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Abstract: This paper examines whether workers' earnings after trade shocks depend on workers' skill specificity. We construct a measure for occupational specificity using task information from an official dataset for career guidance and merge this information to a large register dataset from Germany. We find that rising import competition resulted in larger earnings losses for workers with specific skills than for those with general skills, but workers with specific skills profited more from increasing exports. On average, we even find larger positive net effects for workers with specific skills, but they experience lager earnings inequality in response to increasing international trade.

Keywords: import competition, human capital specificity, skill bundles

JEL Classification: F16, I20, J2

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I. Introduction

A vast amount of literature shows that in response to negative demand shocks, such as displacements and job changes, workers with specific skills experience larger wage losses and longer periods of unemployment than workers with general skills (Couch & Placzek, 2010; Gathmann & Schönberg, 2010; Hijzen, Upward, & Wright, 2010; Jacobson, LaLonde, & Sullivan, 1993; Robinson, 2018). As a result, workers with specific skills might have worse career prospects when trade becomes more international than those with general skills, because increasing international trade has made labor markets more dynamic trough substantial reallocation of jobs[1] (e.g., Autor, Dorn, & Hanson, 2013; Dauth et al., 2014). Indeed, Yi, Müller, and Stegmaier (2017), for example, show that workers with highly industry-specific skills experience large adjustment costs in response to import shocks.

However, increasing international trade has not only made labor markets more dynamic but also led to overall economic growth and prosperity by creating larger demand for scarce products (Dix-Carneiro, 2014; Dollar & Kraay, 2004). Moreover, firms need investments in specific human capital to produce innovative and high-quality goods (Aghion, Bergeaud, Lequien, & Melitz, 2017; Khandelwal, 2010; Martin & Mejean, 2014; Mion & Zhu, 2013). Thus, as specific skills are, by definition, scarcer than general skills, they should generate higher returns for workers in response to positive demand shocks—even more, because firms commonly share the returns to investments in specific human capital with their workers (Becker, 1964). Thus, whether workers with specific skills have worse career prospects when trade becomes more international depends not only on their adjustment costs in response to negative demand shocks but also on the returns to specific skills in response to positive demand

[1] Recent examples of studies providing evidence for the effect of trade on labor market dynamics are: Autor, Dorn, Hanson, and Song (2014); Dauth, Findeisen, and Suedekum (2014); Dauth, Findeisen, and Südekum (2016); Ebenstein, Harrison, McMillan, and Phillips (2013); Keller and Utar (2016); Lu and Ng (2013); Baumgarten, Geishecker, and Görg (2013); Balsvik, Jensen, and Salvanes (2015); Kemeny, Rigby, and Cooke (2014).

shocks. Unfortunately, previous research has not analyzed whether and to what extent returns to specific skills increase in response to positive demand shocks.

This paper provides a more complete picture of the relationship between returns to specific skills and changes in demand by analyzing how returns to general and specific skills vary by import competition and export exposure. Our analysis relies on detailed and accurate register data from Germany. Germany is ideal for our analysis, because the country was exposed to a substantial increase in import competition from Eastern Europe and China at the same time that German exports to those countries were accelerating. For example, the German annual import volume from China rose to more than 50 billion Euros in 2008, corresponding to a growth rate of 1,608 percent since 1990. This growth rate was far higher than that of any other trading partner. At the same time, German exports to China rose by 900 percent. These dynamics allow us to exploit substantial variation within and across different industries and occupations to analyze how returns to specific and general skills vary by negative (import competition) and positive demand shocks (export exposure).

To achieve this goal, we combine three unique data sources. First, to measure the specificity of skills, we rely on the BERUFENET, an occupational task dataset constructed by the German employment agency for career guidance and job placement. Comparable to the U.S. O*Net, the BERUFENET contains information on the required tasks, equipment, working conditions, and required qualifications for all occupations in Germany. Following Eggenberger, Rinawi, and Backes-Gellner (2018), we use these data to construct a measure that captures the transferability of the skill bundle of a particular occupation to the skill bundle requirements in the overall labor market. This measure closely corresponds to Lazear's (2009) skill-weights definition of specific human capital and captures the probability of finding a new job that requires a similar skill bundle. Second, to measure the trade flows between Germany and other countries, we follow Autor et al. (2014) and Dauth et al. (2014) by using trade data from the United Nations (UN) Commodity Trade Statistics Database (Comtrade). These data, which contain detailed information about commodity types, provide information on trade flows between more than 170 countries. Third, to follow workers' careers over long periods, we use register data from the Federal Employment Agency of Germany. These data contain highly accurate information about workers' wages, employment status, and common demographic characteristics (e.g., age, nationality, and education) and allow us to analyze the long-term consequences of international trade for workers with specific and general skills. Moreover, the data allow us to link workers to firms, so that we can account for detailed firm characteristics.

Our empirical analysis relies on two main identification assumptions. First, we have to assume that German workers and firms were unable to foresee which industries, and therefore which labor market regions, would be affected by the development of international trade. While this assumption is key to all approaches following Autor et al. (2014), it is even more important for our specific analysis, because the expected consequences of increasing international trade may have influenced workers' occupational choices and, therefore, their human capital investments. On one hand, to reduce the negative consequences of import shocks, workers may have chosen occupations and industries that demand less specific human capital. On the other hand, firms may have increased their investments in specific skills (thereby, making them more general) in anticipation of trade developments.

To address this concern, we restrict our sample to include only West-German workers who chose their jobs before 1990, and we calculate their skill specificity according to their baseline job in that year. Before 1990, the German population was largely unable to foresee the rapid globalization of trade in the 1990s and 2000s, because the German population could not have predicted the fall of the Iron Curtain as a shock that would trigger trade between Germany and the former Soviet bloc countries (Chevalier & Marie, 2013; Fuchs-Schundeln, 2008).

Second, we must assume that the trade exposure measures do not reflect domestic shocks to German industries. To tackle this issue and isolate the effects of trade from other confounders, we follow common practice by building on the estimation strategy developed by

Autor et al. (2014) and Dauth et al. (2014) and instrumenting the increase in trade exposure from China and Eastern Europe to Germany with the trade between these low-wage countries and other “third-party” high-income countries.

