Adjusting to Globalization in Germany*

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Abstract

We study the impact of trade exposure on the job biographies of 2.4 million manufacturing workers in Germany. Rising export opportunities lead to two equally important sources of earnings gains: on-the-job, and via employer switches within the same industry. Highly skilled workers benefit the most. Import shocks mostly hurt low-skilled workers, especially when they possess lots of industry-specific human capital. They also destroy workers' rents when separating from high-wage plants, and they leave strongly scarring effects in the event of a mass layoff. 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 (2017) for Brazil, and Dauth, Findeisen, and Suedekum (2014) for Germany.[1] Another recent and theoretical literature has analyzed the effect of international trade in models with heterogeneous workers and firms and self-selection of the latter 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. In contrast to most of the previous empirical literature, we analyze the reallocation process – how workers move across firms within and across industries, and sectors – in response to both import and export 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, it 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. We consider two trade shock episodes which hit the German economy in the aftermath of important political events in the early 1990's. The

[1] 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.

first one is the fall of the iron curtain, which led to a rapid transformation of the former socialist countries in Eastern Europe, and the second one is the rise of China and its integration into the world economy. 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.[5] 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 our main results, we find that workers who were initially employed in industries with more export exposure see robust and lasting earning gains relative to less exposed workers. Those gains are mostly realized on *two different margins* with roughly equal importance: first, on-the-job with the original employer, and second, in a different firm within the original industry. This means, in order to profit from globalization, many workers in Germany have adjusted by switching their employer, and made full use of their accumulated industry specific human capital. The firm switching channel for individual workers to realize earnings gains is a key mechanism in many theoretical trade models, and our paper documents its empirical importance.

Our next contribution is to detect important heterogeneity in the export adjustment mechanisms. In line with the previous literature, we focus on workers' skills. 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), from now on referred to as the *AKM* model. We show that the firm switching channel is driven by the re-allocation of the most highly 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 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 workers' rents at the highest paying companies. But at lower paying firms workers seem to be mostly sheltered from import competition.

Although the total effects of import competition are rather moderate, our findings suggest that job separations of exposed workers from their original employers are involuntary in import competing industries. An influential literature, which is naturally related to our analysis on the

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

effects of import competition, has focused on the long-run consequences of job loss, following the pioneering work by Jacobson, LaLonde, and Sullivan (1993). This literature focuses on mass-layoff events, as they are arguably exogenous from the individual's perspective. 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. This is in line with recent evidence that the scarring effects of displacement in a mass-layoff are more severe if the layoff happened during adverse macroeconomic conditions (Davis and von Wachter, 2011).

Our article contributes to the literature on the labor market effects of international trade. A recent strand of studies at the worker-level consequences of trade using administrative data. Dix-Carneiro and Kovak (2019) analyze how workers respond to Brazil's trade liberalization in the early 1990s. They find that regions facing steeper tariff removals experience larger declines in labor demand, and that transitions into the informal sector, a very salient feature in the Brazilian context, are an important margin of adjustment to the negative shock for workers.

Autor, Dorn, Hanson, and Song (2014) exploit industry variation in the exposure to Chinese import competition for US workers. They find large and persistent negative effects on cumulative earnings, concentrated on low-wage workers who rank lowest in the cohort-specific wage distribution. They do not study export shocks, however. Regarding the earnings losses from import competition, our study adds two main insights. First, the availability of employer-employee matched data allows us to analyze heterogenous effects also from a firms' perspective. We rank firms using the *AKM* method and show that earnings losses from import competition are most pronounced for workers in high-wage plants. This is consistent with the interpretation that import shocks destroy rents for workers. Second, using person fixed-effects as obtained from the *AKM* model – arguably a better measure for the earnings potential of workers, since the *AKM* method filters out the plant-based wage component – we can complement the finding of Autor, Dorn, Hanson, and Song (2014) that low-wage workers take the hardest hit.

For workers in the Danish textile sector, Utar (2018) presents compelling evidence how China's WTO accession harmed especially low-skilled workers. Her paper stresses the importance of human capital suitable for a successful transition into the service sector. Our paper also touches on the role of industry-specific human capital. We find that the positive labor demand shocks of exports are increasing in the specificity of human capital. For imports, on the other hand, consistent with Utar (2018), industry- specific human capital appears to be detrimental for the transition into other industries. In the bigger picture, while our paper is different in several respects from the literature on the worker-level impacts of import competition, the most important point of departure is the new and central focus on exports, which enables us to shed light on the positive labor demand effects of globalization from the perspective of workers in developed economies.

While the worker-level literature has mostly ignored adjustments to exporting opportunities, Verhoogen (2008) and Amiti and Davis (2012) study responses to export shocks from the firms' side. They show that wage inequality has increased between exporting and non-exporting firms in Mexico and Indonesia. Our longitudinal data set allows us to introduce also the workers' side and test another central theoretical prediction of most trade models, namely the re-allocation of workers within export industries. Krishna, Poole, and Senses (2014) argue that in Brazil, following liberalization, the (positive) sorting of workers to firms increases. We obtain consistent results, as we find stronger mobility responses by high-skilled workers in export industries.

Finally, in a previous paper, we have documented that import competition from China and Eastern Europe had a negative effect on manufacturing employment across German local labor markets. This negative impact, however, is smaller than the positive effects from export opportunities (Dauth, Findeisen, and Suedekum, 2014).[6] In the current study, we shift our focus to the adjustment process at the level of individual workers. This allows us to better understand the mechanisms how trade exposure affects labor markets. In particular, we can follow individual workers over a long period of time, and observe how export and import exposure drive different margins of adjustments in their job biographies – including their mobility across firms, industries, and sectors. Thereby we empirically investigate several mechanisms that are highlighted in the recent theoretical literature on how trade affects labor markets.

In Section 2 we describe our data. Section 3 provides baseline estimates on the cumulative effects of export and import shocks on workers' careers over a ten-year horizon. Section 4 analyzes the typical individual adjustment dynamics to trade shocks, while Section 5 considers heterogeneity with respect to workers' skills and firm-specific wage premia. In Section 6 we discuss how our empirical findings are related to the recent theoretical literature on trade and labor. Section 7 shows how the scarring effects of layoffs are affected by import competition. Finally, Section 8 concludes and discusses some policy implications for Germany and other developed countries.

[6]In a smaller companion study on job flows at the regional level, we show that a least a part of the aggregate effect stems from import competition diverting labor market entrants to take up their first job in the service sector instead of the manufacturing sector (Dauth, Findeisen, and Suedekum, 2017).

2 Data and measurement

2.1 Labor market data

Our main 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 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 data set for several reasons. We can observe if people died or emigrated to another country during the observation period, while being employed or registered as unemployed, and we drop the full biographies of those people from our data. Other reasons for dropping out are retirement, withdrawal from the labor market, taking up a job as a sworn civil servant or transitioning into self-employment. Since we cannot observe those cases, we assume that all other people who drop out of the data set but neither died nor emigrated are non-employed with zero earnings.[8] Below we conduct a robustness check how this procedure affects our empirical results.

As the wage information is subject to right-censoring at the social security contribution ceiling,

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

[8] As for self-employment, bear in mind that Germany ranks among the countries with the lowest entrepreneurship rates in the world (Global Entrepreneurship Monitor, 2017). Even if someone becomes a so called "necessity entrepreneur" as an alternative to collecting unemployment insurance benefits, this kind of self-employment tends to be highly unstable and does not yield a substantial income (see Block and Wagner, 2010).

we apply the imputation procedure by Card, Heining, and Kline (2013). Moreover, we convert 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 for 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 detailed annual trade statistics for over 170 reporter countries detailed by industries. We 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.

From the German perspective, the fall of the Iron Curtain and Chinas opening towards the world markets were important but virtually unanticipated shocks. Starting in the beginning of the 1990ies, suddenly new export markets and new competitors emerged not only in Germany's direct eastern neighbors but also in Russia and in the far east. Due to this simultaneity, it is hard to disentangle the contribution of individual countries to the overall effect. We therefore define "the East" as China and all 21 countries that were locked behind the Iron Curtain until 1991, which include the former USSR and all of its successor states as well as other Eastern European countries.[11] Figure 1 illustrates the evolution of German industry-level trade, both with respect to the East and the world as a whole. 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

[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. Instead of normalizing with base year earnings of a single year, we can also take an average over a few years. Results are very similar.

