitude, the import and export coefficients increase. This implies a negative correlation between industry export demand shocks from China/Eastern Europe for German goods and German industry labor demand shocks; and a positive correlation between import demand shocks and German industry labor demand shocks. Going from column 2 to column 3, one sees again that the export coefficient is reduced by the inclusion of plant size dummies.

Industries that face greater import competition may also be on a general downward trend that is confounded with negative trade shocks. Relatedly, industries that face greater export opportunities may be on a general upward trend, correlated with the positive trade shock. That is why we include dummies four four different manufacturing industry groups in column 5, the most demanding model. The same hold true for local shocks and motivates the inclusion of 141 commuting zone dummies. This means we identify effects by comparing workers across different sub-industries within the same manufacturing sector/commuting zone. Controlling for confounding shocks is indeed important and reduces the effects from column 4 to column 5 for exports and imports.

To convert these estimates into economically meaningful magnitudes, consider a worker with average annual income in the base year 1990 (42,870 €, see Table 1) who experiences a rise in import exposure at the 75^{th} percentile ($\Delta ImE_j = 32.34$) and compare to a worker with median income but import exposure at the 25^{th} percentile ($\Delta ImE_j = 7.02$). Our estimates imply that the former earns $-0.10 \times (32.34 - 7.02) \times 42,870/100 = -1,085$€ less, which equals $1,411 using the average 2010 € /$ exchange rate.[16] For the second decade, the magnitudes are $-1,206$ € (=$1,568). Interestingly, these effects are much smaller than what Autor, Dorn, Hanson, and Song (2014) estimate for the China shock effect on US workers. This may be caused by differences in re-training systems, employment protection, and the stronger unions in Germany. Performing an analogous interquartile comparison for export exposure, we find an earnings difference of $0.52 \times (27.00 - 9.19) \times 42,870/100 =$ +3,990€ (=$5,187) in the first decade and + 7,865€ (=$10,224) in the second decade.

Panels C and D show that our instruments have sufficient power. The respective F-statistics

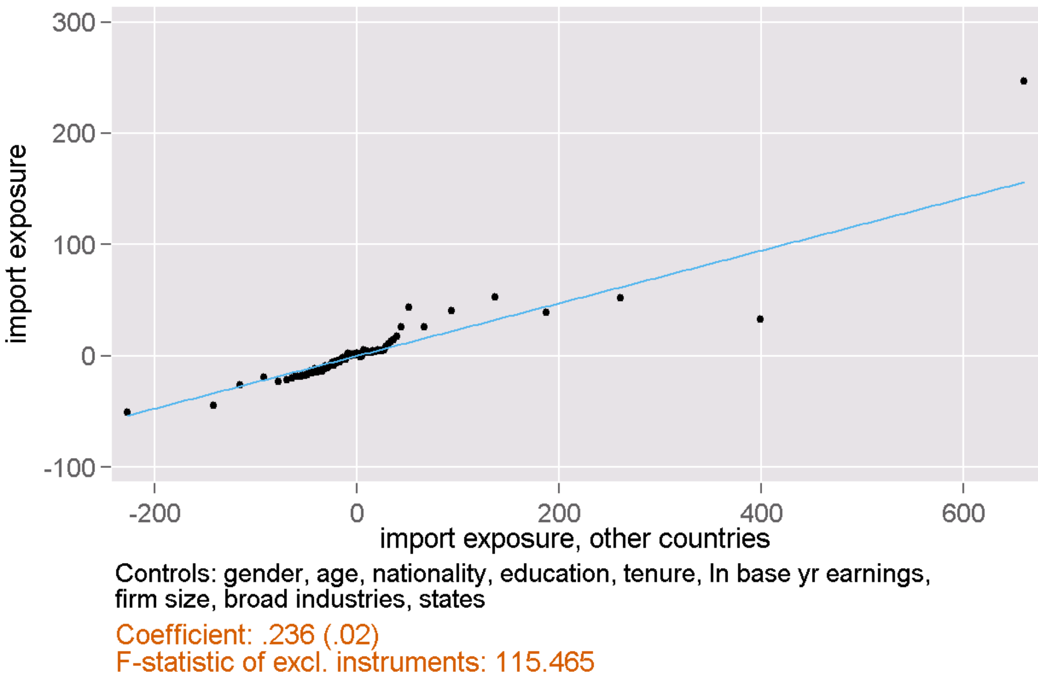
[16] We use a value of 1.3.

in column 4 – our preferred model – are 115 and 198. There is strong predictive power of trade growth in other high-income countries for German trade growth with the former Eastern Bloc and China. Figure 2 shows the 1st stage relationships.

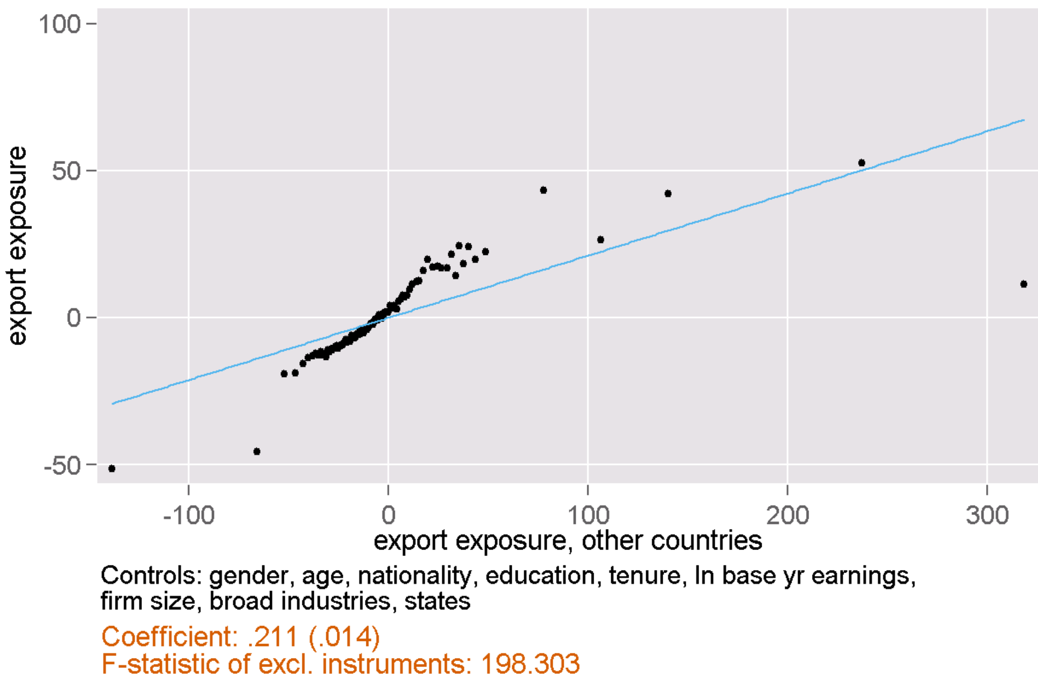
Robustness. In Table A.4 in the appendix, we check the robustness of those baseline results along several margins. One concern might be that our approach picks up the specific developments in Eastern Germany, which is included in the second time period starting in 2000. Since Eastern German manufacturing was not able to compete with western German firms, this sector declined strongly after the reunification. The employment share of the manufacturing sector is substantially lower in Eastern than in Western Germany and hence, only around five percent of all observations started in an East German plant. While controlling for region dummies should further mitigate this concern, we also drop all workers from Berlin or one of the Eastern states but find very similar results. Another concern might be that our measure for trade exposure is too narrow since trade shocks may be transmitted along the value chain. We follow Acemoglu, Autor, Dorn, Hanson, and Price (2016) and augment the measures of import and export exposure for each industry j with the weighted exposure of all downstream industries.[17] When using those comprehensive measures, we estimate similar coefficients. This suggests that our results remain robust when taking input-output linkages into account. Next, we consider the alternative strategy where *net* trade exposure is constructed from the residuals of a preceding gravity estimation (see Appendix B). For reference, we first report in column 3 the instrumental variable result when using the net exposure of industry j constructed from (1), instead of import and export exposure separately. That exercise yields very similar quantitative predictions as before. The coefficient in column 4 is also highly significant, and multiplied with the observed changes in the gravity measure implies consistent (though somewhat more conservative) magnitudes.[18] Finally, we are concerned that our results may pick up industry-specific pre-trends. To explore this possibility, we run a placebo regression to analyze if there is a correlation between past earnings trends and the future rise of trade exposure. Specifically, we regress cumulated earnings 1981-1990 of manufacturing workers in 1980 on the increase of net export exposure over the period 1990-2010, controlling for the same variables as in the baseline and using analogous instruments. We obtain an insignificant and small estimate in column 4, which is reassuring that our results do not

[17]The intuition is that the steel industry, for example, is not only directly affected by import shocks, but also indirectly as other negatively affected sectors may demand less raw steel. Similarly, the car parts industry not only benefits directly from more export opportunities, but also via its most important downstream customer, the automotive industry. See the Appendix A for more details.