Our analysis provides three main results. First, in line with previous evidence, we find that workers with specific skills experience larger earnings losses in response to negative demand shocks (i.e., when import exposure increases). For a 1,000 Euro increase (roughly $ 1,340 in 2010) in imports, workers with very specific skills (i.e., one standard deviation above the mean skill specificity) experienced a cumulated earnings loss of approximately 12 percent of their base-year income over a 10-year period. In contrast, workers with very general skills experienced only a cumulated earnings loss of approximately six percent. However, our results go beyond the existing literature by showing that workers with specific skills benefit more from positive demand shocks through rising exports than those with general skills. For example, with a 1,000 Euro increase in exports, the cumulative earnings of workers with the most specific skills significantly increased by approximately 18 percent. In contrast, the cumulative earnings of workers with very general skill bundles only increased by six percent. Most importantly, our results reveal that increasing international trade in Germany has led on average to larger positive net effects for workers with very specific skills than for those with very general skills. Thus, workers with specific skills do not necessarily have worse career prospects when trade becomes more international; rather their career prospects depend on the balances of trade.

Second, we find that trade effects are more heterogeneous for workers with specific skills than for those with general skills. In more detail, workers with specific skills who are located in regions with large trade deficits experience larger net earnings losses than workers with very general skills. In contrast, workers with specific skills who are located in regions with large trade surpluses experience larger net earnings gains than those with general skills. Thus, investments in specific occupational skill bundles lead to a risk-return tradeoff, as the net effect of trade has led to a higher income variance for workers with the most specific skills.

Third, our results show important heterogeneities for different subgroups of workers. In more detail, we find no significant relationship between workers' skill specificity and trade exposure for workers who were exposed to the trade shocks when they only had low tenure (below 5 years), and workers who were very young (below 40) experience no negative consequences from import shocks but still appear to be able to collect the benefits from increasing exports. In contrast, we find large and precisely estimated effects for long-tenured and older workers. These results suggest that workers adjust to the consequences of trade when their adjustment costs are low enough. Thus our results suggest that the gains and losses from specific human capital investments should reduce towards zero in the long run, and further examinations of later periods appear to support this argument.

Our results contribute to at least two strands of the literature. First, we contribute to the literature on human capital theory (Becker, 1964; Lazear, 2009). While human capital theory implies that workers with specific skills should suffer more from negative demand shocks (e.g., worker displacements) than workers with general skills, it also clearly implies that they should profit more from positive demand shocks. However, although many empirical studies have shown that workers with specific skills incur larger wage losses and longer periods of unemployment in response to negative demand shocks (e.g., mass layoffs, firm closures) (Couch & Placzek, 2010; Hijzen et al., 2010; Jacobson et al., 1993) and that occupation and task-specific skills are important for workers' wage development (Gathmann & Schönberg, 2010; Robinson, 2018), our results contribute to the literature by providing evidence that workers with specific skills indeed benefit more from positive demand shocks than those with general skills.

Second, we contribute to the large literature that has analyzed how international trade influences labor markets (e.g., Autor et al., 2014; Dauth et al., 2014; Ebenstein et al., 2013; Utar, 2018). While this literature has focused on the general effects on wages and employment or heterogeneous effects for low and high-skilled workers, we extend this literature by focusing on another dimension of workers' skills, i.e., their level of skill-specificity. Our results reveal that workers' skill specificity is an important determinant for the labor market consequences of increasing international trade and that increasing international trade produces inequalities even for workers with the same level of formal qualifications. Understanding this relationship between international trade and workers' returns to skills is essential for understanding the long-term consequences of globalization across different countries and for designing adequate educational policies.

The remainder of this paper is structured as follows. Section II presents our theoretical model. Section III explains our estimation strategy. Section IV presents the data and explains the empirical construction of our measure for occupational specificity. Section V shows our empirical results and robustness checks. Section VI concludes.

II. Theoretical considerations: Specific occupations and trade shocks

This section provides a simple theoretical framework that is based on Lazear's (2009) "skill-weights" model of human capital to guide the interpretation of our empirical results. According to the skill-weights model, all skills are "general" in that there are always other jobs that value each of these skills. Nonetheless, these general skills are used in different jobs in different combinations and with different weights attached to them, thereby giving skill combinations varying degrees of specificity. Lazear originally formulated the model such that skill bundles vary between firms. However, we transfer the idea to occupations and assume that skill bundles vary between occupations, because this approach is more consistent with the structure of our data. Moreover, the literature on human capital specificity suggests that occupational skill bundles are more tied to workers' compensation than firm-, industry-, and even occupation-specific skills (Gathmann & Schönberg, 2010; Poletaev & Robinson, 2008).[2] Thus, when we talk about job changes in the following sections, we refer to workers changing to a new job in the same occupation, requiring the same skill weights, or to a different occupation, requiring different skill weights. From the model's perspective, although expanding the view to occupations changes the terminology, the implications remain the same.[3]

In the basic model, there are two completely general skills, A and B. Different jobs require these skills in different combinations to produce output. The relative weight of skill A in job *i* is denoted with λ_i, where $0 < \lambda_i < 1$. Suppose a worker's current job *i* requires λ_i. The productivity of a worker with skills A and B in job *i* is given by:

$$y_i = \lambda_i A + (1 - \lambda_i) B \tag{1}$$

Thus, workers with different investments into A and B will have different productivity levels in different jobs depending on λ_i.

We assume that there are two time periods. The first period corresponds to the base period before the trade shocks occurred (the period before the fall of the Iron Curtain; see Section III for more details). The second period corresponds to the period of the trade shocks, i.e., the period after the fall of the Iron Curtain. In the first period, workers receive random assignments to jobs and invest in skills A and B. In the second period, they can switch to other jobs, and the number of job offers in the second period depends on the volume of international trade. In other words, we assume that workers receive more job offers when exports increase, because firms demand more labor to satisfy the increasing demand for their goods. In contrast,

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[2] Earlier studies suggested that industry- and occupation-specific skills are more important for workers‘ wage development than firm-specific human capital (Gibbons, Katz, Lemieux, & Parent, 2005; Kambourov and Manovskii (2009); Neal (1995); Parent (2000).

[3] Likewise, when we refer to “specific skills,” we always refer to specific occupational skills.

firms demand less labor when the demand for their goods declines in response to rising import competition.

In principle, workers would decide how much to invest in skills A or B by considering the value of their skills in the current job (λ_i) and the value of their skills in other jobs to which they can switch in the second period (λ_j). However, in our case, workers in the first period cannot foresee the development of international trade in the second period (i.e., they are unable to foresee the fall of the Iron Curtain, see Section III for more details). Thus, in contrast to Lazear (2009), they cannot build adequate expectations about the number of job offers in the second period. As a result, their skill investments in the first period are independent of the trade shocks in the second one.