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

[11] Namely, these are Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, the former USSR, and its successor states the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. In Section 3, we separately examine trade with Eastern Europe and China and show that it is sensible to combine them due to the very similar patterns of German exports.

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.

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 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 penetration from labor-abundant countries with substantially lower wages. Importantly for the contribution of our paper, it also involves the surging export opportunities, which reflects the rising demand for German products from those areas.

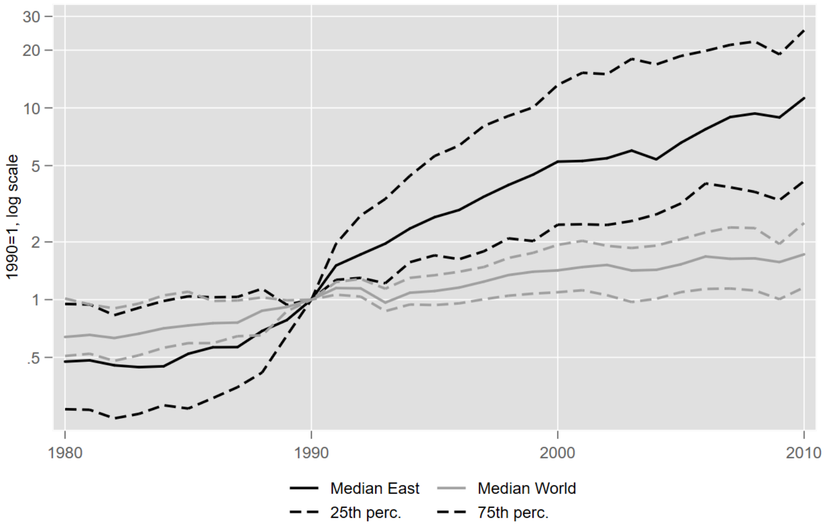
Figure 1 highlights the strong differences in industry-level trade exposure. The broken lines depict the evolution of the trade volumes of the industry at the upper and lower quartiles of the respective distribution of trade flows. With respect to the East, imports and exports have increased across the whole distribution relative to 1990, but with considerable variation across industries. 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 where China and some 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:

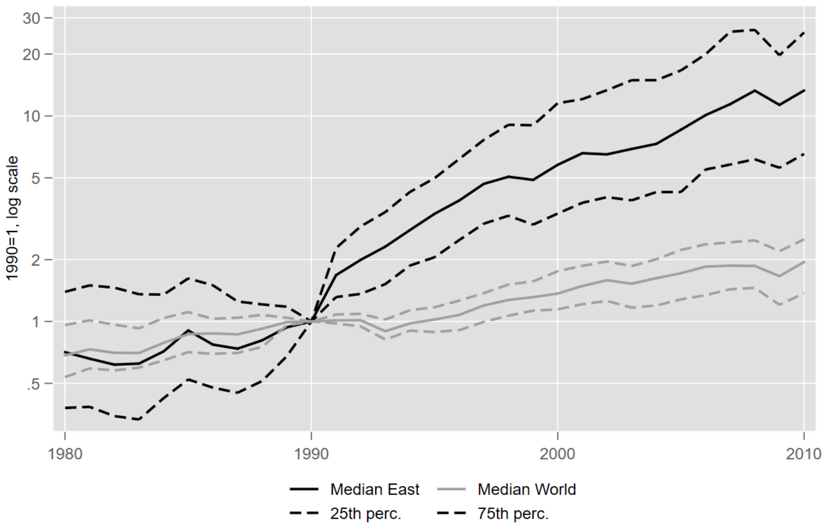
$$ImE_{jt} = \frac{IM_{jt}^{EAST \to D}}{\overline{w}_{j(t-1)} L_{j(t-1)}} \qquad \text{and} \qquad ExE_{jt} = \frac{EX_{jt}^{D \to EAST}}{\overline{w}_{j(t-1)} L_{j(t-1)}} \tag{1}$$

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

[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.



(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).

Table 1 reports descriptive statistics for the individual trade exposure measures. There we 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 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.[13]

3 The overall effects of export and import 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 j, 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. 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[14] – allows us to decompose the total effects of export and imports into different channels of adjustment (Autor, Dorn, Hanson, and Song, 2014), because it permits the inclusion of all observations even when a worker's earnings from some source are equal to 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:

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

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

[13] At this point, we drop the comparatively small industry of manufacture of knitted and crocheted articles that comprises only 0.04 percent of the national wage bill in 1990 but is an extreme outlier with an increase in import exposure of 1860 percent of the industry's initial wage bill.

[14] 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.

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 $\phi_{J(j)}$.[15] 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.[16]

In Table 2 in Panel A, we 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 $\times$ commuting zone $\times$ 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. Adding plant size indicators in Column 3, reduces the export coefficient by about a third. This suggests 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, the import and export coefficients increase in absolute terms. 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 can again observe 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. Similarly, 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 for four different manufacturing industry groups in column 4, the most demanding model. The same hold true for local shocks and motivates the inclusion of 141 commuting zone dummies. Effectively we thus compare 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 3 to column 4 for exports and imports.

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

[16]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 %.

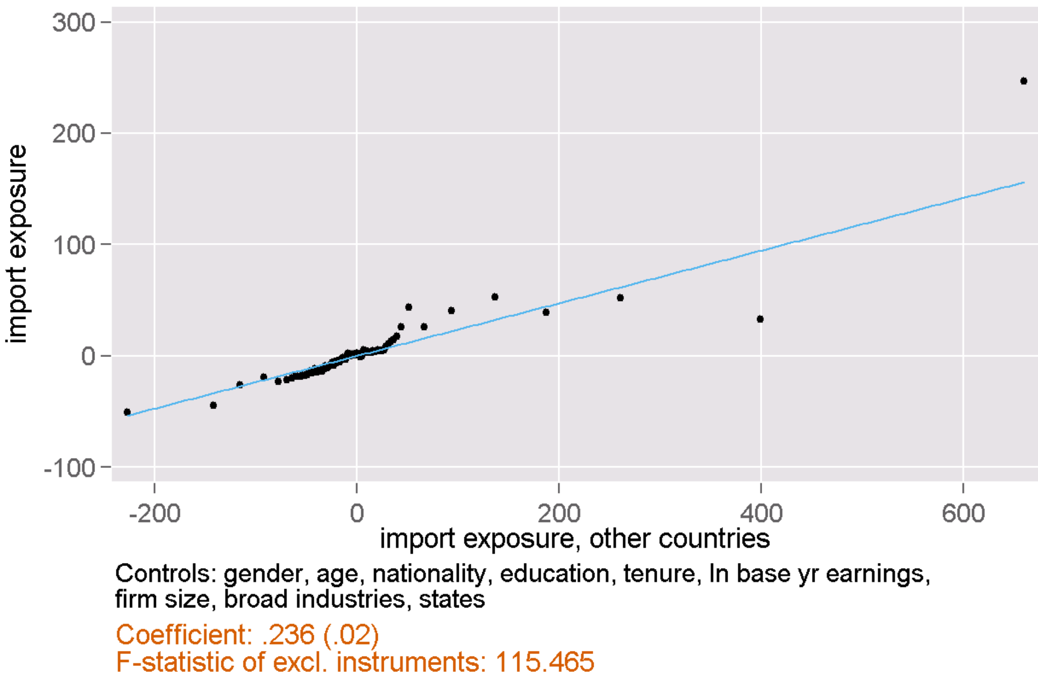
To convert these estimates into economically meaningful magnitudes, consider two workers in 1990 who experience a rise in import exposure at the 75^{th} percentile ($\Delta ImE_j = 32.34$) and at the 25^{th} percentile ($\Delta ImE_j = 7.02$) over the following 10-year period, respectively. Our estimates from Table 2, Panel B, column 4 (-0.10 for import exposure and 0.52 for export exposure) imply that, cumulated over those ten years, the former worker's earnings will have declined by $-0.10 \times (32.34 - 7.02) = 2.5$ percentage points more relative to their respective earnings in the base year. If both workers had earned the average annual income in the base year 1990 (42,870 €, see Table 1), then this difference would amount to $-1,085$€, which equals $1,411 using the average 2010 € /$ exchange rate (which is equal to 1.3.) For the second decade, the percentage point difference is also 2.5 percentage points, which amounts to a difference of $-1,206$ € (=$1,568). At the local labor market level, an earlier paper of ours (Dauth, Findeisen, and Suedekum, 2014), has documented stronger negative import effects at the regional level. The effect on local labor markets, by contrast, can work not only via incumbent workers but also includes reduced demand for labor market entrants or potential job switchers from other sectors, as shown in Dauth, Findeisen, and Suedekum (2017). Consistent with the relatively strong employment protection laws and unions present in Germany, the results imply that incumbent workers are partly shielded from the negative consequences of import competition.