[18]Comparing a worker at the first and third quartile of the increase of net export exposure, our traditional approach suggests a difference of $(21.12 - (-5.47)) \times 0.17 = 4.57$ percent of base year earnings and the gravity approach a difference of $(2.33 - (-0.58)) \times 0.62 = 1.80$ percent of base year earnings.



(a) import exposure



(b) export exposure

Figure 2: 1st Stages

Notes: Based on 2,438,845 workers. The figures visualize the correlations of our trade exposure measures and the respective instruments. Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. The instruments are analogously constructed from tradeflows of other high-income countries. First both variables are residualized from the other instrument relating to the other tradeflow and all control variables from table 2. Then the residuals of the instrument are classified into 100 percentiles. The dots represent the average values of both residualized variables for each of the 100 bins.

capture industry trajectories but causal effects of rising trade exposure.

4 Firm Switching and Manufacturing Exits

This section presents the first set of main results. We will exploit the granularity of our data and that we have information on the complete labor force history of our workers with daily precision, which allows to measure employment very finely.

We will also connect with a growing theoretical literature which integrates the heterogenous firm paradigm in the spirit of Melitz (2003) and labor market imperfections. The central building block is the self-selection of the most productive firms in an industry into export markets, which leads to an increased labor demand at these firms. Since we study things from the worker perspective, guided by the theoretical literature, we should observe that a substantial part of the earnings gains from exports for manufacturing workers are realized in different firms than the original employer. This churning and sorting after trade shocks takes place in models with ex ante homogenous workers (Helpman, Itskhoki, and Redding, 2010) and heterogenous workers (Sampson, 2014). In particular, given our research design comparing similar workers across industries and the importance of industry specific human capital, these effects should show up in earnings gains in different plants within the same industry. We will find positive evidence for this channel central to the theoretical literature and the quantitative magnitudes are substantial.

It is also important to understand how the earnings losses for workers in import competing industries come about, as has been studied by Autor, Dorn, Hanson, and Song (2014) for the US. In the case of Germany – where export industries expand in terms of output – a plausible hypothesis is that the earnings losses of workers in the import competing sector are mitigated by transitions within the manufacturing sector into exporting industries. We will find, however, that this is *not* the case – the main margin of adjustments is the manufacturing exit and entry into the service sector.

To proceed, we decompose Y_{ij} into different parts and add up all earnings or days of employment that worker i has collected during the respective decade in the original establishment, in different establishments within the same 2-digit manufacturing industry, in different manufacturing industries, or outside of manufacturing.[19] The results are in Table 3. In column 1, we repeat our estimation from column 4 of Table 3, before, in columns 2–5, we investigate how trade shocks to the initial industry j have affected the different additive components of total cumulative earnings. Notice that the coefficients in columns 2–5 add up to the coefficient in column 1 by

[19] The results are robust to using the same 3-digit industry.

Table 3: **Adjustment**

[A] Earnings	(1) All employers	(2)	(3) Same sector	(4)	(5) Other Sector
Same 2-dig industry		yes	yes	no	no
Same employer		yes	no	no	no
export exposure	0.5245***	0.3528*	0.3017**	0.0344	-0.1644*
	(0.084)	(0.213)	(0.149)	(0.062)	(0.092)
import exposure	-0.1038**	-0.5469***	-0.1159**	0.1141***	0.4449***
	(0.043)	(0.111)	(0.055)	(0.023)	(0.063)

[B] Employment	(1) All employers	(2)	(3) Same sector	(4)	(5) Other Sector
Same 2-dig industry		yes	yes	no	no
Same employer		yes	no	no	no
export exposure	0.7078***	0.5393	0.9181*	-0.0080	-0.7416**
	(0.188)	(0.713)	(0.504)	(0.200)	(0.299)
import exposure	-0.5798***	-1.9069***	-0.3852**	0.3468***	1.3656***
	(0.112)	(0.374)	(0.187)	(0.076)	(0.182)

Notes: Based on 2,438,845 workers. The outcome variables are 100 x earnings normalized by earnings in the base year (Panel A) and cumulated days of employment (Panel B), both cumulated over the ten years following the base year. For column 1, the outcomes are cumulated over all employment spells in the 10 years following the base year. Panel A: For column 2 the outcomes are cumulated only when they occurred at the original workplace. For the other columns, the outcomes are cumulated only when they occurred at a different plant in the same industry (3), at a plant in a different manufacturing industry (4), and outside the manufacturing sector (5), respectively. Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. In Panel B, this is instrumented by analogous measures constructed from tradeflows of other high-income countries. All regressions include the same control variables as in column 4 of Table 2. Standard errors, clustered by industry x commuting zone x base year in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

construction.[20]

4.1 Exports: Worker Churning Across Firms

We start by discussing the results for exports and earnings in Panel A. In column 2, the point estimate of 0.35 shows that the earnings increases within the original firm are the largest contributor to the total effect. In column 3, however, we see that around an economically and statistically significant part of the total earnings effects comes from higher earnings at other firms within the same industry. The size of the effect – 0.30 – is in fact very close to the value in column 2. It shows that exports cause wage gains *on-the-job* but also cause workers to change workplaces within industries and that both adjustment mechanisms are of similar economic magnitude.

[20] Autor, Dorn, Hanson, and Song (2014) introduce this decomposition.

Earnings are the product of employment and wages. We can look directly at employment by exploiting that we observe every worker on a daily level. We replace the dependent variable in equation (2) by the (cumulated) days of employment in Panel B. As expected from the earnings results, export exposure stabilizes employment, as seen in column 1. The most important finding here, though, is that the coefficient in column 3 with a value of 0.92 is larger – and almost twice the size of the coefficient in column 2. An exogenous rise in export exposure causes turnover or the churning of workers across firms, in line with the prediction of expanding employment at the most productive firms in heterogenous firm models. The economic size of this effect is considerable. We can again compare workers at the 75^{th} percentile to the 25^{th} percentile of the export exposure distribution. In the industry with higher export exposure, days worked at a different firm within the same industry increase by 10 percent.

Column 4 shows relatively precise zero effects of export exposure on earnings and employment in other industries within manufacturing. Labor reallocations happen within industry, suggesting firms which expand do so by poaching workers from other competing firms in the same industry. This is consistent with industry specific human capital. Finally, column 5 shows there is an offsetting force to the increase in employment in a worker's original industry. Earnings and employment in the service sector are reduced.

4.2 Imports: Manufacturing Exits

The import estimates strikingly show the importance of labor market adjustments in Germany. While the total response in column 1 is relatively modest and muted – remember from the last section that comparing workers at the 75^{th} to the 25^{th} percentile in import exposure, we find that the former earn 1,206€ ($1,568) less over 10 years – this hides large effects on earnings and time spent with the original employer. In column 2, one sees that earnings losses at a worker's original firm are more than five times as large compared to the overall response in column 1. For days employed, the effect in column 2 is still about three times larger compared to column 1. How do workers adjust then to import pressure? The answer is by transitioning to the service sector. For earnings, the coefficient in column 5 is around 80% of the size, when scaled by the own firm response in column 2. For employment, the value is 72%. Interestingly, changes in the transition rates within the manufacturing sector roughly cancel each other out. From columns 3 and 4 in both panels, we get the result that transitions within the original industry decrease but this is offset by an increase of similar proportion for earnings/employment in other manufacturing industries.

In summary, laid-off workers in import competing industries only make up a very small part of their total losses in other manufacturing industries. Instead, they are moving out of manufacturing. In the bigger picture, this may be a surprising finding, considering that in the trade integration episodes we study (the collapse of the Iron Curtain and the opening of China) and also in general, Germany is running a trade surplus. Our findings suggest that workers affected by import competition are only partially absorbed by the expanding export industries.

5 Heterogeneity of Firms and Workers: AKM Effects

We now consider heterogenous effects for firms and workers. A recent literature explicitly models the interaction of trade and labor market imperfections with heterogenous workers and firms, see e.g. Sampson (2014). The selection of firms into exporting creates interesting implications for labor income inequality in these models. Because skilled workers are more likely to work in firms which self-select into exporting (by positive assortative matching), one should expect an increase in earnings inequality between workers of different skills. More productive firms also increase their demand for skilled workers in these models, and one should expect that skilled workers switch firms within industry to profit from the increased export opportunities.[21]

In this section, we exploit the German setting with its large industry differences in export exposure to provide empirical evidence on some of these channels predicted by models with heterogenous workers and firms. We measure skill for workers and firm characteristics by using pre-estimated two-way fixed effects models. The methodology was introduced by Abowd, Kramarz, and Margolis (1999) and has since then be widely applied, prominently by Card, Heining, and Kline (2013) for Germany. In particular, their wage regression is: $ln(\text{wage}_{it}) = \alpha_i + \psi_{p(it)} + x'_{it} + r_{it}$, where observable worker characteristics x'_{it} are education-specific age profiles. The person effects α_i can therefore be interpreted as unobservable worker skills that are rewarded equally across different employers. Similarly, the establishment-fixed effects $\psi_{p(it)}$ are proportional pay premiums (or discounts) by plant p to all its employees. They may stem, for example, from rent-sharing or efficiency wage considerations, and serve as a proxy for workplace quality.