For simplicity, we normalize the wage in the first period to zero ($w_0 = 0$). Following Lazear (2009), the wage in the second period is determined by a Nash bargaining framework. More specifically, at the beginning of the second period, a worker might leave his or her initial job and accept a new job that requires a different skill weight λ_j. This λ_j is a realization of the random variable λ, which has the probability density function f(λ), representing the distribution of skill weights (or jobs) in the labor market. If the worker would only get one draw from f(λ) at the beginning of the second period; then, after comparing the wages in the new and the old job, he or she decides whether to switch to the new job with λ_j.[4]

The Nash bargaining solution thus implies that the worker's wage in the second period is (cf. Lazear, 2009):[5]

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[4] Lazear's (2009) model also features the possibility that the worker is exogenously separated from his or her initial job with probability q. For our purpose, changing q does not change the analysis, and we therefore assume q=0.

[5] As the worker's productivity in job 1 (in firm 1) is $y_1 = \lambda_1 A + (1 - \lambda_1)B$, firm 1 would be willing to pay up to this amount for the worker's services. Thus the disagreement outcomes are the productivity of the worker in the current firm 1 and the productivity of the worker in firm j, i.e., the worker's outside option, which is drawn at the beginning of the second period. Although the worker will move to the firm that makes the most efficient use of his or her skill bundle, the same wage will be paid in both the new and the old firms. If the worker's productivity is higher in the old firm, the worker stays, and the new firm constitutes his or her outside option. If the worker's productivity is higher in the new firm, then the worker changes, and the old firm constitutes his or her outside option.

$$w_2 = \frac{1}{2}\{[\lambda_1 A + (1-\lambda_1)B] + [\lambda_j A + (1-\lambda_j)B]\} \quad (2)$$

What are the model's implications for the wages of workers with specific and general skill investments in the presence of trade shocks? As we have already mentioned, we model trade as an increase—or decrease—in market thickness. An increase of market thickness in the model is equated with an increase in the number (N) of independent draws of λ a worker receives before the start of the second period. If a region is exposed to more import competition, the demand for the region's output mix decreases, and the worker receives fewer job offers. If the region can increase its export intensity, demand for the region's output increases, and the worker receives more job offers for a given search effort. If the worker receives more job offers, he or she can select a job that best suits his or her prior investment. An increase in market thickness thus always improves the worker's outside option and bargaining position. However, a change in market thickness has a larger effect on the wages of workers with more unbalanced, i.e., specific, skill investments.

Consider the case in which the worker has invested such that A>B.[6] In this case, the worker prefers to work in jobs with a high λ, because these jobs use more of the worker's abundant skills and thus produce more output given the worker's skill combination. With each additional draw of λ, the worker has a chance to find a higher-λ job, which improves his or her outside option. The highest expected draw of λ_j with N draws can be written as $E(Y) = \int_0^1 (1 - F(\lambda)^N)dy$, with F(.) denoting the cumulative distribution function of λ (see Appendix A). The expected wage in the second period with N draws can thus be written as:[7]

[6] For workers specializing in skill B, although the model works the other way around, the logic is identical.
[7] As with one single draw (N=1), the wage is the same in both firms, but the higher the number of draws N, the more likely a higher outside option and the less likely that the worker stays with his or her initial option.

$$w_2 = \frac{1}{2}\left\{\lambda_1 A + (1-\lambda_1)B + \left[\left(\int_0^1 (1-F(\lambda)^N)dy\right) * A + \left(1 - \int_0^1 (1-F(\lambda)^N)dy\right) * B\right]\right\} \quad (3)$$

If we take the derivative of w_2 with respect to *N*, we obtain:

$$\frac{\partial w_2}{\partial N} = \frac{1}{2}\left\{-\int_0^1 (F(\lambda)^N \ln(F(\lambda)) * (A-B)\right\} \quad (4)$$

This expression is clearly positive, because $F(\lambda)^N \ln(F(\lambda))$ is negative. Moreover, the larger the difference between A and B, i.e., the more unbalanced or idiosyncratic the worker's initial investment, the larger the derivative becomes. Thus, for a given investment, an unexpected increase in *N* has a larger positive effect on wages for workers with more specific, or idiosyncratic, investments than for workers with more balanced investments. In other words, a worker with a highly specific investment profits more from finding a job with a high λ, because a high-λ job makes more efficient use of the workers' skill bundle and finding such a job is more likely in thicker markets. However, workers do not necessarily have to change jobs to receive higher wages. Given the Nash bargaining structure of our framework, it is sufficient if the increasing number of job offers increases the workers' outside options. Finally, if the increase in *N* was unexpected, it can be equated with a larger wage difference between the first and second periods, because the first period wage is deterministic and was set before the changes were known.

Thus, the main implication of our framework differs from the result in Lazear (2009) where wage gains from job changes go to zero when more job offers arrive. The reason is that the workers in our study are exogenously hit by trade shocks, i.e., they do not anticipate the increase or decrease in job offers and their skill investments are exogenous. In contrast, the workers in Lazear (2009) adjust their skill investments in response to the increasing or decreasing rate of job offers.[8] The distinction between expected and unexpected shocks provides important implications for our empirical analysis. For unexpected trade shocks, we expect workers with more idiosyncratic skill investments to experience (a) a larger wage growth if export exposure increases and (b) a larger wage decline if import exposure increases, compared to workers with general skill investments. In contrast, if changes in trade patterns are expected and fully reflected in the investment decision and the first period wage, we expect no effects on workers' wage growth. Our results from Section V.D confirm these implications.

Overall, our framework thus suggests two key implications for our empirical investigation: First, workers with specific occupational skills are more affected by unexpected import exposure, i.e., they experience larger earnings declines than workers with less specific skills. Second, workers with specific skills also profit more from unexpected export intensity, i.e., they experience larger earnings growth than workers with less specific skills.

III. Empirical strategy

This paper examines whether workers with specific skills adjust differently to the labor market consequences of accelerating international trade (imports *and* exports) than workers with general skills. Therefore, we analyze how workers in occupations with different combinations of skills—i.e., specific or general—adjust to import and export exposure on regional labor markets.