For export exposure, performing an analogous benchmarking or interquartile comparison, we find a difference of $0.52 \times (27.00 - 9.19) = 9.3$ percentage points relative to the base year earnings in the first decade and of 16.8 percentage points in the second decade. This amounts to an absolute difference of +3,990€ (=$5,187) in the first decade and + 7,865€ (=$10,224) in the second decade if both workers had earned the average base year earnings.

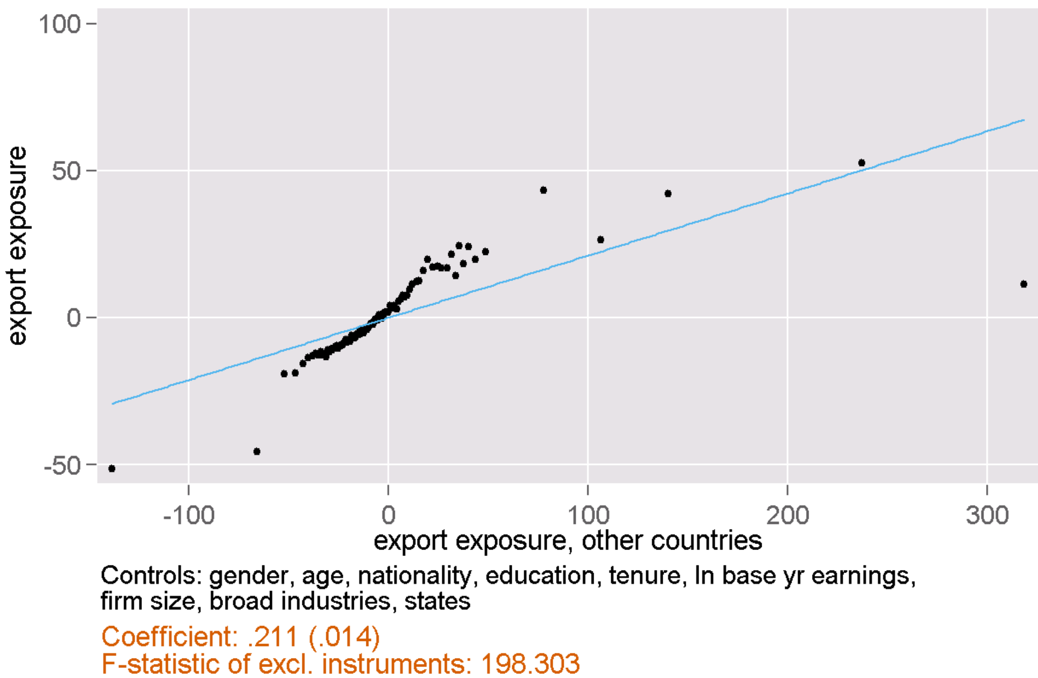
Panels C and D show that our instruments have sufficient power. The respective F-statistics in column 4 – our preferred model – are 115 and 198. There is strong predictive power of trade growth in other high-income countries for German trade growth with the former Eastern Bloc and China. Figure 2 shows the 1st stage relationships.

3.1 Eastern Europe versus China

Throughout our main analysis, we aggregate imports and exports from/to China and Eastern Europe. We do this because their rising importance on the world markets happened roughly at the same time. For a country like Germany, which has close trade linkages with both, it is therefore difficult to analyze one independently of the other. Nevertheless, it is interesting to analyze which trading partner is mainly driving our results. In Table A.2 in the Appendix, we report



(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.

results of several different variants.[17] First, we repeat the baseline specification in column 1. In columns 2 and 3, import and export exposure are only constructed from trade with either Eastern Europe or China. We find very similar coefficients for export exposure, which are about twice the size as the original coefficient for "the East". This is because both are strongly correlated, causing an upwards bias in the coefficient when only one is included.

The effect of Chinese import penetration appears to be virtually zero, while the coefficient for imports from Eastern Europe is significantly negative and even larger than the baseline coefficient. This is in line with the more detailed analysis in Dauth, Findeisen, and Suedekum (2014). There we argued that this is because of the greater similarities in industry structures between Germany and Eastern Europe, which suggests that imports from there imply more direct competition for German industries and workers.

To analyze the effects of Eastern Europe and China jointly, we construct two measures for the net export exposure to each trading partner of industry j, which is the difference of the respective terms for export and import exposure from (1).[18] For reference, we first report in column 4 the result when using the net exposure, instead of import and export exposure separately. That exercise yields very similar quantitative predictions as before. Including net export exposure with both trading partners jointly in column 5 again yields a similar result, where the original coefficient of aggregate net exports is in between the coefficients of the separate variables.

3.2 Robustness checks

Returning to our baseline approach, in Table A.4 in the Appendix, we check the robustness of our results along several additional margins. The German social security data, unfortunately, does not cover self-employed individuals or civil servants (*Beamte*), who cannot be laid-off and have their own pension system. Lacking further information on the specific reasons why people disappear from the data, other than death or emigration, we assumed so far that all other workers who drop out of the data during the observation period are non-employed with labor earnings set to zero. However, our results on import competition would be too pessimistic if those workers become public servants or self-employed rather than dropping out of the labor force. To check whether this affects our results, we change our outcome variable to be unaffected by the times an individual is not observed in the data. We re-define employment as the percentage of the days an individual is registered as employed relative to the total number of days this person is observed in the data. This variation now comes purely from times that a person is either registered as employed, or as receiving benefits from unemployment insurance. In column 1, we see that

[17] Summary statistics of the modified measures for trade exposure are reported in Table A.3 in the Appendix.
[18] The instrument is constructed analogously.

an increase of import exposure by one percentage point reduces the employment time by 0.9 percentage points. To compare this coefficient to the results for earnings, one must divide it by 10 since this outcome is normalized by the total duration over 10 years and not just the base year. The results of this exercise are therefore in the same ballpark as our baseline findings.

Next, we scrutinize the decision to drop the industry "manufacture of knitted and crocheted articles" (see footnote 13). This is a very small industry but its import exposure is around three times as large as the second most exposed industry. However, given its small size, omitting this industry does not substantially affect our results.

Another concern is 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 mostly not competitive, 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 east German states, but find very similar results as in column 3.

Our measure for trade exposure might be too narrow, since trade shocks could 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.[19] When using those comprehensive measures, we estimate similar coefficients as in our baseline. This suggests that our results remain robust when taking input-output linkages into account.

Next, we consider an alternative estimation strategy where *net* trade exposure is constructed from the residuals of a preceding gravity estimation (see Appendix B). For reference, we again report in column 5 the coefficient for the net trade exposure constructed as the difference of the terms in (1). The coefficient in column 6 is also highly significant, and multiplied with the observed changes in the gravity measure implies consistent (though somewhat more conservative) magnitudes.[20]

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 earn-

[19]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.

[20]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.

ings 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 7, which is reassuring that our results do not capture industry trajectories but causal effects of rising trade exposure.

4 Individual adjustments to export and import shocks

This section presents our first set of main results regarding how individual workers adjust to import and export shocks. We will exploit the granularity of our data, which allows us to measure employment with daily precision, and thus to reconstruct the complete labor force history of all workers in our sample highly accurately. In this Section we describe our empirical approach and the main results. In Section 5 we investigate heterogeneous effects for different workers, and in Section 6 we will connect our empirical results to the large and growing theoretical literature on trade and labor markets.