To implement this approach, we use the fixed-effects estimates from Card, Heining, and Kline (2013), which are based on the universe of social security records in Germany and can be merged to our 30% sample via unique person and establishment identifiers. It is important to note that those fixed effects are identified from time windows that *precede* the start of our two decades, since they would otherwise be endogenous to the later trade exposure trends.[22] We then define

[21]Such reallocations may also take place between industries, of course. Consistent with the notion of industry-specific human capital and the geographical concentration of industries, we will find empirically a stronger effect on within industry reallocations.

[22]For the first decade of our analysis, we use their estimated fixed effects from the 1985–1991 time interval, and for the second decade their estimates for the 1996–2002 period. The estimation of the fixed effects requires all firms to be

Table 4: **Adjustment by Worker Quality**

Earnings	(1) All employers	(2)	(3) Same sector	(4)	(5) Other Sector
Same 2-dig industry		yes	yes	no	no
Same employer		yes	no	no	no
ExE bottom tercile	-0.8571***	-0.4721**	0.0662	-0.1570***	-0.2942***
	(0.118)	(0.189)	(0.158)	(0.046)	(0.057)
ExE middle tercile	0.3202***	0.4885**	0.1612	-0.0416	-0.2879***
	(0.083)	(0.197)	(0.124)	(0.048)	(0.075)
ExE top tercile	1.9012***	0.8281***	0.5501***	0.3132***	0.2098
	(0.138)	(0.243)	(0.181)	(0.092)	(0.132)
ImE bottom tercile	-0.5063***	-0.5608***	-0.1883***	0.0833***	0.1595***
	(0.067)	(0.104)	(0.064)	(0.022)	(0.033)
ImE middle tercile	-0.1865***	-0.5535***	-0.0574	0.1013***	0.3231***
	(0.049)	(0.111)	(0.055)	(0.023)	(0.049)
ImE top tercile	0.2584***	-0.5745***	-0.1041	0.1491***	0.7878***
	(0.083)	(0.155)	(0.075)	(0.037)	(0.108)

Notes: 2SLS results, based on 2,277,914 workers. The outcome variables are 100 x earnings normalized by earnings in the base year, cumulated over the ten years following the base year. For column 1, the outcomes are cumulated over all employment spells in the twenty years following the base year. For column 2 the outcomes are cumulated only when they occurred at the original workplace. For the other columns, the outcomes are cumulated only when they occurred at a different plant in the same industry (3), at a plant in a different manufacturing industry (4), and outside the manufacturing sector (5), respectively. The table reports coefficients of interactions of Import (export) exposure (ImE and ExE) with dummies indicating the tercile of a worker's individual fixed effect from Card, Heining, and Kline (2013). Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. All trade exposure variables are instrumented by analogous measures constructed from tradeflows of other high-income countries. All regressions include the same control variables as in column 4 of Table 2. Standard errors, clustered by industry x commuting zone x base year in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

three dummy variables that indicate the terciles of the person and the establishment fixed-effects distributions, in the latter case pertaining to the observed worker-plant matching in the respective base year, which we interact with our measures for trade exposure. We then repeat our empirical estimations and let the coefficients of import and export exposure vary with the tercile of the person and the establishment fixed-effects distributions. Essentially, these are triple difference estimates. Table 4 contains the results for the worker skill rankings and Table 5 for the firm "quality" rankings. We start our discussion with the worker skill results.

Column 1 in Table 4 shows that export exposure has a strong effect on the returns to skill. The

connected by worker mobility. Firms or workers that were not part of this connected set have no fixed effects and can hence not be used in our analysis in this Section. This reduces the number of observations by around 6.6 percent. We thank Joerg Heining for making these estimates available to us.

most skilled workers from the top tercile of the skill distribution in export exposed industries see large earnings gains relative to highly-skilled workers in industries which are not exposed to trade. To put the effect into quantitave perspective, note that its magnitude of 1.90 is almost four times the size of the benchmark coefficient of 0.52 (column 1 of Table 3, Panel A). Second low- and medium skilled workers from the bottom and middle tercile, respectively, experience small or even negative effects of export exposure. Taken together, in highly export-exposed industries, the most skilled German workers – as measured by their AKM person effect – received large earnings gains compared to lower skilled workers in the same industries. Skilled workers profited the most from trade globalization in Germany.

Next, when focusing on columns 2 and 3, we see that a significant part of these gains for high-skilled workers stems from firm mobility within the original industry of employment. As with column 1, the majority of the average effect of earnings gains from intra-industry firm mobility from column 3 in Table 3, Panel A is driven by the highest skilled workers in Germany. This is consistent with increased labor demand for skills within the export industries driven by firms which self-select into new markets. In Table A.2 in the appendix, we can confirm these mobility patterns across skills groups by directly looking at employment instead of earnings. In more export exposed industries, highly skilled actually see a decrease in their employment with their original firm, but this decrease is dominated by an increase in the days employed at competitor firms within the same original industry. In sum, studying heterogeneity in the adjustment patterns by workers' skills reveals empirical results which are in line with existing theories how trade liberalization affects the labor market in the presence of worker heterogeneity. In particular, (relative) earnings gains in export exposed industries are driven by high-skilled workers who profit on-the-job but also by switching to different firms within the same industry (Sampson, 2014).

The import results in Table 4 reveal that the negative consequences are mostly borne by low-skilled workers. A key finding here is that the result is driven by the differential ability to adjust by skill group. Column 2 shows remarkably similar effects for earnings with the original employer. Columns 4 and 5 reveal that higher skilled workers can soften and even overcompensate the initial loss by transitions to the service sector and other manufacturing industries.

Table 5 displays the 2SLS coefficients when we let the effects of export exposure and import exposure vary with the rank of a worker's initial employer in the firm effects distribution. Remember that the firm effects measure a (proportional) pay premium of the plant (controlling for the skill of the workforce). One expects a positive correlation of the firm effects with the productivity level of the firm, but it has been widely discussed in the literature that the estimated effects shouldn't be literally interpreted as productivity (Card, Cardoso, Heining, and Kline, 2018). Additionally, according to the Melitz (2003) model , we will observe the self-selection of the more productive firms within an industry into new export markets. Finally, some of the newly created rents will be shared with the workforce at these firms. In sum, under these mechanisms, we first expect to find the largest earnings gains for workers starting out at establishments with large fixed effects. Second, the earnings gains for these workers materialize to a large extent at the original employer.

These two predictions are validated by our results in Table 5. First, in column 1, the coefficient for workers from firms in the top tercile is significantly larger than for the over two terciles. The effects are precisely estimated. Second, in column 2, we reassuringly observe that for workers from firms in the top tercile the earnings gains happen, indeed, with the original employer. For workers starting out with a firm in the lower two terciles, in contrast, we can't find statistically significant gains on the job. Interestingly, workers starting out in firms in the middle of the distribution, see sizable gains in different firms but within the same industry (column 3). Presumably, industry export exposure increased labor demand by exporting firms and allowed these workers to move up in the establishment ladder.

For the import results, we see in column 1 that the negative effects are driven by workers starting out in the plants which – before the trade shocks materialized – paid the largest wage premia to all its workers. Column 2 shows clearly – with a strongly negative coefficient of -1.35 – that this stems from earnings losses with the original firm. In Appendix Table A.3, we can narrow down the channel further by looking at employment directly. There we find that workers in importing competing industries starting out at high-wage plants see a very large reduction in employment at their original firm. Taken together, the negative labor market consequences of import competition are borne by workers at high paying plants that lay off workers. Subsequently, these workers lose their workplace specific rent they enjoyed at the original firm.