We define local labor markets according to the classification of the German Federal Office for Building and Regional Planning (BBR), a classification based on commuter flows between municipalities. This classification assigns geographic regions to functional

[8] Of course, had the trade shock been *expected*, workers would have adjusted their investment strategies. In particular, workers would have had incentives to invest in more unbalanced skills in expectation of an increase in market thickness.

subeconomies (Kropp & Schwengler, 2011). Following Autor et al. (2013) and Dauth et al. (2014), we assign trade flows to regions according to their industry structure and define local labor market exposure to import competition (*ImE*) as follows:

$$\Delta ImE_{rt}^{East\to D} = \sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta IM_{jt}^{East\to D}}{L_{rt}} \quad (5)$$

where $\Delta IM_{jt}^{East\to D}$ stands for the change of industry $j's$ imports (i.e., imports of industry j's final goods) from Eastern Europe and China to Germany between the periods *t* and *t+1*. We divide this share by region *r*'s total labor force (L_{rt}) and weight the measure by region *r'*s share of total (national) industry employment at time *t* (L_{rjt}/L_{jt}). We calculate an analogous measure for exports ($\Delta ExpE_{rt}^{D\to East}$). The variation of our main explanatory variables stems from two sources: initial differences in manufacturing employment across regions and the specialization of import- or export-intensive industries within the local manufacturing sector.

We use these measures for trade exposure in the following regression equations:

$$\begin{aligned} \sum_{t_0}^{t_0+10} Y_{it} &= \propto + \beta_1 \Delta ImE_{rt}^{East\to D} + \beta_2 \Delta ExpE_{rt}^{D\to East} + \beta_1^I \Delta ImE_{rt}^{East\to D} \times Spec_0 \\ &\quad + \beta_2^I \Delta ExpE_{rt}^{D\to East} \times Spec_0 + \gamma Spec_0 + \delta w_0 + X_{it}'\gamma + J_t \\ &\quad + Reg_t + \varepsilon_{it} \end{aligned} \quad (6)$$

where $\sum_{t_0}^{t_0+10} Y_{it}$ denotes individual *i*'s cumulated (normalized) labor market incomes over a 10-year period following the base year t_0. w_0 describes the workers' annual earnings in the base year. If earnings are closely related to workers' productivity, w_0 should capture most of the workers' unobserved productivity differences that may persist between workers in the base year. The vector X_{it} contains further controls for the worker's gender, nationality, age, plant size, and tenure. Moreover, we include controls for four broad industry groups (J_t), region fixed effects (Reg_t), and an indicator for the base year. To allow for correlation in error terms of workers originally employed in the same labor market regions, we cluster the standard errors at the regional level.

The coefficients of the interaction terms between workers' skill-specificity and trade exposure—β_1^I and β_2^I—are the coefficients of main interest. These coefficients measure the extent to which the consequences of international trade differ for workers with general and specific skills. We assign workers to trade shocks based on their initial work region and not on their firm or industry. Thus, first, the coefficients β_1^I and β_2^I measure the extended consequences of trade exposure, i.e., they also include any effects that occur after workers have resorted into different occupations, regions, or industries after the base year. Second, we consider that the trade shocks induce spill overs between industries in the same labor market region, i.e., even if workers are employed in firms or industries that are not directly affected by trade shocks, they may benefit or suffer from trade shocks to other firms and industries in the region. See Helm (2019) for evidence of spillover effects from trade shocks in Germany.

Identification of interaction terms β_1^I and β_2^I

That OLS estimations of the isolated terms β_1 and β_2 are biased if $\Delta ImE_{rt}^{East\to D}$ and $\Delta ExpE_{rt}^{D\to East}$ are endogenous or contain measurement error is well established in the literature. On one hand, changes in import exposure may correlate with domestic demand shocks to German industries, so that workers' income and changes in import exposure might correlate with unobserved shocks to product demand. On the other hand, workers' income and changes in exports may correlate with unobserved shocks to product supply. Moreover, as we assign trade exposure to regions based on the regional industry structure, we have good reason to believe that $\Delta ImE_{rt}^{East\to D}$ and $\Delta ExpE_{rt}^{D\to East}$ suffer from measurement error.

To overcome these sources of bias, we can simply follow the common solution to this problem and instrument the increase in trade exposure from Eastern Europe and China to Germany with the trade between these low-wage countries and other "third-party" high income countries (e.g., Autor et al., 2013; Dauth et al., 2014; Helm, 2019).[9] More specifically, we can instrument $\Delta ImE_{rt}^{East\rightarrow D}$ and $\Delta ExpE_{rt}^{D\rightarrow East}$ by $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta IM_{jt}^{East\rightarrow Other}}{L_{rt}}$ and $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta EXP_{jt}^{Other\rightarrow East}}{L_{rt}}$ where $\Delta IM_{jt}^{East\rightarrow Other}$ and $\Delta EXP_{jt}^{Oth\quad\rightarrow East}$ denote the trade between Eastern Europe, China and other "third party" high wage countries.

However, in our case the coefficient estimates of main interest are not the isolated coefficients for trade exposure but the interaction terms between trade exposure and workers' human capital specificity (β_1^I and β_2^I). The identification of these interaction terms additionally requires that the workers' skill specificity ($Spec_0$) and the omitted variable bias are jointly independent of the instruments. Nizalova and Murtazashvili (2016) show that if the source of heterogeneity and the omitted variable bias of an endogenous variable are jointly independent of an exogenous variable, then the OLS estimate of the interaction term between the exogenous and the endogenous variable is consistent. Thus, our *first stage* and *reduced form* estimates for the interaction terms between our instruments and our measure for workers' skill specificity will be consistent if $(Spec_0, \varepsilon_{it})$ is jointly independent of $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta IM_{jt}^{East\rightarrow Other}}{L_{rt}}$ and $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta EXP_{jt}^{Other\rightarrow East}}{L_{rt}}$. As a result, the 2SLS estimates of β_1^I and β_2^I will be consistent,[10] because 2SLS estimates are a combination of the reduced form and the first stage estimates.[11] See Appendix B for a more detailed discussion of this identification assumption.

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[9] We use the same instrument countries as Dauth et al. (2014): Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. To mitigate any possible simultaneity bias, we follow the literature and use lagged employment (3 years before the start of the period) to construct the instrument and apportion trade flows from the East to the labor market regions. Using contemporaneous employment shares to construct the instrument has no significant effects on our results.

[10] Bun and Harrison (2018) rely on the same argument to show that interaction terms between endogenous and exogenous variables can be used as instruments for endogenous those endogenous variables.

[11] See Acemoglu, Autor, and Lyle (2004) for a similar argument. The authors exploit the mobilization of World War II for analyzing how female labor supply effects the wage structure in the midcentury. Their main specification includes an interaction term between a time variable that may be related to other unobserved time trends and a variable for state-specific female labor supply that may be related to other unrelated state-specific effects.