So far we have studied total cumulative earnings over ten years, irrespective of where they accrued. To proceed, we now 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.[21] The results are in Table 3. In column 1, we repeat our estimation from column 4 of Panel B in Table 2. In columns 2–5, we then 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 construction.[22]

4.1 Exports: workers switching across firms

We start by discussing the results for exports and earnings in Panel A of Table 3. 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 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.

Earnings are the product of employment and wages. We can look directly at employment by

[21] The results are robust to using the same 3-digit industry.
[22] Autor, Dorn, Hanson, and Song (2014) introduce this decomposition.

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. 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. Both 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 %.

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, however, 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 re-allocation of workers across firms, in line with the prediction of expanding employment at the most productive firms in heterogeneous firm models. The economic size of this effect is considerable. Comparing again workers at the 75^{th} percentile to the 25^{th} percentile of the export exposure distribution, we calculate that 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 re-allocations happen within industry, suggesting firms which expand do so by poaching workers from other competing firms in the same industry. This is consistent with the importance of industry-specific human capital that we will investigate in more detail below. 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 of Table 3 is relatively modest – 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 81% of the size of 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.

4.3 Industry-specific human capital

Our results so far have shown that mobility within an industry is an important margin for workers to adjust to an export shock. At the same time, workers who move out of their original industry recover most, but not all of their losses at their original plant due to an import chock. This suggests that a crucial determinant of successful adjustment is specific human capital. Workers who possess a lot of industry-specific human capital might be particularly attractive for other firms in expanding industries, but might also find it more difficult to adjust to a negative shock and transition to different industries. In this subsection, we analyze this in more detail.

We measure the importance of industry-specific human capital according to the index proposed by Utar (2018). She argues that some occupations require only general human capital, which allows workers to easily move between industries. An example are janitors. Other occupations, such as tailors for example, are so specific that workers are "locked" into their original industry. She measures an occupation's industry specificity IndSpec_{oj} as the ratio of workers of occupation o in industry j relative to the total number of workers in occupation o. Workers with an occupation with a high value of IndSpec_{oj} possess human capital that is very industry-specific and therefore difficult to transfer to different industries. The advantage of this measure is that it also varies within and not only between industries.[23] We compute this index for all combinations of 89 2-digit occupations and 22 2-digit manufacturing industries observed in the respective base year, normalize it to have a standard deviation of one, and interact it with our original measures for export and import exposure. The results are reported in Table A.5 in the Appendix.

The isolated coefficients of export and import exposure in column 1 are similar to the original results for total earnings. The coefficients of the interaction term of import exposure and industry specificity in columns 1 and 2 are relatively small and insignificant. Workers in very specific occupations have no additional losses in terms of own-industry earnings. However, while mobility between manufacturing industries allows to compensate for some of the initial losses in general according to column 3, this adjustment channel is at least partly obstructed by specificity of human capital. This is consistent with Utar (2018), who also finds that Danish workers with high industry specific human capital are less likely to move to a different industry in response to an import shock.

By contrast, the positive effects of exports are magnified for workers with higher industry specific human capital. Since investment in specific human capital is costly, these workers are more attractive for firms that expand because of the export shock and, therefore, they are able to reap more of the benefits from exports.

5 Heterogeneity of workers and firms: AKM effects

We now consider heterogeneous effects of export and import shocks for workers with different skills, and for workers employed at firms of different quality.

[23] Neal (1995) and Parent (2000) analyze the rewards to industry specific experience as opposed to plant tenure. In principle, one could modify their approach and allow this measure to vary over industries. However, adapting this for the present context is not straightforward, as one would have to deal with endogeneity concerns discussed in the original studies and make strong assumptions on the functional form to obtain a single measure.

5.1 Measurement

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.[24] We define 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 and, since we normalize cumulative earnings by pre-period earnings, the effects can again be interpreted on a proportional scale, similar to looking at percentage changes.

5.2 Results

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 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

[24]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 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.

Table 4: **Earnings Adjustment by 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	-0.8571***	-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 %.

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.6 in the Appendix, we can confirm these mobility patterns across skill groups by directly looking at employment instead of earnings. In more export exposed industries, highly skilled workers actually see a decrease in their employment in their original firm, but this decrease is dominated by an increase in the days employed at competitor firms within the same original industry.

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 more highly skilled workers can soften or 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 should not be literally interpreted as productivity (Card, Cardoso, Heining, and Kline, 2018).

Turning to the results in Table 5, we observe in column 1 that the coefficient for workers from firms in the top tercile is significantly larger than for the other two terciles. All 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 cannot 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.7, 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

Table 5: **Earnings Adjustment by Plant 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	0.1302	-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 %.

lose their workplace specific rent they enjoyed at the original firm.

5.3 Trade and the quality of worker-firm matching

One of the main insights of this paper is that exports induce mobility of high skilled workers to high paying plants. A complementary question is where in the wage distribution of their new workplaces those movers end up.

To answer this question, we modify our empirical approach. For each year in the observation periods 1991-2000 and 2001-2010, we identify those from the 2,438,845 individuals who have either stayed continuously with their original employer (incumbents) or have moved from their original employer to a new plant in the same industry (movers).[25] We then regress the log daily wage on a dummy indicating a mover and a number of control variables. To analyze if those wage differences vary with respect to the exposure to international trade, we interact this dummy with our measures for export and import exposure. We run this regression separately for movers and stayers observed either two or five years after the start of the respective period.

A simple comparison of all movers and stayers might be problematic in several ways. Even if movers receive random job offers, they are likely to chose to move only if the new job is more lucrative. We therefore control for how well a plant pays their workers in general by including the plant effect from Card, Heining, and Kline (2013), estimated in the period that ends at the beginning of the respective observation window. Since movers are also likely a positive selection of the workforce in their old plant, we furthermore control for the pre-estimated worker effect, age, and labor market experience. To account for structural differences across industries, we also include 3-digit industry fixed effects. This means that the isolated export and import exposure variables are perfectly collinear to the industry effects but their interactions with the mover dummy are still identified. In a final specification, we also account for the fact that incumbents have accumulated firm specific human capital by including a linear term for tenure, which is zero for movers.

The results in Appendix Table A.8 indicate that early movers receive around three percent higher wages compared to incumbent workers. Since this even holds when observed and unobserved characteristics of the two groups are accounted for, the only explanation is that those movers are better matches to their new firms compared to their incumbent coworkers. The difference between movers and stayers increases when we account for the fact that movers start with no firm specific human capital. For people who move five years after the beginning of the period, we only observe a higher wage if their lack of tenure is accounted for. While import exposure neither increases nor decreases this relation, the wage difference between movers and incumbents is bigger in industries with a strong export exposure. Apparently, the matching of movers and their new firms improves due to exports. In addition to the increased assortative matching we found in this section, the quality of the new matches themselves seems to be better than for the incumbent workers. This finding is in line with Krishna, Poole, and Senses (2014) who find that trade liberalization leads to an increase in worker ability in Brazilian exporting firms and an increase in the quality of worker-firm matches.

[25]Since our data only offer information on daily wages, we drop all observations of part-time employment since their daily wages are not comparable to full-time workers.

6 Relationship to theory

In this Section we will connect our empirical findings with the growing theoretical literature integrating heterogeneous firms in the spirit of Melitz (2003) with various 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 focus on the workers' perspective in this paper, 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. If parts of workers' human capital is industry-specific, those effects should show up in earnings gains in different plants within the same industry. In Section 4, we have found evidence in Table 3 that is precisely in line with this key channel of the theoretical literature. Moreover, we found that the quantitative importance of this re-allocation channel is substantial, and indeed as important for individual workers as on-the-job earnings gains from exporting.

The baseline Melitz model assumes identical workers and competitive labor markets. Thus, the baseline model makes no predictions for the effect of trade for earnings inequality, since wages are homogeneous across all workers and firms. A next generation of papers, including Sampson (2014), Egger and Kreickemeier (2012), Amiti and Davis (2012), or Helpman, Itskhoki, and Redding (2010), studies the interaction of labor market frictions or worker heterogeneity with trade. Those models make a richer set of interesting predictions for the labor market effects of trade, and our empirical results also speak to this theoretical literature.