6 Trade and its Impact on the Costs of Job Displacement

We have so far followed the literature in estimating the labor market impacts of trade by comparing workers across their start-of-period industry affiliation. A related and influential literature has focused on the long-run consequences of job loss, following the pioneering work by Jacobson, LaLonde, and Sullivan (1993). The methodology used in the *mass-layoff* literature employs an event-study design to relate the discrete shock of a worker's layoff to counterfactual labor market outcomes. In this section, we combine the two sources of variation – industry affiliation before the trade shocks and exploiting mass-layoff events – to ask how import competition affects the cost

Table 5: **Adjustment by Plant Quality**

[A] Earnings	(1) All employers	(2)	(3) Same sector	(4)	(5) Other Sector
Same 2-dig industry		yes	yes	no	no
Same employer		yes	no	no	no
ExE bottom tercile	0.1302	-0.0199	-0.0761	0.1937***	0.0325
	(0.092)	(0.202)	(0.134)	(0.052)	(0.081)
ExE middle tercile	0.5644***	0.1675	0.4940**	0.0387	-0.1358
	(0.101)	(0.285)	(0.210)	(0.081)	(0.101)
ExE top tercile	0.8215***	0.9797***	0.3650*	-0.1316	-0.3915**
	(0.128)	(0.330)	(0.209)	(0.104)	(0.164)
ImE bottom tercile	-0.0689	-0.2571**	-0.0754	0.0473**	0.2163***
	(0.043)	(0.111)	(0.069)	(0.021)	(0.041)
ImE middle tercile	-0.0610	-0.5029***	-0.1545**	0.1575***	0.4389***
	(0.074)	(0.142)	(0.073)	(0.039)	(0.089)
ImE top tercile	-0.2252**	-1.3495***	-0.0982	0.1607***	1.0617***
	(0.097)	(0.310)	(0.139)	(0.060)	(0.200)

Notes: 2SLS results, based on 2,279,638 workers. The outcome variables are 100 x earnings normalized by earnings in the base year, cumulated over the ten years following the base year. For column 1, the outcomes are cumulated over all employment spells in the twenty years following the base year. For column 2 the outcomes are cumulated only when they occurred at the original workplace. For the other columns, the outcomes are cumulated only when they occurred at a different plant in the same industry (3), at a plant in a different manufacturing industry (4), and outside the manufacturing sector (5), respectively. The table reports coefficients of interactions of Import (export) exposure (ImE and ExE) with dummies indicating the tercile of a worker's workplace fixed effect from Card, Heining, and Kline (2013). Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. All trade exposure variables are instrumented by analogous measures constructed from tradeflows of other high-income countries. All regressions include the same control variables as in column 4 of Table 2. Standard errors, clustered by industry x commuting zone x base year in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

of job displacement. This complements our analysis from the previous section, because now we focus on workers which experience a (mass-)layoff – a group which is presumably more vulnerable to import competition. In our analysis, we will investigate differences in the scarring effects of a layoff and how import competition and globalization influence them. In other words, we are interested in the question if and how increasing trade exposure in Germany affects workers' ability to adjust after layoffs.

6.1 Estimation – The Cost of Job Loss

The pioneering work by Jacobson, LaLonde, and Sullivan (1993) has spurred a large literature in labor economics that analyzes how involuntary job loss affects individual workers' subsequent careers in the long run. Like almost all recent works on this topic, we follow the procedure of Davis and von Wachter (2011) to estimate the cost of job loss.

First, we identify all German manufacturing plants that have plausibly undergone a mass-layoff somewhen between 1990 and 2009. We obtain the full employment biographies of all employees who have been holding their main job for at least three years at one of those plants at the onset of the layoff. We then identify an equal sized control group of workers in our 30 percent random sample of all individuals described in section 2.1. We use propensity score matching with a caliper of 0.005 to search for individuals of the same gender within the same broad manufacturing industry group (food, consumer goods, production goods, capital goods) and the same year with similar characteristics in terms of employment and earnings histories, age, nationality, education, and plant size. We ensure that each individual can only enter either the treatment or control group once. The raw employment biographies consist of all spells of employment or recipience of benefits from the unemployment insurance and include the start and end dates of each spell. We aggregate this information to calendar years and define k the number of years before/after the layoff. The preparation of the mass-layoff data is explained in detail in appendix C.[23]

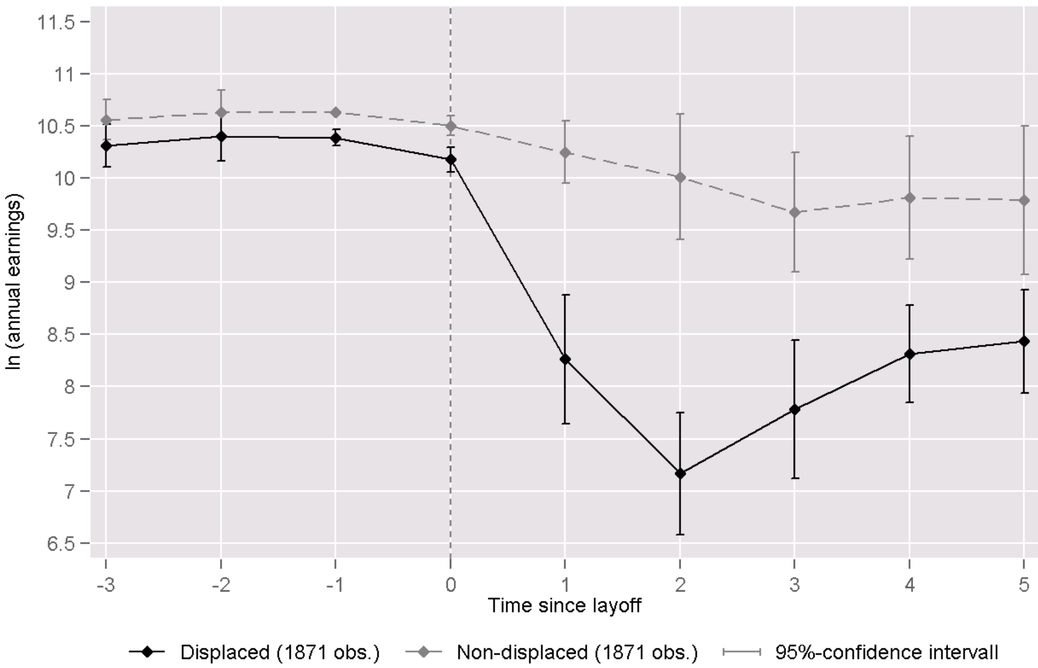
The outcome y_{it} is the log labor earnings per calendar year and our estimation model is:

$$y_{it} = \beta_0 + \sum_{k=-3}^{5} [\delta_k I(t = t^* + k) I(\text{layoff}) + \gamma_k I(t = t^* + k) I(\text{control})] + \alpha_{tc} + \varepsilon_{it} \tag{3}$$

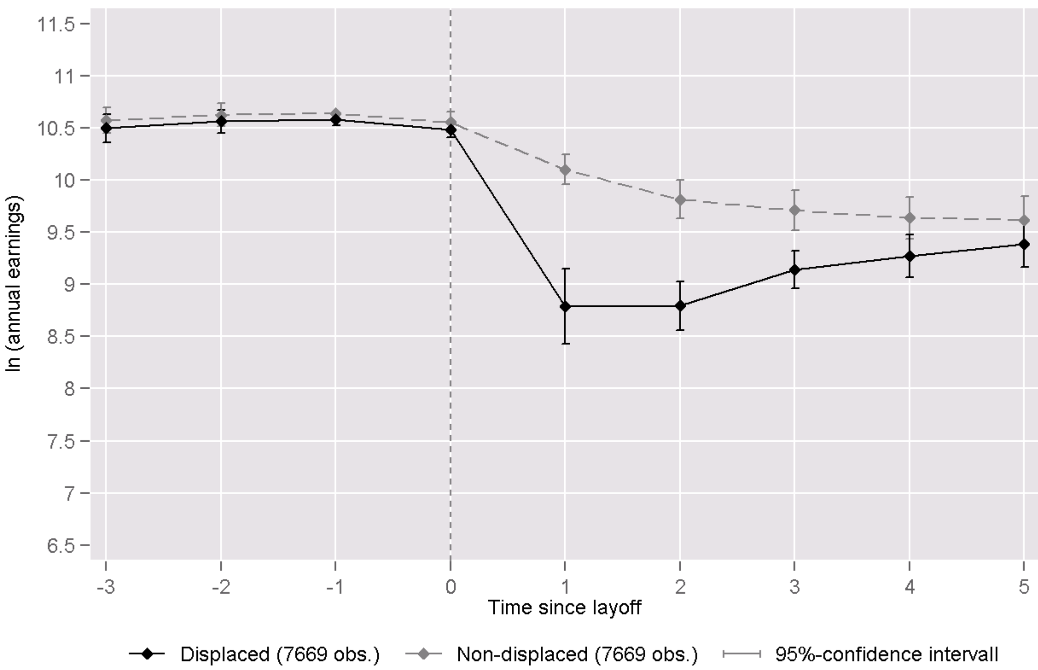
α_{tc} are fixed effects for interactions of calendar year t and birth year c of the respective individuals and ε_{it} is a normally distributed error term which may be correlated across workers laid-off in the same year. The event dummies $I(t = t^* + k)I(\text{layoff})$ and $I(t = t^* + k)I(\text{control})$ indicate the years before/after the event, separately for people actually laid-off and the control group. $I(t = t^* - 1)I(\text{control})$ is omitted as the reference category. We run this regression separately for each 3-digit industry. This means that the workers in the treatment group were laid-off from a plant in the respective sector, while their matches in the control group must be employed in a different plant in the same broad industry group but not necessarily in the same industry.