The literature argues that high-ability workers have larger incentives to choose specialized jobs and to invest in specific human capital (Neal, 1998),[12] because they can expect longer tenure and a lower probability of involuntary separation than low ability workers. Thus, workers' skills specificity $Spec_0$ may systematically correlate with their unobserved ability, such that estimates of the isolated effect of $Spec_0$ are biased. However, the coefficient estimates of the interaction terms β_1^I and β_2^I (our coefficient estimates of main interest) will still be unbiased if the workers' skill specificity and their unobserved ability are jointly independent of the instruments $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta IM_{jt}^{East \to Other}}{L_{rt}}$ and $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta EXP_{jt}^{Oth \quad \to East}}{L_{rt}}$.

However, $(Spec_0, \varepsilon_{it})$ may not be jointly independent of the instruments if workers' job choice and human capital investments depend on their expectations about the future developments of international trade. For example, workers may have chosen whether to invest in general or specific skills in response to the expected trade exposure in their sector. More able workers may have expected increasing international trade to result in lower job stability in certain industries. Given such expectations, and wanting to reduce the negative consequences of potential job loss, they may have chosen occupations and industries that demand less specific human capital. If this selection were to occur, $(Spec_0, \varepsilon_{it})$ would not be jointly independent of $\Delta ExpE_{rt}^{D \to East}$ and $\Delta ImE_{rt}^{East \to D}$ and potentially would also not be jointly independent of the instruments that correlate with $\Delta ExpE_{rt}^{D \to East}$ and $\Delta ImE_{rt}^{East \to D}$. As a result, our estimates of β_1^I and β_2^I would be biased.

To overcome this source of bias, our analysis is based on a restricted sample that only includes West German workers who have chosen their jobs before 1990.[13] Before 1990, the German population was largely unable to foresee the fall of the Iron Curtain, which triggered

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[12] A large literature documents that high wages and turnover are negatively correlated (Krueger & Summers, 1988; Oi, 1962; Pencavel, 1968).
[13] We do not have data on East-German workers before 1991 and thus cannot include them.

trade between Germany and the former Soviet bloc countries in the 1990s and 2000s (Chevalier & Marie, 2013; Fuchs-Schundeln, 2008). Thus, we can plausibly assume that, before 1990, workers did not choose their jobs in anticipation of the rapid globalization of trade throughout the 1990s and 2000s. Indeed, a variety of papers have exploited this historical setting as a quasi-natural experiment (Brülhart, Carrère, & Trionfetti, 2012; Glitz, 2012; Redding & Sturm, 2008).

On this restricted sample we run a version of our main regression equation (6) for which we instrument $\Delta ImE_{rt}^{East \to D}$, $\Delta ExpE_{rt}^{D \to East}$, $\Delta ImE_{rt}^{East \to D} \times Spec_0$, and $\Delta ExpE_{rt}^{D \to East} \times Spec_0$ by $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta IM_{jt}^{East \to Other}}{L_{rt}}$, $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta EXP_{jt}^{Other \to East}}{L_{rt}}$, $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta IM_{jt}^{East \to Other}}{L_{rt}} \times Spec_0$, and $\sum_j \frac{L_{rjt}}{L_{jt}} \frac{\Delta EXP_{jt}^{Other \to East}}{L_{rt}} \times Spec_0$, i.e., we use interaction terms between workers' skill specificity and the "third-party" trade as additional instruments (see Amodio and Martinez-Carrasco (2018) and Aghion, Howitt, and Mayer-Foulkes (2005) for similar approaches).

IV. Data and Measures

This section describes our data sources and the operationalization of our measures. For our analysis, we use three main data sources. First, we use individual data from the Integrated Labour Market Biographies (IEB). Second, to construct our specificity measure, we merge the IEB data with a skill database from the BERUFENET. Third, to measure regional import and export exposure, we merge the IEB data with information from the United Nations Commodity Trade Statistics Database (Comtrade).

A. Employment Histories

The data for workers' labor market outcomes stems from the Integrated Employment Biographies (IEB) provided by the German Federal Employment Agency (BA). The data contains precise register information about the employment histories of all employees required to make German social security contributions (i.e., all German employees who are not self-employed or civil servants). Unique personal and establishment identifiers identify all individuals and establishments, so that we can follow all workers and establishments over more than 40 years. The data contain labor market information about workers' employment status, wages, education, establishments, occupations, and the location of their workplaces. It also contains standard demographic information such as age, gender, and nationality.

We restrict our sample to male[14] West German[15] employees who held a stable full-time job for at least 300 workdays in the base year of 1990,[16] and we follow these workers throughout the observation period between 1990 and 2000. As mentioned in the previous section, we can plausibly assume that workers were unable to foresee the trade integration of Germany and Eastern Europe in 1990.

Most other previous papers on the labor market effects of international trade also analyze the period between 2000 and 2010, which spans China's entry into the WTO. However, previous research on Germany shows that the trade integration of Eastern Europe had much stronger consequences for the labor market of West Germany than China's entry to the WTO (Dauth et al., 2014). The reason is that Germany already tended to import labor-intensive goods from Eastern Europe in the 1990s, and China's entry into the WTO mainly led to a diversion of German import flows from other countries. As a results, the workers' job choices in the 2000's had already been a consequence of increasing international trade throughout the 1990s (see

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[14] We focus our analysis on men, who exhibit more stable labor market patterns than women and are characterized by higher data availability. Our results reveal that assigning zeros when workers have gaps in the data adds a substantial amount of measurement error and women have much more gaps than men. However, we present results for women in the robustness section.

[15] We can follow West German employees and firms from 1975 but East German employees and firms only from 1991.

[16] The workers must be reported as full-time workers by their main employer at least once during the base year. Additionally, we require that they have a strong labor force attachment (i.e., are employed for at least 300 days of that year) and earn more than the marginal part-time income threshold. This definition may include workers with interrupted employment, such as workers on sabbatical, on maternity leave, or on sick leave. We do not include workers registered as apprentices.

Simon, 2018 for evidence that German workers chose apprenticeship training occupations with more specific skills when they were hit by trade shocks in the 1990s). Therefore, our main results rely on the period between 1990 and 2000. However, subsection V.D analyzes the period between 2000 and 2010.

We further follow Dauth et al. (2016) and Autor et al. (2014) and apply two additional data restrictions. First, to ensure that workers had finished their entire education before entering the sample and were below the legal retirement age of 65 throughout the entire 10-year observation period, we restrict our sample to only those workers who were between ages 22 and 54 in the base year 1990. Second, we exclude individuals who died or emigrated during the 10-year window after the base year.