In Sampson (2014) workers are ex-ante heterogenous with regard to their skill level. Matching is positive assortative by (strict) log supermodularity between worker skills and firm productivities. 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 in exposed industries. Our empirical results confirm this prediction. Moreover, since more productive firms also increase their demand for skilled labor, one expects that in particular highly-skilled workers realize earnings gains by switching firms. This is in line with our findings in Table 4. Such re-allocations in response to rising export opportunities may take place within but also between industries. But consistent with the notion of industry-specific human capital, analyzed in Appendix Table A.5, we have empirically found a stronger effect on within industry reallocations.

A different approach is taken in the models of Egger and Kreickemeier (2012) and Amiti and Davis (2012). Firms share the rents from increased revenues with their workers. Firms also select into export markets based on their productivity, since they must cover a fixed exporting cost, so more productive firms also pay higher wages. We should, therefore, expect that in export-exposed industries, earnings for workers employed in more productive firms should increase more than in their low productive counterparts. Unfortunately, direct measures of productivity are not available in our empirical analysis. However, when ranking firms according to their establishment fixed effects from the AKM model, as discussed in Section 5, we indeed find strong evidence in Table 5 that earnings are increased the most for workers in highly ranked firms.

In an influential paper, Helpman, Itskhoki, and Redding (2010) have developed a theory of trade and wages that relies on search and matching in the labor market with homogenous workers, but the productivity of workers in a specific job is a random draw. Firms can screen workers and learn something about the fit of a worker to the firm, but this is costly. Selection into exporting provides productive firms with the strongest incentives to screen, which further increases productivity differences. Since part of the productivity increases are passed on to workers in the wage bargaining process, export exposure will have an effect on earnings inequality between firms within industries.[26] In particular, trade should also improve the quality of worker-firm matching, which is consistent with the results that we report in Appendix Table A.8.

In sum, our empirical analysis reveals results which are firmly 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 firstly driven by high-skilled workers who profit on-the-job. In other words, when employed at plant which is highly ranked, there is no need for workers to switch firms to profit from export opportunities, but the earnings gains for these workers materialize to a large extent at the original employer. But additionally, there are earnings gains from switching to different firms within the same industry in all models, and we indeed find empirical evidence for both channels.

7 Trade and the costs of job displacement

We have so far estimated the labor market impacts of trade by comparing workers across their start-of-period industry affiliation. Our findings suggest that workers in increasingly import competing industries are more likely to leave their original employer. Some are then absorbed by the expanding export industries, but the majority takes jobs in the service sector. Since this is related

[26]In detail, in their model, trade liberalization has non-monotonic effects on income inequality within industries. Starting from autarky, inequality will rise. However, inequality peaks when the fraction of exporters is less than one. When trade costs become so small that all firms decide to export, inequality will fall again to autarky levels. In Sampson (2014), inequality will unambiguously increase in percentage/log terms (and therefore also in absolute terms), because of log-supermodularity of the production function. This is consistent with our results. In the fair wage model by Amiti and Davis (2012), there is no unambiguous prediction for percentage changes. In their empirical application using firm level data from Indonesia on wages, Amiti and Davis (2012) find evidence that inequality increases in log terms, mirroring our results with worker level data. The model by Helpman, Itskhoki, and Redding (2010) is structurally estimated in Helpman, Itskhoki, Muendler, and Redding (2017). Their results imply that trade liberalization in Brazil increased log wage inequality, in line with what we find for Germany.

to a drop in wages, we conjecture that those separations are involuntary.

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). This literature focuses on job losses due to mass-layoff events as they are arguably exogenous from the individual's perspective. 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.[27] Davis and von Wachter (2011) and, more recently, Schmieder, von Wachter, and Heining (2018) show that the long-term costs of job loss vary with the macroeconomic situation at the time of the layoff. Being laid-off during a recession leaves a deeper scar in a worker's earnings biography compared to being laid-off during a boom. Following this logic, we now investigate if exposure to international trade induces a similar heterogeneity. The adjustment paths of workers from different industries may be 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.

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 of job displacement. This complements our analysis from the previous section, because now we focus on workers who experience a (mass-)layoff. In our analysis, we will investigate differences in the scarring effects of this layoff and how this is influenced by globalization. In other words, we are interested in the question if and how increasing import exposure in Germany affects workers' ability to adjust after layoffs.

7.1 Estimation – the costs of job loss

Like almost all recent studies on this topic, we follow the procedure of Davis and von Wachter (2011) to estimate the cost of an involuntary job loss. The first step is to identify plants that have plausibly undergone a mass-layoff somewhen between 1990 and 2009. 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 universe of all employees in the German labor market subject to social security.[28] We trace the evolution of the size of all German plants and only consider manufacturing plants with at least 50 employees and a stable workforce in the preceding two years. We then define a potential mass-layoff event in year t^* if

[27] See Couch and Placzek (2010) or Huttunen, Møen, and Salvanes (2018) for more recent works employing the same identification strategy.

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

there is a permanent drop in employment of at least 30% within one year. In addition, we require that less than 25% of the leaving workers move to the same new plant, because otherwise we suspect that this might be due to restructuring within a firm rather than a layoff.

To estimate the individual cost of job loss, we obtain the full employment biographies of all employees who had been holding their main job at one of those plants for at least three years prior to the mass-layoff event. 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 enters either the treatment or control group only once. The 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.[29] The outcome y_{it} is the log labor earnings per calendar year. Our model is:

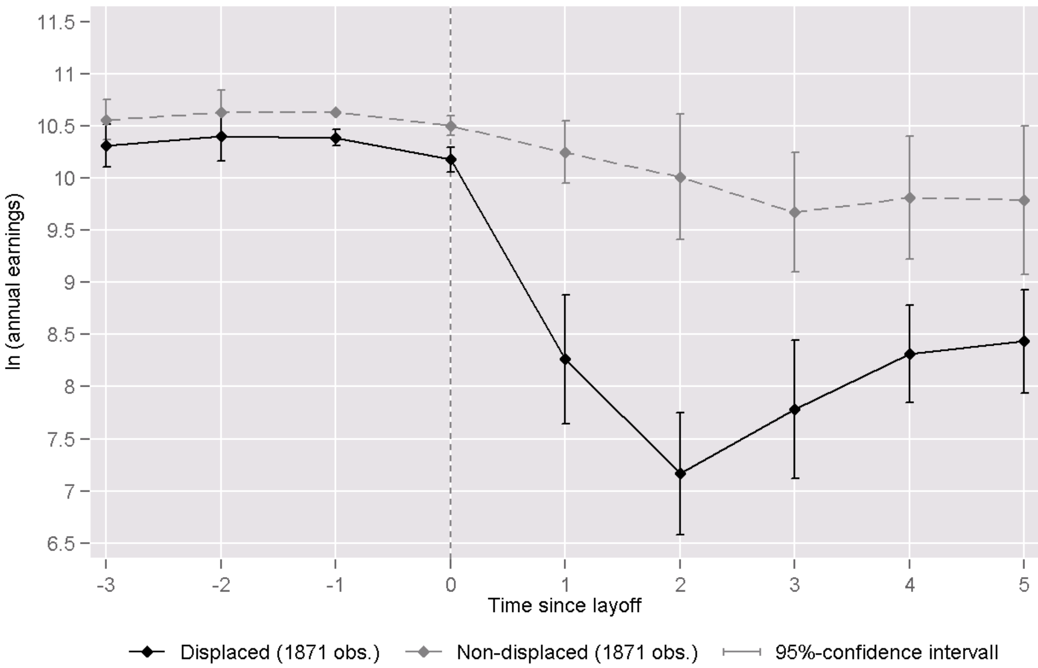
$$y_{it} = \beta_0 + \sum_{k=-3}^{5} [\delta_k I(t = t^* + k) I(\text{layoff}) + \gamma_k I(t = t^* + k) I(\text{control})] + \alpha_{tc} + \varepsilon_{it} \tag{3}$$

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 industry, 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.[30]