Figure 3 displays the coefficients of the time-to-layoff dummies from two separate event studies of two exemplary industries. We see that the earnings of workers in both the treatment and control groups are very similar prior to the layoff. Starting in the year of the event, earnings decline markedly for laid-off workers, while earnings remain much more stable for the control group. There are clear and significant differences how workers from both industries recover. Former employees in TV and Radio Manufacturing have declining incomes until the second year after the mass-layoff. They recover to some extent but their annual earnings remain substantially

[23]We thank Silvina Copestake at IAB's department DIM for handling the full sample data for us.



(a) TV and radio receivers



(b) Special purpose machines

Figure 3: Event study results

Notes: The figures plot the coefficients of dummies indicating the time before/after a mass-layoff from two event study regressions for two exemplary sectors.

below the earnings of comparable workers who were not laid off. By contrast, the average workers in manufacturing of special purpose machines starts to recover already in the second year after the mass-layoff. At any point in time their earnings loss relative to the control group is less severe compared to their counterparts in TV and radio manufacturing. Five years after the layoff, their earnings do not differ significantly from those of the control group.

6.2 Scarring Effects and Trade Competition

One major difference between manufacturing of TVs and radios and manufacturing of special purpose machines is that the former is heavily exposed to increasing trade competition from Eastern Europe and China, while the later is not. Schmieder, von Wachter, and Heining (2017) use very similar German data to show that mass-layoffs during a recession leave deeper scars in workers' employment biographies compared to mass-layoffs that occur during better times. We may presume in a similar way that the adjustment paths of workers from different industries are systematically linked to import competition. If human capital that has been accumulated in one industry is difficult to apply in other industries, laid-off workers in import competing industries are likely hit particularly severely as they might find it more difficult to find a new job in their own industry.

We use the time structure of our data and the matched twins to construct double differences of our outcome variables for each laid-off individual:

$$\Delta_{dd}\bar{y}_{ij,t} = (\bar{y}_{ij,post} - \bar{y}_{ij,pre}) - \big(\bar{y}_{i',post} - \bar{y}_{i',pre}\big) \tag{4}$$

where $\bar{y}_{i,pre}$ is the average log earnings or days employed in $t = t^* - 3, t^* - 2, t^* - 1$ of either worker i from industry j who is displaced in a mass-layoff in year t^*, or of her/his statistical twin i'. $\bar{y}_{i,post}$ is the average of the same variable in $t = t^* + 1, t^* + 2, t^* + 3, t^* + 4, t^* + 5$. This double difference represents the log earnings or employment days a worker loses in the medium run due to the layoff.

We then regress these losses on measures for the exposure to imports and exports at the level of the industry j, constructed analogously to equation (1) with the difference that we measure trade as the increase in imports (exports) from (to) China and Eastern Europe over the period from three years before the layoff to five years after, relative to the industry's total wagebill three years before the mass-layoff.[24] The regression model then is:

$$\Delta_{dd}\bar{y}_{ij,t} = \beta_1 \cdot \Delta ImE_j + \beta_2 \cdot \Delta ExE_j + \beta_3 \text{plantsize}_i + \phi_{J(j)} + \phi_t + \epsilon_{ijt} \tag{5}$$

[24]We also construct instruments from increases of tradeflows of other high wage countries with the East over the same time period relative to industry's total wagebill ten years before the mass-layoff.

As in Section 3, we again control for broad industry group ($\phi_{J(j)}$) and calendar year fixed effects (ϕ_t).

The credibility of this approach hinges on two assumptions. First, the matched control group should provide a valid counterfactual to the earnings of the displaced workers if the mass-layoff had never occurred. In Appendix Table A.6 we report summary statistics for the observable characteristics of both groups. Indeed, the matching appears to have worked reasonably well. There are some scattered statistically significant differences between displacement and control group but none of those differences are large in economic terms. The second assumption is that displaced workers do not differ across industries in a way that is related to trade exposure. The final column of Appendix Table A.6 reports the shares of the between-industry variance relative to the variable's total variation among the displaced workers. For all but one variable the largest share of variation is within rather than between 3-digit industries. However, there are substantial differences in plant sizes across industries. Since this might very well be correlated to trade exposure, we control for the number of employees in the plant from which worker i was fired.

In column 1 of Table 6, we at first do not find any relationship between the costs of mass-layoffs and exposure to international trade. However, this result is entirely driven by the industry "manufacturing of office machinery and computers". This industry is strongly exposed to imports from China and has a comparatively large number of workers who experienced a mass-layoff. Yet, being laid-off apparently has not harmed the workers in this industry. Appendix Figure A.3 shows that the earnings of those workers have never significantly fallen below the earnings of the matched control group, neither during the initial drop, nor during the subsequent recovery. It seems plausible that the computer industry is a somewhat special case. Workers laid-off from this industry hold special skills that are valuable also outside their original industry. This does certainly not apply to the majority of industries exposed to competition from China and Eastern Europe. Once we omit the computer industry, we find a clear pattern of higher losses in more exposed industries. In the most conservative models, we find that each percentage point of import exposure costs a displaced workers an additional 0.25 to 0.31 percent of earnings per year. According to the summary statistics reported in Appendix Table A.7, a worker at the 75^{th} percentile of import exposure is exposed by around 19.8 percentage points more strongly than a worker at the 25^{th} percentile. This means that the former experienced an earnings loss that is on average five to six percentage points stronger in each of the five years after the layoff.

In appendix section C.2 we finally examine whether mass-layoffs are related to an increase of trade exposure. We indeed find that import competition increases the probability of a mass-layoff, while exports reduce it, albeit both by an almost negligible degree.

Table 6: **Trade Exposure and Earnings Losses from Mass Layoffs**

	Dependent variable: Δ_{dd} log earnings		
[A] OLS	(1)	(2)	(3)
export exposure	-0.1430	-0.1590	-0.1879*
	(0.104)	(0.104)	(0.106)
import exposure	-0.0617	-0.2464***	-0.2490***
	(0.067)	(0.068)	(0.074)
R^2	0.004	0.004	0.005
[B] 2SLS	(1)	(2)	(3)
export exposure	-0.5467	-0.3435	-0.3588
	(0.379)	(0.296)	(0.288)
import exposure	-0.0667	-0.2923***	-0.3079***
	(0.098)	(0.094)	(0.107)
log plant size	Yes	Yes	Yes
layoff year dummies	Yes	Yes	Yes
broad industry dummies	No	No	Yes
drop manufacturing of computers	No	Yes	Yes

Notes: These tables show how the individual long term losses of a mass-layoff vary with the trade exposure of the industry from where a worker is laid off. Based on 151,711 (column 1) and 147,517 (columns 2, 3) laid-off workers. The outcome variable is the earnings loss during the five years after the layoff, constructed as the double difference (before vs. after layoff and laid-off vs. matched control group) of log earnings. Import (export) exposure is the increase in imports (exports) from (to) China and Eastern Europe over the period from three years before the layoff to five years after, relative to the industry's total wagebill three years before the mass-layoff. In Panel B, this is instrumented by similar measures constructed from tradeflows of other high-income countries. Standard errors, clustered by industry x layoff year, in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

7 Conclusion

A growing and recent empirical literature has unmarked how trade and in particular import competition can disrupt (local) labor markets (Autor, Dorn, and Hanson, 2016). In this article, we have studied how workers in Germany have adjusted to trade globalization. For Germany, which is regularly considered a world leader in manufacturing, globalization has been synonymous with a strong rise in exports. This gives us the opportunity to investigate how the workers adjusted to increasing export opportunities. The focus on exports makes it much easier to bridge the empirical literature to an equally influential theoretical literature (see the survey by Helpman, 2016), which studies the effect of trade on labor markets, when firms self-select into export markets and the labor market is characterized by frictions. Consistent with the theoretical literature, we find that German workers in export exposed industries realize gains by switching employers (within industries). As models which feature assortative matching between workers and firms predict

(Sampson, 2014), trade openness increases skill demand and we observe an increased reallocation of skilled workers to different employers within industry. For imports, our results suggest relatively small losses for affected workers. Interestingly, the losses are driven by workers who start out in high-paying firms, and subsequently lose these rents as they are forced to switch into the service sector. Finally, our contribution presents novel evidence how import competition negatively affects the scarring effect of a layoff. In this way we connect the trade-labor market literature to a large literature in labor economics which has focused on the cost of job loss.

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Appendix

A Trade exposure including downstream linkages

In our main specifications, we only consider how workers are affected by their own industry's imports and exports. However, if an industry suffers from import competition, it might also reduce demand from its domestic suppliers, whereas it might increase this demand when it exports more. We thus extend our trade measure to account for these linkages.