For all remaining workers, we create balanced panels capturing the workers' employment histories for the entire ten-year period after the base year. As inactivity, unemployment, or early retirement may be consequences of accelerating international trade, we include periods with no labor market income as zero earnings. Thus, we also assign zero labor earnings if workers had gaps in their observed employment histories because the majority of the missing values are due to inactivity or early retirement.[17] We then calculate the total annual labor earnings (measured in 2010 Euros) for each worker by multiplying his or her daily wages by the total duration of all employment spells in that year.[18]

Although the employment and earnings data are highly reliable, because the BA collects this information for calculating social security benefits, the data have three minor limitations. First, the education variables are sometimes inconsistent and contain missing values.[19] To

[17] Although this approach is common in the literature, it may overstate the negative consequences of trade shocks, because workers who have gaps in their employment histories may instead have become civil servants or self-employed. Thus, to emphasize the robustness of our results, we additionally present results for which we excluded workers with gaps in their employment histories.
[18] We do not include earnings from employment data that cannot be observed for the entire observation period, e.g., marginal employment.
[19] As the BA does not need this information for administrative purposes, it records these variables with lower quality than the earnings and employment variables.

eliminate these inconsistencies and to impute the missing values of the education variables, we follow the standard approach of previous studies (e.g., Dustmann, Ludsteck, & Schönberg, 2009) and apply the imputation procedure of Fitzenberger, Osikominu, and Völter (2005).[20] Second, the earnings data are censored (top-coded) for high wage workers at the annual social security contribution ceiling, which applies to approximately 10 percent of all workers. To impute the missing upper tail of the wage distribution, we again follow the standard approach in the literature (e.g., Card, Heining, & Kline, 2013) and apply a two-stage stochastic imputation procedure.[21] Third, as a result of the regulations for data protection and server restrictions of the Institute for Employment Research (IAB), which provided us with the data, we only have access to a 52 percent sample of the target population for this study.

B. Skill Data and Specificity

We measure human capital specificity at the occupational level by approximating the transferability of skill bundles across occupations. We focus on occupational skill bundles because the literature on human capital specificity suggests that occupational skill bundles are more tied to workers' compensation than firm-, industry-, and even occupation-specific skills (Gathmann & Schönberg, 2010; Poletaev & Robinson, 2008).[22]

[20] Specifically, we perform an imputation in the style of the IP1 procedure described in Fitzenberger et al. (2005). If an individual is observed in multiple parallel spells in the same period, we assign all observations to the individual's highest education category. As a worker's highest education cannot decline over time, we then forward extrapolate an individual's highest educational degree to all following spells. Additionally, in case of missing data, we write an individual's degrees back to the age when these degrees are typically obtained (as observed in the data).

[21] In a first stage, we fit a series of Tobit models for each year and education group. In a second stage, we calculate the imputed values for each censored observation using the estimated parameters of the first-stage models plus a random draw from the associated (left-censored) distribution. The control variables contain the worker's gender, age, age2, a dummy for "older" individuals, tenure and tenure squared. We then use these imputed values for a second round of imputations, where we include each worker's average log wage in all other periods and the average annual wage of his current co-workers (leave-out means). If a worker is only observed once, we set his mean wage in all other years to the sample mean and include a dummy in the model. Similarly, we set the wage of the co-workers to the sample mean and include a dummy if a worker is the firm's only employee.

[22] Earlier studies suggested that industry and occupation-specific skills are more important for workers' wage development than firm-specific human capital (Gibbons, Katz, Lemieux, & Parent, 2005; Kambourov and Manovskii (2009); Neal (1995); Parent (2000).

More specifically, we use skill data from the BERUFENET database, an expert database and information portal of the German Federal Employment Agency (Bundesagentur für Arbeit, BA). The BERUFENET data, which are very similar to the U.S. O*NET data, contain information on the required skills, equipment used, working conditions, and required qualifications for all occupations in Germany. Since 2003, the BA has been building the BERUFENET for career guidance and job placement and has continuously updated the data. Thus we assume that workers possess the skills that experts consider essential for performing the required tasks in their occupation. To date, the data contain approximately 3,900 (8-digit) occupations (Dengler, Matthes, & Paulus, 2014).

To measure the skill requirements of occupations, BA experts collect data on occupational skill requirements and qualifications from training or study guidelines and from applications and job offers. Using this information, the experts assign a bundle of *core skills* (i.e., skills essential for performing the relevant tasks in an occupation) to each single occupation.[23] Thus, overall, the data contain information on approximately 8,000 different skill items. Table A1 in the Appendix gives an example by listing the core skills for the occupations "tool mechanic," "precision mechanic," and "construction carpenter."

Following Matthes and Vicari (2017), we used the BERUFENET data to calculate the distances between all pairs of occupational skill bundles in the German labor market by calculating the Euclidian distance between their respective skill vectors.[24] These distances depend on the total number of skills in each occupation, and the number of shared skills between two occupations. In the example in Table A1, the skill distance between tool- and precision mechanics is smaller than that between tool mechanics and construction carpenters, as tool

[23] The BA uses the German word "Kompetenzen" (competencies) for skills.
[24] Occupations are classified at the 3-digit level plus a one-digit indicator for (at most) four "requirement levels." These requirement levels represent the complexity of the tasks and the education level that is commonly required to work in the occupation. Together, these two dimensions result in 422 (3+1)-digit combinations and 88,831 pairwise distance measures.

mechanics share four out of their nine core skills with precision mechanics but only one skill with construction carpenters.

Gathmann and Schönberg (2010) and Poletaev and Robinson (2008), for example, have calculated similar distance measures and have directly used them to assess the transferability of skills between different occupations. However, for the purpose of our study, we calculated a weighted average skill distance from any one occupation to all other occupations in the labor market. This average distance represents our measure of specificity of an occupational skill bundle:

$$Spec_o = \sum_{p=1}^{N} dist_{op} * \frac{emp_p}{emp_{tot}} \tag{7}$$

where *dist*$_{op}$ is the skill distance between two occupations *o* and *p,* and $(\frac{emp_p}{emp_{tot}})$ are the relative employment shares of occupations to weight the skill distances by the number of alternative jobs. While the simple distance measures of previous studies only allowed assessing the transferability of skills between different occupations, our index measures the overall demand for the skill bundle of the respective occupation *o.*

Because the index of equation (7) takes into account that the specificity of workers' skills is endogenous to the usage of skills in the market, the index closely follows the theoretical concept of Lazear's skill weights approach. For example, an individual with a skill bundle that is used in only very few occupations might still be quite general if those few occupations demanding similar skills (including the worker's own) are large and offer a considerable number of jobs. As a result, our specificity measure correlates with the size of a worker's occupation, because the distance to jobs in the same occupation is zero. However, our measure does not simply reflect differences between small and large occupations. In fact, the correlation between the size of occupations and skills specificity is only moderate (Pearson correlation 0.55). Most of the variations stems from the variation of skill distances. Thus smaller occupations are not necessarily more specific than larger ones. For example, very small occupations, such as pharmacist, can be general, while large occupations, such as building construction worker, can be specific. Table A2 in the Appendix shows the five most specific and the five least specific occupations.