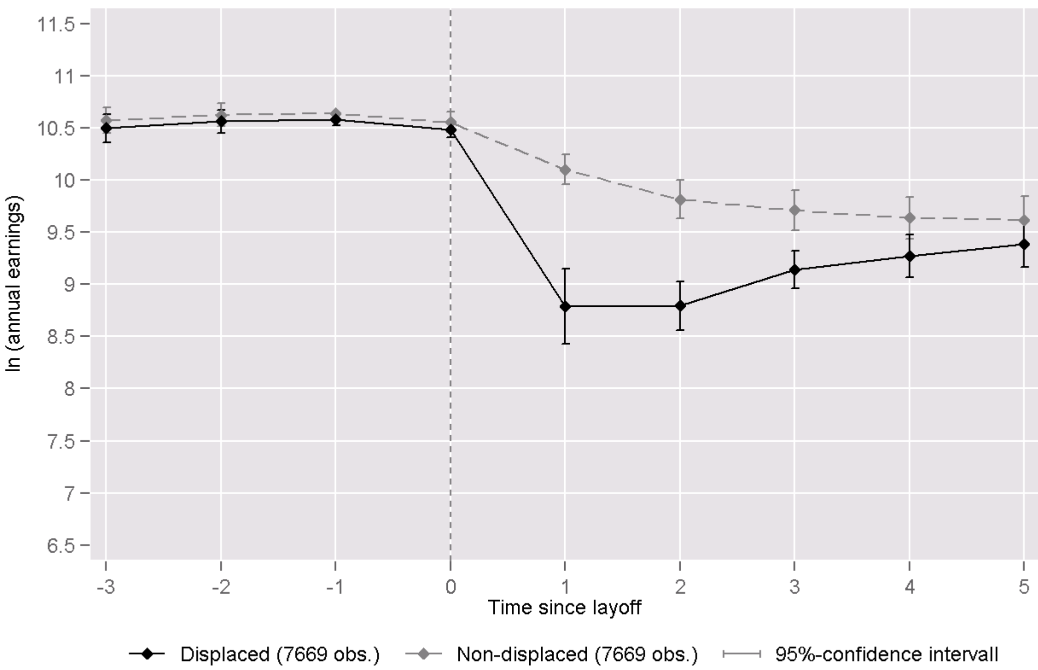
Figure 3 visualizes the coefficients of the time-to-layoff dummies from two separate event studies of two exemplary industries. We see that the earnings of workers in both the treatment and control groups are very similar prior to the layoff. Starting in the year of the event, earnings decline markedly 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. For-

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

[30] In this exercise, we aim to study the effect of a layoff on individual earnings. Since import competition increases the probability of being laid-off irrespective of whether it happens during a mass-layoff or as an isolated case, drawing the control group from the same 3-digit industry, would not yield a valid counterfactual.



(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.

mer 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 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.

7.2 Scarring effects and import 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. We may thus presume that the adjustment paths of workers from those different industries are systematically linked to import competition.

We follow Schmieder, von Wachter, and Heining (2018) and use the time structure of our data and the matched twins to construct double differences for each laid-off individual:

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

where $\bar{y}_{i,pre}$ is the average log earnings 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 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 wage bill three years before the mass-layoff. The regression model is:

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

As in Section 3, we again control for broad industry group ($\phi_{J(j)}$) and calendar year fixed effects (ϕ_t). In the 2SLS model, we also use instruments constructed from increases of tradeflows of other high wage countries with the East relative to the industry's total wagebill ten years before the mass-layoff.

The credibility of this approach hinges on two assumptions. First, the matched control group

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: The table shows 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 %.

should provide a valid counterfactual to the earnings of the displaced workers if the mass-layoff had never occurred. In Appendix Table A.9 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.9 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 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.2 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 model, we find that each percentage point of import exposure costs displaced workers an additional 0.25 to 0.31 percent of earnings per year. According to the summary statistics reported in Appendix Table A.10, 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.

Interestingly, the coefficient of export exposure is also negative but very imprecisely estimated. In fact, it is not clear ex ante what happens to workers in plants that experience a mass layoff even though their industry's market is expanding. One possibility could be that those plants were comparatively unproductive and were displaced from the market from firms that expand because of increased export opportunities as in the model by Melitz (2003). If there is assortative matching as suggested by Sampson (2014), then the workers at those firms are also the least productive. But according our findings in Section 5, firm switchers that benefit from switching within industries are positively selected. Expanding exporting firms apparently are reluctant to hire unproductive workers displaced from unproductive firms. By contrast, successfully exporting firms offer high firm-specific rents due to rent sharing and fair wage considerations (Egger and Kreickemeier, 2012). If a mass layoff happened because of bad management decisions or other reasons unrelated to productivity, then the laid-off workers' loss of firm-specific rents are particularly high.

7.3 Import competition and the incidence of mass layoffs

Workers in industries that face increasing competition from abroad find it more difficult to recover from losing their job in a mass-layoff event. It is also possible that the probability of a mass-layoff event itself might be related to increasing trade with the East. It 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

Table 7: **Trade Exposure and the Incidence of Mass-Layoffs**

	Dependent variable: Dummy, 1 = plant experienced a mass-layoff		
[A] OLS	(1)	(2)	(3)
import exposure	0.0197*	0.0220*	0.0057
	(0.011)	(0.012)	(0.006)
export exposure	-0.0187*	-0.0193*	-0.0090*
	(0.010)	(0.011)	(0.005)
R^2	0.011	0.012	0.021
[B] 2SLS	(1)	(2)	(3)
import exposure	0.0335	0.0444	0.0103
	(0.025)	(0.035)	(0.021)
export exposure	-0.0845	-0.1005	-0.0275
	(0.065)	(0.084)	(0.046)
log plant size	Yes	Yes	Yes
founding year dummies	Yes	Yes	Yes
broad industry dummies	No	No	Yes
drop manufacturing of computers	No	Yes	Yes

Notes: The table shows the relationship between plants experiencing a mass-layoff and trade exposure. Based on a cross-section of 32,131 (column 1) and 31,885 (columns 2 and 3) manufacturing plants with at least 50 employees and a stable workforce in the proceeding two years anytime in 1990-2010. The outcome variable is a dummy variable that indicates a plant that experienced a mass-layoff. Import (export) exposure is the increase in imports (exports) from (to) China and Eastern Europe over the period 1990-2010, relative to the industry's total wagebill in 1990. In Panel B, this is instrumented by similar measures constructed from tradeflows of other high-income countries. Standard errors, clustered by industry in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

examine this, we use a cross section of all manufacturing plants who meet the first two criteria of identifying mass-layoffs laid out in Section 7.1, namely a minimum size of 50 employees and a stable workforce in the proceeding two years anytime in 1990-2009. Out of those 32,131 plants, 10.0 percent also fulfill the other criteria, a permanent drop in employment of at least 30% within one year and less than 25% of the leaving workers moving to the same new plant.

We regress a dummy indicating a mass-layoff on the increase of import and export exposure at the industry level in the period 1990-2010. The results are reported in Table 7. We find some weak and barely significant evidence that plants that operate in industries that benefit from access to new markets in the East are less likely to layoff a large share of their workforce. By contrast, there is no opposing effect of imports. While we do find that individual workers face a higher probability to leave their original workplace if they work in industries with higher import competition, there is no such effect on the probability that firms fire a large share of their employees or even close. Note, however, that this might also be due to the way we identify mass-layoffs. Our heuristic minimizes the risk that we falsely identify mass-layoff events that are actually related to restructuring. This means that we cannot rule out false negatives, i.e. that we do not detect all events that happened in our observation period. This procedure is therefore better suited to analyze the effects of mass-layoffs on individuals rather than their incidence itself.

8 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 shocks. For Germany, globalization led to a strong rise in exports. This gives us the opportunity to investigate how the workers adjusted to increasing export opportunities. This focus on exports makes it 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 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 earnings gains partly on-the-job, and partly by switching employers within industries. For imports, our results suggest relatively small losses for affected workers. But if incumbent workers are laid off nonetheless, their 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 paper presents novel evidence how the scarring effect of a layoff are more severe in import-competing industries. In this way we connect to a large literature in labor economics, which has focused on the cost of job loss.