We use the 1995 input-output table from the German Statistical Office to calculate what share of its output an industry sells to each other industry. This table contains information on linkages between 69 2-digit industries. We can expand this matrix to our 221 3-digit industries under the assumption that each industry causes linkages that are proportional to its size. We therefore first duplicate all rows and columns of the 2-digit table to the number of 3-digit industries they include. Then we multiply each element of this matrix by the employment share of the corresponding 3-digit industry in its 2-digit industry and obtain a 221×221 matrix. Finally, we use the Kronecker product of this matrix and a $T \times T$ identity matrix to get a matrix W that reflects the downstream linkages of all industries in all years of our dataset.

Multiplying W by the $J \times T$ vectors of trade exposures ImE or ExE from equation (1) would yield the additional exposure an industry receives from its direct buyers. We follow Acemoglu, Autor, Dorn, Hanson, and Price (2016) and compute the Leontief inverse of the input-output matrix to account for the additional exposure of the whole value chain. Our augmented measures for trade exposure are then defined as $ImE_{+down} = ((I - W)^{-1})' ImE$ and $ExE_{+down} = ((I - W)^{-1})' ExE$. These capture both the direct effects of the own industry's exposure as well as the weighted indirect effects of all downstream industries. Average values of these measures are shown in Table A.5.

B The estimation approach with gravity residuals

In our baseline specifications we use an instrumental variables strategy that is well established in the related literature. However, one caveat of this approach is that the exclusion restriction would be violated if trade between the East and the countries we use to construct our instrumental variables is correlated with domestic German shocks. While we believe that this correlation is negligible, it cannot completely ruled out as practically everything is related in general equilibrium. As a robustness check, we therefore adapt an approach based on a gravity model of trade which was introduced as a robustness check in Autor, Dorn, and Hanson (2013) and was also employed in Dauth, Findeisen, and Suedekum (2014).

The basic idea of this approach is that one derive expressions for the East's exports in industry j to any country k and Germany's exports to the same country from a standard gravity equation à la Anderson and Wincoop (2003). Taking logs and subtracting both terms shows that the relative exports from the East and Germany to the same country are a function of the East's comparative advantage in industry j (relative to Germany) and the relative accessibility of this country.[25]

Using bilateral trade data, we can represent this in the following regression equation:

$$ln(EX_{jt}^{EAST \to k}) - ln(EX_{jt}^{D \to k}) = \phi_j + \phi_k + \mu_{jtk}, \tag{A.6}$$

where ϕ_j and ϕ_k are industry and destination country fixed effects. The former absorbs the mean comparative advantage in industry j while the latter captures the differential accessibility of country k. Estimating this model for a panel, we obtain the average residual for industry i at time t across importers. Taking ten-year differences, $exp(\overline{\mu}_{jt+10}) - exp(\overline{\mu}_{jt})$ can be interpreted as an increase of the comparative advantage of the East relative to Germany in producing industry j's goods.

In addition, we run an analogous regression of Germany's exports of industry j's goods to the East relative to its exports to other countries:

$$ln(EX_{jt}^{D \to EAST}) - ln(EX_{jt}^{D \to k}) = \phi_j + \phi_k + \pi_{jtk} \tag{A.7}$$

Again averaging the residual across importers and taking ten year differences, we obtain $exp(\overline{\pi}_{jt+10}) - exp(\overline{\pi}_{jt})$. This reflects the East's importance as a destination for German exports of industry j's goods in year t relative to all other countries.

Taken together, these two measures represent the change in relative comparative advantage and import demand of the East vis à vis Germany. We can use them to compute the predicted increase in Germany's net export exposure (but not distinguish between exports and imports):

$$\Delta NetE_{jt}^{gravity} = \frac{(EX_{jt}^{D \to EAST} - IM_{jt}^{EAST \to D}) \cdot \left[exp(\overline{\pi}_{j(t+10)}) - exp(\overline{\pi}_{jt}) - [exp(\overline{\mu}_{j(t+10)}) - exp(\overline{\mu}_{jt})]\right]}{\overline{w}_{j(t-10)} L_{j(t-10)}} \tag{A.8}$$

Table A.5 displays the predicted 10-year change of both the net export exposure from our standard trade measures and from the gravity approach.

[25] See the online appendices of Autor, Dorn, and Hanson (2013) and Dauth, Findeisen, and Suedekum (2014) for details of this derivation.

C Preparing the mass-layoff analysis

C.1 Identifying plants who experienced a mass-layoff

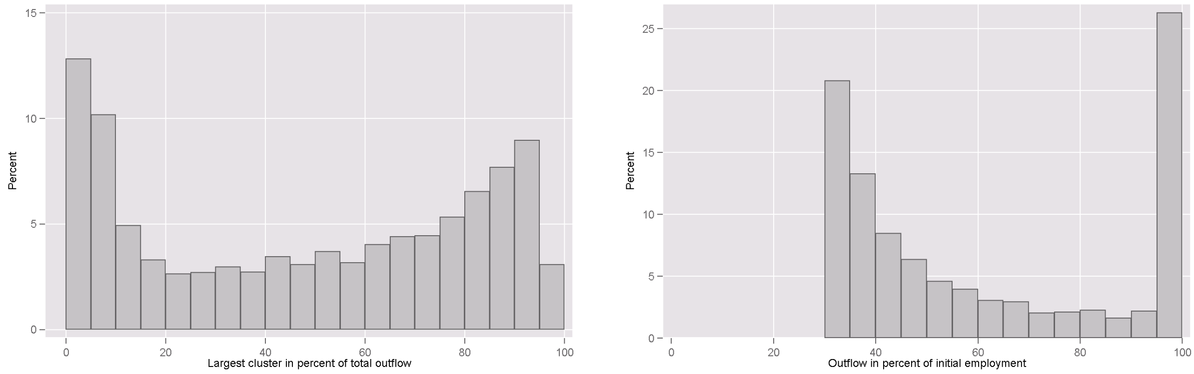
In this section we explain how we identify workers who plausibly experienced a mass-layoff. The first step is to find plants where a mass-layoff event happened. For this task, we use the Establishment History Panel (BHP) of the IAB. The BHP is a plant level aggregation of all social security notifications that cover June 30 of a given year pertaining to the full universe of all employees in the German labor market subject to social security.[26] We use this data to follow the development of the size of all German plants. We define a potential mass-layoff event in year t^* if the following conditions apply:

1. a plant has 50 or more employees on June 30 of year t^*
2. the number of employees contracts by 30 to 100 percent until June 30 of year $t^* + 1$
3. the number of employees on June 30 of year $t*$ is not less than 80 percent and not more than 120 percent of employment in $t^* - 1$ and $t^* - 2$
4. the number of employees does not recover by more than 50 percent of the initial drop by June 30 $t^* + 2$ or $t^* + 3$

The entity of a plant is defined by unique plant id issued by the plant id service ("Betriebsnummernservice") of the German Federal Employment Agency. A plant id does not allow any inference on whether the plant belongs to a larger firm. An issue that is discussed in length by Hethey-Maier and Schmieder (2010) is that the disappearance of a plant id might reflect either a plant closure or a restructuring within a larger firm. The same might apply to changes of the plant size. We hence follow their approach to identify true mass-layoffs by analyzing worker flows from those potential mass-layoff plants. To this end, we use the full worker level information on June 30 of each year from the Employee History (Beschäftigtenhistorik – BEH, Version V10.01.00 - 160816) of the Institute for Employment Research to create a mobility matrix of worker flows between plants for each year. This matrix reveals clusters of outflows when several workers move from one plant to the same new plant.

The left panel of Figure A.1 shows the distribution of the size of the clustered outflow. Hethey-Maier and Schmieder (2010) use the same data to compute correlations of the number of firm deaths and the business cycle per size category of the largest clustered outflow. They find that the this correlation declines with the relative size of the largest cluster and becomes insignificant for clusters that are larger than 25 percent of the total outflow. We follow their reasoning and suspect

[26] A detailed description can be found in Spengler (2008).



(a) TV and radio receivers

(b) Special purpose machines

Figure A.1: Identifying mass-layoffs

Notes: The figures report the distribution of size of a plant's largest clustered outflow relativ the total plant size and relative to the total number of leavers, respectively (panel A), and the distribution of the relative size of the total outflow of the remaining plants that experience a mass-layoff (panel B).

that if the largest cluster accounts for more 25 percent of all workers leaving the same plant in one year, this is due to restructuring and workers do not actually face the threat of becoming unemployed.

We then end up with a sample of 3606 plants in the manufacturing sector that plausibly experienced a mass-layoff in a year between 1990 and 2009. The right panel of Figure A.1 shows the distribution of the percentage of workers that left the plant within one year.