C. Trade Data

To measure trade shocks, we use trade data from the UN Commodity Trade Statistics Database (Comtrade). These data provide information on trade flows between more than 170 countries and contains detailed information on commodity types. To merge the trade data with our labor market data, we follow Dauth et al. (2014) who use a crosswalk from the UN Statistics Division that allows to link each product category in Comtrade (consisting of 1031 SITC rev. 2/3 product codes) to one of the NACE industries in our labor market data. This crosswalk allows to unambiguously assign 92 percent of all commodities to single industries. To calculate trade values for the remaining commodities, we use national employment shares from 1978 to calculate weighted averages of trade values across multiple industries. In line with Dauth et al. (2014), we drop all workers in industries related to the primary sector and fuel products, because these industries are subject to specific trade restrictions. These data restrictions leave us with detailed trade data on 97 NACE (WZ73) manufacturing industries.

V. Results

A. Descriptive statistics

Table 1 shows descriptive statistics used to analyze the differences in observable characteristics between workers with very specific skills and workers with very general skills. For this purpose, we have divided our sample into two subsamples. The first subsample contains the 33 percent of workers with the most general skills; the second one contains those 33 percent with the most specific skills. The third column shows the differences between both subsamples, and descriptive statistics for the entire sample appear in the fourth column of the table.

—Table 1 about here—

The first row reveals that average base year earnings of workers with the most specific skills are significantly larger than for workers with the most general skills. In 1990, workers with the most specific skills earned approximately 3,669 Euros (i.e., approximately eight percent) more than those with the most general skills. On one hand, more able workers may have self-selected into occupations with a more idiosyncratic demand for skills (see Neal, 1998 for a similar argument). On the other hand, workers with specific skills are more likely to earn above market wages, because they commonly share the returns to their investments in specific human capital with their employers (Becker, 1964). Thus, even in the absence of ability differences, human capital theory predicts that workers with specific skills should earn more than those with general skills (cf. Eggenberger et al., 2018). Moreover, the results reveal that workers with specific skills are more educated and somewhat less likely to have German citizenship.

Although the descriptive results of Table 1 suggest positive self-selection of workers with higher ability into occupations with more specific skills, the estimates of our interaction terms will still be consistent if workers' skill specificity and the unobserved heterogeneity (i.e., $Spec_0, \varepsilon_{it}$) are jointly independent of our instruments (see Section III). Unfortunately, we cannot empirically test whether this is true—just as we cannot test the validity of instruments in regular instrumental variable approaches.

However, we know that our main identification assumption is unlikely to hold if the workers in our sample would have chosen their occupations in anticipation of the development of trade in Germany. Thus, to support our identification assumption, Figure 1 shows the development of total imports and exports between the East (i.e., Eastern Europe, and China) and Germany between 1980 and 2000. The figure reveals that German trade with the East was negligible before the end of the 1980s. In 1990, German imports from and exports to the East suddenly increased, and the growth in trade persisted until 2000. For example, German exports to the East increased from approximately 18 billion Euros in 1990 to approximately 70 billion Euros in 2000. Imports increased at similar magnitudes. Thus, the data clearly indicates a shock in the development of trade after the fall of Iron Curtain that workers were unlikely to have been able to anticipate.

—Figure 1 about here—

Figure 2 shows the regional variation of workers' exposure to increasing imports and exports between 1990 and 2000 and the regional variation of workers' skill specificity in 1990. In more detail, Panel A and B show how exports and imports increased on average per worker across the different labor market regions of West-Germany. We created the measures for average trade exposure per worker by combining the trade data with the industrial structure of the labor market regions (see Section III). Between 1990 and 2000 imports increased on average by 2,958 Euros per worker and exports by approximately 2,675 Euros. However, both maps reveal considerable variation of exports and imports across regions. Moreover, although import and export exposure are strongly correlated across regions, the figure still reveals substantial variation between export and import-oriented regions. For example, the labor market region of Bremerhaven, at present a region with high rates of unemployment, was strongly exposed to import exposure (i.e., imports increased by approximately 2,700 Euros per worker) while exports increased by only approximately 470 Euros. In contrast, Bodensee, a region that has become famous for hosting many small and medium-sized tech-companies, experienced a similar increase in imports (3,600 Euros), but with approximately 5,150 Euros per worker a much stronger increase in exports.

—Figure 2 about here—

Panel C of Figure 2 shows the regional variation of workers' skill specificity in 1990. Although the figure reveals some regional variation in workers' skill specificity, only a few regions with an average skill specificity that lies above or below one standard deviation of the mean exist (note that we standardize our measure for skill specificity). Moreover, Figure 2 does not reveal a systematic correlation between regional trade exposure and workers' skill specificity. Indeed, the correlation between workers' skill specificity and import exposure is only 0.002 and between their skill specify and export exposure only -0.002.

Although Figure 2 reveals no systematic correlation between workers' skill specificity and trade exposure, workers' skill specificity may still correlate with our *instruments* for trade exposure. If this were true, our main identification assumption, i.e., that $(Spec_0, \varepsilon_{it})$ is jointly independent from our instruments, would be violated. In more detail, if workers' skill specificity correlates with both *the error term* and *our instruments* $(Spec_0, \varepsilon_{it})$ cannot be jointly independent from our instruments. As $(Spec_0, \varepsilon_{it}) \neq 0$ is very likely, orthogonality between workers' skill specificity and our instruments for trade becomes a necessary condition.[25]

Therefore, Table 2 provides the results from a regression of workers' skill specificity on our instruments for trade exposure. Column I shows the results without control variables, and

[25] Note that orthogonality between workers' skill specificity and our instruments is not a sufficient condition, because even if $Spec_0$ does not correlate with our instruments $(Spec_0, \varepsilon_{it})$ may still jointly depend on them. As already mentioned, we cannot empirically test the sufficient condition.

column II shows the results with control variables (as described in Section III). For completeness, columns III and IV also show regressions of the workers' skill specificity on our measures of regional trade exposure. All coefficient estimates are very small (i.e., no coefficient estimate is large than 0.01 standard deviations of the dependent variable) and not significantly different from zero at conventional levels.