How representative are our results for other high-income countries? First, with respect to trade, Germany is regularly considered a manufacturing powerhouse and exhibits a record-high trade surplus. This surplus, however, is mostly with other high-income countries, while trade has been roughly balanced vis-a-vis "the East" on which we focus in this paper. In that respect, Germany is a more typical case than the United States, which built up a massive trade deficit with China since the mid 1990s. This special constellation is also a strong driver of the "China shock" in America, which has seen very little positive labor market effects from rising exports to the newly emerging markets. We believe that our paper therefore adds an important perspective, by showing that this globalization episode has not only been about rising import penetration.

On the labor market, Germany also has some special features that differ notably from other countries. Nowadays, unemployment rates are very low, but this has not always been the case during the observation period. Quite the opposite, during the 1990s and early 2000s, Germany was often referred to as the "sick man of Europe" and exhibited very rigid labor market institutions and high unemployment. Our empirical analysis therefore refers to a case that, on average, is not very different from other high-income countries but should reveal representative patterns.

What policy lessons can be learned from our empirical analysis? The most important one seems to be that low-skilled workers with lots of industry-specific human capital in import-competing industries seem to be hurt the most from adverse trade shocks, since they have a harder time to adjust than medium- or high-skilled workers. If educational systems, and labor market institutions more broadly, are tailored such that this mobility could be enhanced, it would benefit those workers who currently lose the most from trade liberalization. Which particular reforms are most conducive to those goals – for example, more generous trade assistance programs as recently analyzed by Hyman (2018), or an expansion of the apprenticeship system which provides some general skills to non-college workers and thus facilitates their occupational mobility later on – is an important topic for future research.

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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.3.

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.[31]

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

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

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:

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

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):

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

Table A.3 displays the predicted 10-year change of both the net export exposure from our standard definition and from the gravity approach.

[31] 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.[32] 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 on June 30 of year t^* is not less than 80 percent and not more than 120 percent of employment in $t^* - 1$ and $t^* - 2$**
3. The number of employees contracts by 30 to 100 percent until June 30 of year $t^* + 1$
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 the 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 disappearing plant ids 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 that if the largest cluster accounts for more 25 percent of all workers leaving

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

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.

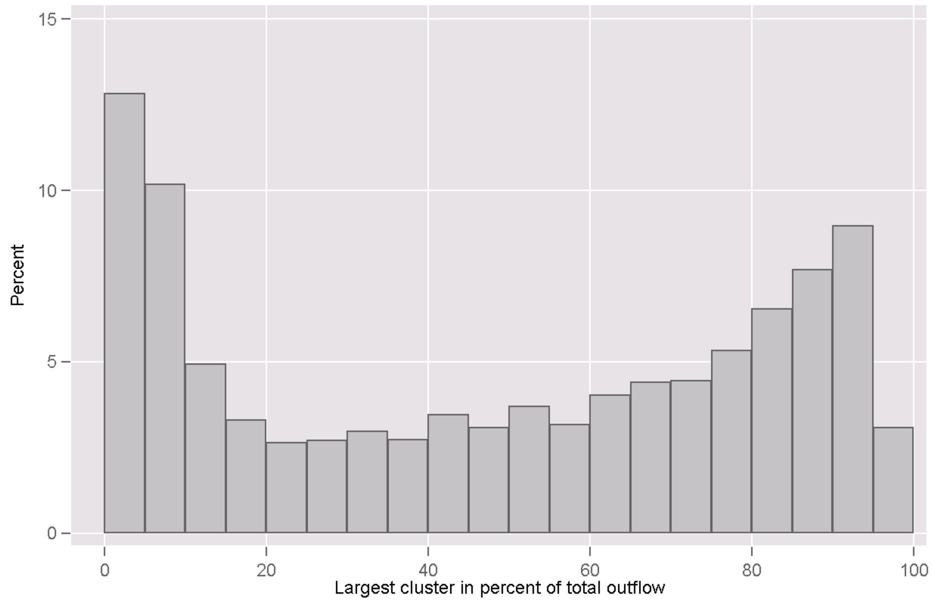
C.2 Identifying workers who experienced a mass-layoff

The next step is to identify all workers who were employed at one of those plants 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 consider 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.

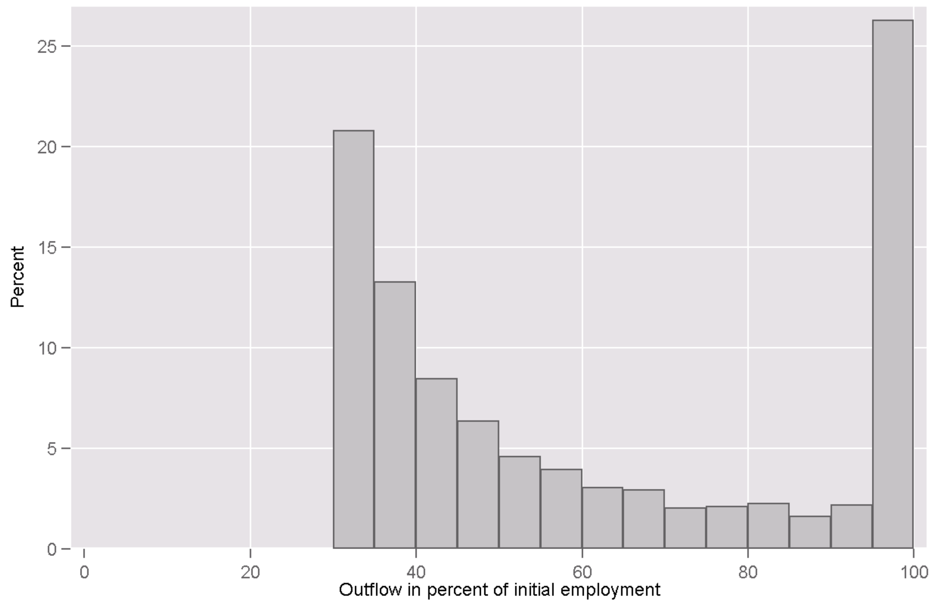
C.3 Selection of a control group

Since manufacturing has been 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 with respect to 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 for 1.4 percent of all displaced workers. Our final sample thus has 151,711 individuals in each the treatment and control group. In Appendix Table A.9 we report summary statistics for the observable characteristics of both groups. There are only few and seemingly unsystematic differences in the characteristics between both groups.

D Appendix Figures



(a) Size of largest outflow cluster



(b) Relative size of total outflow

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).

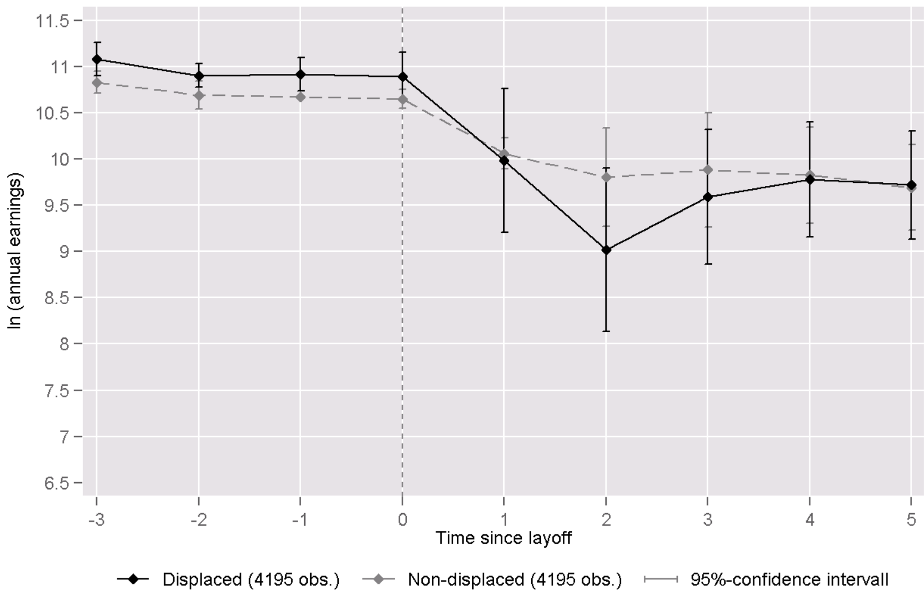


Figure A.2: Event study results for manufacturing of computers

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

E 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: **Eastern Europe versus China**