C.2 Mass layoffs and exposure to international trade

Is there a relation between the probability of a plants to be involved in a mass-layoff and exposure to trade with the East? Is is plausible that an increase in import competition increases the probability of a plant to be in distress and fire a substantial share of its workforce, whereas new opportunities to export should reduce this probability. To examine this, we take all plant/year observations that fulfill the above criteria and belong to an industry with observable trade exposure with the East. 1.2 percent out of those 266,041 observations are related to a mass-layoff. We regress a dummy indicating a mass-layoff on the increase of import and export exposure at the industry level from section 6.2. Conditional on the year of observation, log plant size and broad industry categories, we find indeed a statistically highly significant albeit economically small relationship: each percentage point of import competition increases the probability of a mass-layoff by 0.004 percentage points while the same increase of exports reduced this probability by the same magnitude. Given that the quartile spread of the increase of import exposure is 18 percentage points and that of export exposure is 23 percentage points, we can conclude that

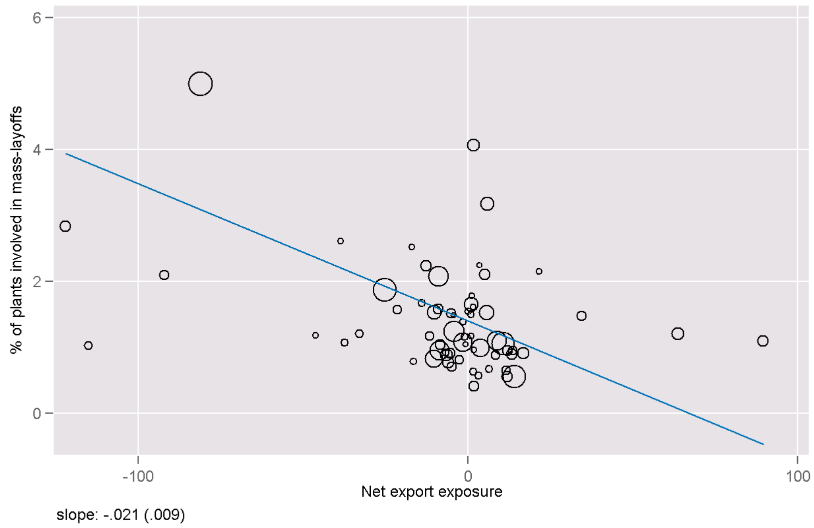


Figure A.2: Incidence of mass-layoffs and trade exposure

Notes: The figures plot the share of all plants that experienced a mass-layoff (among the plants that fulfill all above criteria except the initial drop) against net export exposure for 65 industries with a least 500 laid-off workers. The size of the markers represent the number of cases per industry.

this relationship is measurable but small.

C.3 Identifying workers who experienced a mass-layoff

The next step is to identify all workers who were employed at one of those plant at the onset of the mass-layoff event. To this end, we return to the spell level data of the full sample of all German workers subject to social security in the Integrated Labor Market Biographies (IEB V12.00.00 - 2015.05.15). Using the plant id, we extract the full biographies of all workers who held their main job in one of the affected plants on June 30 of year t^*. Following the literature on mass-layoffs, we only considered workers who were highly attached to the plant prior to the event and likely to have stayed in the plant if the mass-layoff would not have happened. We hence restrict the sample to workers aged 24 to 50 who had a regular full-time job for at least three years and left the plant anytime between June 30 of year t^* and June 29 of year $t^* + 1$. We end up with a sample of 157,603 workers in 89 manufacturing industries. Our procedure unfortunately does no allow us to identify *all* workers who experienced a mass-layoff but it minimizes the risk of committing type-2 error, i.e. including workers in the sample that left their plants not related to a mass-layoff event.

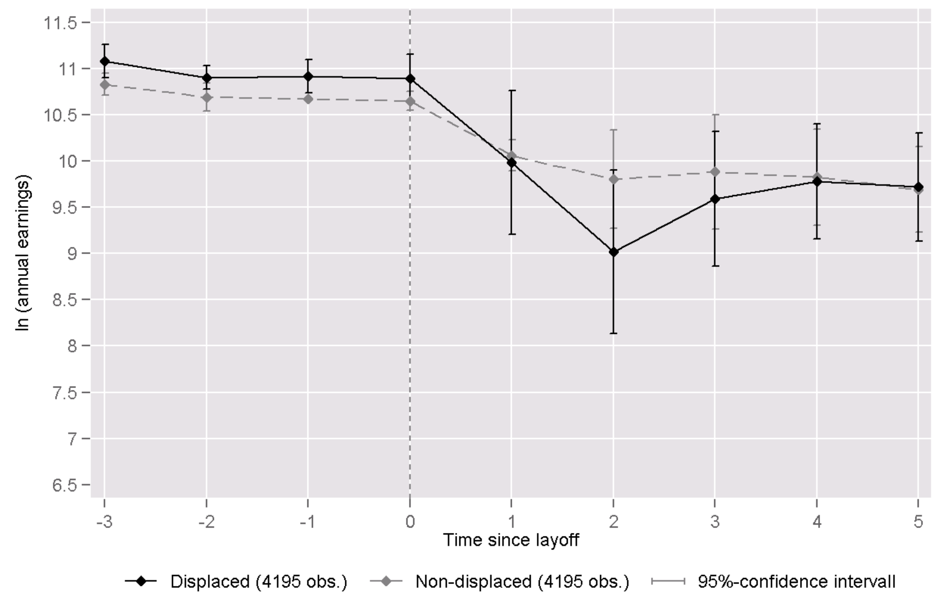


Figure A.3: Event study results for manufacturing of computers

Notes: The figures plot the coefficients of event dummies indicating the time before/after a mass-layoff from two event study regressions.

C.4 Selection of a control group

Since manufacturing is secularly declining in Germany for the last decades, the workers in the mass-layoff sample might have left their plants even in absence of the event. Extrapolating their previous biographies would hence not yield a useful counterfactual. We therefore select a control group from the 30 percent sample of the Integrated Labor Market Biographies (IEB V12.00.00 - 2015.05.15) described in section 2. We again take the full employment biographies and mark all spells that span over June 30 of any year between 1990 and 2009 and conform to the same restrictions in age and tenure as for the mass-layoff sample. If a person has more such spells in different years (which is usually the case), we randomly select one. We then use propensity score matching to identify the nearest neighbor of a person in the mass-layoff sample , age, tenure, previous log earnings, and plant size within cells defined by gender year, and broad industry group. We only keep matches within a caliper of 0.005 which means that we were not able to find a suitable match 1.4 percent of all displaced workers. Our final sample thus has 151,711 individuals in each the treatment and control group.

D Appendix Tables

Table A.1: **Industries with highest trade volumes with the East** (in billion € of 2010)

Exports		**Year**		
		1990	**2000**	**2010**
1	Motor vehicles	0.58	4.99	18.49
2	Parts and accessories for motor vehicles	0.37	4.51	13.22
3	Other special purpose machinery	2.29	4.68	10.00
4	Mach. for the prod. and use of mech. power	0.54	2.61	8.96
5	Basic chemicals	1.10	2.76	7.19
6	Electricity distribution and control apparatus	0.22	2.54	6.80
7	Other general purpose machinery	0.82	2.38	6.25
8	Plastic products	0.21	2.85	5.70
9	Machine-tools	1.36	2.09	5.61
10	Pharmaceuticals	0.33	1.41	5.16

Imports		**Year**		
		1990	**2000**	**2010**
1	Office machinery and computers	0.05	3.71	13.61
2	Motor vehicles	0.21	7.62	8.89
3	Parts and accessories for motor vehicles	0.04	2.80	8.64
4	Electronic valves and other components	0.02	0.82	8.25
5	Other wearing apparel and accessories	2.57	6.52	7.86
6	Television and radio receivers, recording app.	0.53	2.12	7.04
7	Basic precious and non-ferrous metals	1.03	3.40	5.57
8	Furniture	0.53	3.09	5.29
9	Building and repairing of ships and boats	0.01	0.27	5.14
10	Electrical equipment n.e.c.	0.11	2.75	4.87

Table A.2: **Employment Adjustments by Worker Quality**

Worker Quality	(1) All employers	(2)	(3) Same sector	(4)	(5) Other Sector
Same 2-dig industry		yes	yes	no	no
Same employer		yes	no	no	no
ExE bottom tercile	0.2448	0.1932	0.6114	-0.1590	-0.4008*
	(0.217)	(0.658)	(0.541)	(0.154)	(0.210)
ExE middle tercile	1.5325***	2.0001***	0.6293	-0.0808	-1.0161***
	(0.174)	(0.649)	(0.421)	(0.161)	(0.258)
ExE top tercile	0.0529	-1.0583	1.1799**	0.2981	-0.3668
	(0.190)	(0.810)	(0.590)	(0.281)	(0.387)
ImE bottom tercile	-0.3420***	-0.9884***	-0.4497**	0.4023***	0.6939***
	(0.132)	(0.346)	(0.222)	(0.077)	(0.122)
ImE middle tercile	-0.1978*	-1.5985***	-0.1209	0.3879***	1.1336***
	(0.113)	(0.366)	(0.188)	(0.081)	(0.160)
ImE top tercile	-1.0482***	-2.9991***	-0.5306**	0.2889**	2.1926***
	(0.147)	(0.501)	(0.251)	(0.115)	(0.305)