	(1) All	(2) Eastern Europe	(3) China	(4) All	(5) Joint
export exposure	0.5245***	1.0543***	1.3590***		
	(0.084)	(0.241)	(0.248)		
import exposure	-0.1038**	-0.3463**	-0.0015		
	(0.043)	(0.143)	(0.060)		
net export exposure (all)				0.1720***	
				(0.043)	
net export exposure (Eastern Europe)					0.4624**
					(0.181)
net export exposure (China)					0.0622
					(0.063)
R^2	0.126	0.124	0.126	0.125	0.125

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. This is instrumented by analogous measures constructed from tradeflows of other high-income countries. The trade exposure variables in columns 1 and 4 are constructed after aggregating tradeflows of Eastern Europe and China. The trade exposure variables in columns 2-3 and 5 are only constructed from German trade with Eastern Europe and China respectively. All trade exposure variables are instrumented by analogous measures constructed from tradeflows of other high-income countries. All models include control variables for age, gender, nationality, education, tenure, ln base year earnings, plant size, and fixed effects for board industry groups and commuting zones 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: **Trade exposure measures used in robustness checks**

	1990-2000		2000-2010	
observations	1,230,897		1,207,948	
	mean	(sd)	mean	(sd)
[A] 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]	
[B] Trade with Eastern Europe				
Δ import exposure	17.7	(15.4)	21.3	(20.5)
p10-p90 interval	[3.3 ; 37.8]		[3.1 ; 49.3]	
p25-p75 interval	[7.8 ; 23.5]		[10.5 ; 29.6]	
Δ export exposure	16.6	(17.4)	11.4	(25.2)
p10-p90 interval	[1.1 ; 36.2]		[-0.1 ; 31.0]	
p25-p75 interval	[4.4 ; 23.4]		[1.9 ; 12.6]	
Δ net export exposure	1.1	(18.8)	9.8	(26.0)
p10-p90 interval	[-16.6 ; 20.0]		[-8.7 ; 24.5]	
p25-p75 interval	[-2.9 ; 7.7]		[1.9 ; 15.6]	
[C] Trade with China				
Δ import exposure	2.5	(4.0)	13.7	(14.9)
p10-p90 interval	[0.1 ; 6.2]		[0.2 ; 37.7]	
p25-p75 interval	[0.6 ; 3.3]		[2.0 ; 21.7]	
Δ export exposure	6.2	(14.9)	16.7	(50.2)
p10-p90 interval	[0.0 ; 16.9]		[0.5 ; 21.6]	
p25-p75 interval	[0.3 ; 5.6]		[0.9 ; 10.0]	
Δ net export exposure	-3.7	(14.8)	-3.1	(54.7)
p10-p90 interval	[-14.9 ; 3.0]		[-19.6 ; 36.4]	
p25-p75 interval	[-4.3 ; 0.8]		[-1.6 ; 15.4]	
[D] 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]	
[E] 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, net exposure is the net of export and import exposure. In Panels B and C, all measures for trade exposure are only constructed from trade with China and Eastern Europe, respectively. In Panel D, the measures for import and export exposure are expanded by trade exposure of downstream industries, weighted their share in the upstream industry's total sales. In Panel E, the increase of net exposure is predicted by the increase of residuals from the estimation of a gravity model of trade.

Table A.4: **Robustness**

	(1) No dropping out of data	(2) Incl. outlier industry	(3) Drop East Germany	(4) I/O-links	(5) Net exports	(6) Gravity	(7) Placebo
export exposure	0.0137***	0.5270***	0.5151***	0.5386***			
	(0.004)	(0.088)	(0.087)	(0.077)			
import exposure	-0.0091***	-0.1112***	-0.1117**	-0.0938**			
	(0.002)	(0.035)	(0.046)	(0.043)			
net export exposure					0.1720***	0.6184***	0.0379
					(0.043)	(0.097)	(0.025)
R^2	0.115	0.126	0.128	0.126	0.125	0.125	0.161

Notes: Based on 2,431,779 workers (column 1) 2,440,170 workers (column 2), 2,267,153 workers (column 3), 2,438,845 workers (columns 4-6), and 1,240,480 workers (column 7), respectively. The outcome variable is 100 x the share of employment days in the total time observed in the social security records (column 1) and 100 x earnings normalized by earnings in the base year and cumulated over the ten years following the base year (columns 2-7). 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 columns 1-5 and 7, this is instrumented by analogous measures constructed from tradeflows of other high-income countries. In column 1, we include the otherwise omitted outlier industry "manufacture of knitted and crocheted articles". The trade exposure variables in column 3 include the trade exposure of downstream industries, weighted by their share in an industry's total sales. The trade exposure variable in column 6 is constructed by multiplying level trade exposure in the base year by differences is gravity residuals from a preceding gravity regression. All models include control variables for age, gender, nationality, education, tenure, ln base year earnings, plant size, and fixed effects for board industry groups and commuting zones 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.5: **The Role of Industry Specific Human Capital**

	(1) All employers	(2)	(3)
Same 2-dig industry		yes	no
export exposure	0.4476***	0.4340**	0.0136
	(0.094)	(0.180)	(0.137)
export exposure × industry specificity	0.2539**	0.3328**	-0.0789
	(0.113)	(0.147)	(0.072)
import exposure	-0.1198***	-0.6691***	0.5493***
	(0.045)	(0.094)	(0.077)
import exposure × industry specificity	-0.0475	0.0457	-0.0932**
	(0.041)	(0.064)	(0.038)
industry specificity	-29.2416***	-13.1860***	-16.0556***
	(2.387)	(3.031)	(1.502)
R^2	0.129	0.073	0.073

Notes: Based on 2,438,845 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 10 years following the base year. For column 2 the outcomes are cumulated only when they occurred in the original industry. For column 3 the outcomes are cumulated only when they occurred in a different than the original industry. 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. Industry specificity is the industry's share in the aggregate employment of the worker's occupation in the base year. The variable has been normalized to have a standard deviation of 1 to facilitate the interpretation of the interaction terms. 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.6: **Employment Adjustment by Worker Quality**

	(1)	(2)	(3)	(4)	(5)
	All employers		Same sector		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.7: **Employment Adjustment by Plant 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.8: **Wages of Within-industry Plant Movers versus Incumbent Workers**

	(1)	(2)	(3)	(4)	(5)	(6)
	2 years after beginning of period			5 years after beginning of period		
dummy, mover	3.4629	3.6250*	6.2367***	0.5825	-0.2806	3.1622*
	(3.346)	(2.130)	(1.890)	(2.616)	(1.863)	(1.745)
mover x export exposure	0.2444**	0.1785**	0.1855**	0.1607**	0.1204***	0.1254***
	(0.112)	(0.074)	(0.075)	(0.063)	(0.042)	(0.042)
mover x import exposure	-0.0540	-0.0189	-0.0212	-0.0066	0.0293	0.0266
	(0.054)	(0.030)	(0.030)	(0.038)	(0.027)	(0.026)
CHK plant effect	78.3850***	85.7056***	85.4262***	78.6762***	86.2676***	85.9949***
	(7.397)	(6.042)	(6.052)	(6.838)	(5.416)	(5.424)
CHK worker effect		44.0696***	43.9874***		42.0270***	41.9525***
		(2.535)	(2.564)		(2.506)	(2.533)
experience		0.3185***	0.1764**		0.2120**	0.0696
		(0.091)	(0.071)		(0.093)	(0.073)
tenure			0.2841***			0.2795***
			(0.060)			(0.061)
R^2	0.074	0.244	0.246	0.075	0.243	0.244

Notes: Based on 1,306,303 workers (columns 1-3) and 1,219,242 workers (columns 4-6). The outcome variable is 100 log daily wage of workers who have either stayed in their original plants since the base year or have moved to a different plant in their original industry two years (columns 1-3) or five years (columns 4-6) after the base year (movers). 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. Both interaction terms are instrumented by analogous terms constructed from tradeflows of other high-income countries. All regressions a dummy indicating the second period and 3-digit industry fixed effects and those in columns 2-3 and 5-6 include two age dummies. Standard errors, clustered by industry in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table A.9: **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.10: **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).