Notes: Based on 2,277,914 workers. The outcome variables are cumulated days of employment, cumulated over the ten years following the base year. For column 1, the outcomes are cumulated over all employment spells in the twenty years following the base year. For column 2 the outcomes are cumulated only when they occurred at the original workplace. For the other columns, the outcomes are cumulated only when they occurred at a different plant in the same industry (3), at a plant in a different manufacturing industry (4), and outside the manufacturing sector (5), respectively. The table reports coefficients of interactions of Import (export) exposure (ImE and ExE) with dummies indicating the tercile of a worker's individual fixed effect from Card, Heining, and Kline (2013). Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. All trade exposure variables are instrumented by analogous measures constructed from tradeflows of other high-income countries. All regressions include the same control variables as in column 4 of Table 2. Standard errors, clustered by industry x commuting zone x base year in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table A.3: **Employment Adjustment by Plant Quality**

Firm Quality	(1) All employers	(2)	(3) Same sector	(4)	(5) Other Sector
Same 2-dig industry		yes	yes	no	no
Same employer		yes	no	no	no
ExE bottom tercile	0.3728*	-0.0275	-0.1650	0.5325***	0.0327
	(0.204)	(0.649)	(0.463)	(0.167)	(0.256)
ExE middle tercile	0.6393***	-0.2104	1.4951**	0.0266	-0.6719**
	(0.242)	(0.953)	(0.705)	(0.263)	(0.333)
ExE top tercile	1.0543***	2.2203*	1.0672	-0.6120*	-1.6212***
	(0.287)	(1.134)	(0.709)	(0.338)	(0.522)
ImE bottom tercile	-0.1855	-0.6216*	-0.2655	0.0998	0.6018***
	(0.113)	(0.370)	(0.228)	(0.068)	(0.134)
ImE middle tercile	-0.5660***	-1.8950***	-0.4984**	0.4873***	1.3401***
	(0.156)	(0.479)	(0.251)	(0.131)	(0.227)
ImE top tercile	-1.6362***	-5.2237***	-0.3281	0.5474***	3.3681***
	(0.298)	(1.038)	(0.472)	(0.209)	(0.602)

Notes: Based on 2,279,638 workers. The outcome variables are cumulated days of employment, cumulated over the ten years following the base year. For column 1, the outcomes are cumulated over all employment spells in the twenty years following the base year. For column 2 the outcomes are cumulated only when they occurred at the original workplace. For the other columns, the outcomes are cumulated only when they occurred at a different plant in the same industry (3), at a plant in a different manufacturing industry (4), and outside the manufacturing sector (5), respectively. The table reports coefficients of interactions of Import (export) exposure (ImE and ExE) with dummies indicating the tercile of a worker's workplace fixed effect from Card, Heining, and Kline (2013). Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. All trade exposure variables are instrumented by analogous measures constructed from tradeflows of other high-income countries. All regressions include the same control variables as in column 4 of Table 2. Standard errors, clustered by industry x commuting zone x base year in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table A.4: **Robustness**

2SLS	(1) Drop East Germany	(2) Include downstream links	(3) Net exports	(4) Gravity	(5) Placebo
export exposure	0.5151***	0.5386***			
	(0.087)	(0.077)			
import exposure	-0.1117**	-0.0938**			
	(0.046)	(0.043)			
net export exposure			0.1720***	0.6184***	0.0379
			(0.043)	(0.097)	(0.025)
R^2	0.128	0.126	0.125	0.125	0.161
age, gender, nationality dummies	Yes	Yes	Yes	Yes	Yes
education and tenure dummies	Yes	Yes	Yes	Yes	Yes
ln base yr earnings	Yes	Yes	Yes	Yes	Yes
plant size dummies	Yes	Yes	Yes	Yes	Yes
broad industry dummies	Yes	Yes	Yes	Yes	Yes
commuting zone dummies	Yes	Yes	Yes	Yes	Yes

Notes: Based on 2,267,153 workers (column 1), 2,438,845 workers (columns 2-4), and 1,240,480 workers (column 5), respectively. The outcome variable is 100 x earnings normalized by earnings in the base year and cumulated over the ten years following the base year. Import (export) exposure is the 10-year increase in imports (exports) from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. In Panel B, this is instrumented by analogous measures constructed from tradeflows of other high-income countries. The trade exposure variables in column 2 include the trade exposure of downstream industries, weighted by their share in an industry's total sales. The trade exposure variable in column 4 is constructed by multiplying level trade exposure in the base year by differences is gravity residuals from a preceding gravity regression. Standard errors, clustered by industry x commuting zone x base year in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table A.5: **Trade exposure measures used in robustness checks**

	1990-2000		**2000-2010**	
observations	1,230,897		1,207,948	
	mean	(sd)	mean	(sd)
[A] Trade exposure including downstream linkages				
Δ export exposure	26.8	(27.3)	33.7	(54.7)
p10-p90 interval	[4.0 ; 50.1]		[2.7 ; 75.4]	
p25-p75 interval	[8.4 ; 41.0]		[11.8 ; 32.3]	
Δ import exposure	24.2	(17.4)	41.1	(31.0)
p10-p90 interval	[5.1 ; 48.0]		[7.0 ; 75.0]	
p25-p75 interval	[12.0 ; 31.7]		[23.1 ; 58.0]	
[B] Net export exposure				
Δ net export exposure	-2.6	(26.0)	6.8	(56.0)
p10-p90 interval	[-30.5 ; 19.1]		[-28.2 ; 48.1]	
p25-p75 interval	[-10.2 ; 9.2]		[0.0 ; 33.5]	
[C] Net export exposure from gravity approach				
Δ net export exposure	0.9	(6.1)	1.1	(9.3)
p10-p90 interval	[-0.9 ; 5.1]		[-4.2 ; 4.7]	
p25-p75 interval	[-0.6 ; 1.1]		[-0.4 ; 2.7]	

Notes: Trade exposure is the 10-year increase in trade volumes from (to) China and Eastern Europe, relative to the industry's total wagebill in the year before the base year. In Panel A, this measure is expanded by trade exposure of downstream industries, weighted their share in the upstream industry's total sales. In Panel B, net exposure is the net of export and import exposure (not including downstream exposure). In Panel C, the increase of net exposure is predicted by the increase of residuals from the estimation of a gravity model of trade.

Table A.6: **Balance check of matching displaced workers with statistical twins**

	(1) displaced	(2) control	(3) difference	(4) between industry in total variance
ln earnings	10.460	10.520	-0.060 **	20.9 %
	[0.470]	[0.473]	(0.023)	
tenure	8.993	8.489	0.504 ***	3.5 %
	[5.551]	[5.521]	(0.165)	
age	37.825	37.974	-0.149	0.6 %
	[6.992]	[7.302]	(0.383)	
female	0.278	0.253	0.025 ***	18.8 %
	[0.448]	[0.435]	(0.008)	
foreign	0.132	0.119	0.013	5.2 %
	[0.339]	[0.324]	(0.010)	
missing skill	0.017	0.016	0.002	1.8 %
	[0.130]	[0.124]	(0.002)	
low skilled	0.189	0.164	0.025 *	7.7 %
	[0.391]	[0.370]	(0.013)	
med skilled	0.714	0.732	-0.017 **	5.2 %
	[0.452]	[0.443]	(0.007)	
high skilled	0.079	0.089	-0.009	7.6 %
	[0.270]	[0.284]	(0.011)	
plant size	885	1799	-914	72.1 %
	[3115]	[5622]	(543)	

Notes: Based on 151,711 laid-off workers and the same number of matched twins. The table summarizes observed characteristics of the displaced workers and their statistical twins in the year prior to the mass-layoff event. Numbers in brackets are standard deviations and the numbers in parentheses are standard errors (clustered by layoff year). Levels of significance: *** 1 %, ** 5 %, * 10 %. The numbers in column 4 are the shares of the between industry variance relative to the variable's total variation among the displaced workers.

Table A.7: **Summary statistics of mass-layoff sample**

	all industries		without PC manuf.	
observations	151,711		147,517	
	mean	(sd)	mean	(sd)
[A] Outcomes, differences-in-differences				
Δ_{dd} days employed	-52.9	(151.7)	-53.5	(152.0)
Δ_{dd} log earnings	-59.7	(302.6)	-60.3	(303.4)
[C] Trade exposure				
Δ export exposure	20.1	(22.0)	19.1	(21.3)
p10-p90 interval	[3.1 ; 45.3]		[3.1 ; 41.0]	
p25-p75 interval	[7.1 ; 29.4]		[7.0 ; 28.1]	
Δ import exposure	27.3	(49.7)	22.2	(34.7)
p10-p90 interval	[1.8 ; 63.5]		[1.7 ; 49.7]	
p25-p75 interval	[5.3 ; 27.3]		[5.2 ; 25.0]	

Notes: Trade exposure is measured as industry level 8-year changes in imports or exports relative to the industry's total wage bill (extrapolated from a 30% sample).