—Table 2 about here—

B. Main results: 2SLS estimates

This section shows the estimates of the relationship between earnings effects of trade shocks and workers skill-specificity according to variants of the two stage least square model (2SLS) presented in Section III. The estimations in Table 3 stem from a sample that followed workers between 1990—the base year—and 2000. The table reports the estimated effects of trade exposure on the cumulative labor earnings between 1990 and 2000. Thus, the job (or the occupation, respectively), and region of the base year 1990 determine the skill specificity and the trade flows that we assign to each worker in this sample. To instrument trade exposure of German industries we use trade exposure from other high-income countries.

—Table 3 about here—

The first column of Table 3 starts with the most parsimonious specification. The specification only includes our core variables of regression equation (6) and the workers' earnings in the base year to account for the workers' unobserved heterogeneity before the trade shock. The isolated coefficient estimate of import exposure is negative, and the isolated one for export exposure is positive. The coefficient estimates of the interaction terms—our estimates of main interest—are precisely estimated at conventional significance levels and point in the expected direction, i.e., the coefficient estimate for the interaction term between workers' skill specificity and import exposure is negative, and the one between workers' skill specificity and export exposure is positive.

The second specification adds further firm-level controls (i.e., industry categories, firm size) and region-specific fixed effects, and the third one adds individual controls, (i.e., education, age, and a dummy variable for German nationality). All control variables are measured in the base year to avoid including bad instruments in the sense of Angrist and Pischke (2009). Adding firm-level controls and region-specific fixed effects barely changes the results, while the individual control variables reduce the size of the coefficient estimates quite a bit. However, all results remain meaningful and significant at conventional levels. Moreover, the lower part of the table reports the Sanderson-Windmeijer F-statistics for all three 2SLS specifications. These F-statistics allow to assess the power of instruments in regressions with more than one endogenous variable. All F-values are large and reveal that our instruments have strong predictive power for all specifications.

Overall, our results are consistent with previous evidence, because they show that workers with specific skills suffer more from *negative demand shocks*. However, they go beyond the literature by showing that workers with specific skills profit more from *positive demand shocks* than those with general skills. For example, the full specification (Column III) shows that workers with rather specific skills who have a skill-specificity of approximately one standard deviation above the mean ($Spec_0 = 1$, e.g., medical-technical assistants have a skill-specificity of 1.02) lose approximately 12 ($-0.087 - 0.031 \cdot (1) \approx -0.118$) percent of their (base-year) income over a period of 10 years when imports increase by 1,000 Euros. However, they gain approximately 18 percent when exports increase by 1,000 Euros. In contrast, workers with rather general skills with a skill-specificity of approximately one standard deviation below the mean ($Spec_0 = -1$, e.g., sales personnel have a skill-specificity of approximately -1.09) only lose approximately six percent ($-0.087 - 0.031 \cdot (-1) \approx 0.056$) if imports increase by a 1,000 Euros, but they also only gain approximately six percent when exports increase. Thus, although workers with specific skills suffer on average more from import shocks than those with general skills, they profit more from rising exports.

Throughout our observation period imports increased on average by 2,958 Euros per worker and exports by 2,675 Euros. Thus, over the entire observation period, our estimates imply a positive average net effect of rising trade exposure that amounts to approximately 12 percent of their average base income for workers with very specific skills ($Spec_0 = 1$) and approximately minus two percent for workers with very general skills. In other words, our results imply that workers with very specific skills profit on average enough from rising exports to overcompensate the negative consequences of increasing import exposure.

However, our results also imply that the effects of increasing trade exposure are more heterogeneous for workers with specific skills than for those with general skills. To visualize this effect heterogeneity, Figure 3 shows the distribution of the conditional net effects of trade evaluated at the average regional trade intensities. The upper panel shows the distribution of conditional average net effects for workers with very specific skills (setting $Spec_0 = 1$) and the lower panel for workers with very general skills (setting $Spec_0 = -1$). The figure reveals that the mass of the distribution for workers with specific and general skills lies in the area between 0 and 0.1, implying that conditional average net effects are mostly positive for both groups. This result is in line with previous evidence showing that the positive effects of increasing exports overcompensated the negative ones from increasing imports in Germany (Dauth et al., 2014).

—Figure 3 about here—

Nevertheless, the distribution of average net effects is much wider for workers with very specific skills than for those with very general skills. Again, the comparison of the two extreme labor market regions of Bremerhaven, were imports increased by 2,700 Euros and exports by 470 Euros, and Bodensee, were imports increased by 3,600 Euros and exports by 5,150 Euros provides an intuitive example. The conditional average net effect for workers who were located in the labor market region of Bremerhaven in 1990 amounts to -28 percent (of the base-year income) for workers with very specific skills and to -18 percent for workers with very general skills. In contrast, workers who were located in the Bodensee region in 1990 were exposed to an average net effect of approximately 50 percent (of the base-year income) for workers with specific skills but only of approximately 20 percent for workers with general skills.

This section concludes with the fourth specification showing the standard OLS results (including all control variables), and the fifth presenting the results of the reduced form. Most OLS estimates are insignificant (excluding the interaction term between exports and workers' skill-specificity) and much smaller than the 2SLS estimates.[26] In contrast, the reduced form parameters are precisely estimated at conventional levels.[27] As in previous papers using this type of identification strategy, these results suggests that measurement error and simultaneity bias associated with German industry supply and demand shocks attenuate the naïve OLS estimates towards zero (Autor et al., 2013; Dauth et al., 2014; Helm, 2019).

C. *Dynamic effects*

This subsection analyzes how the effects of trade exposure evolved over time. Therefore, Table 4 shows results from regression equation (6) for ten different sub-periods. The first sub-period ranges from 1990 to 1991, the second one from 1990 to 1992, and so on until

[26] Although our results show a quite large inflation of our 2SLS estimates, such differences in magnitude are quite common in the literature (Autor, Dorn, & Hanson, 2013; Helm, 2019).
[27] Only the coefficient estimate for the isolated effect of imports is at the margin of being significant at the 10 percent level.

the tenth period that ranges from 1990 to 2000 (thus replicating our results form Table 3). To provide a more intuitive presentation of the regression results, Figure 4 visualizes the results by showing the conditional trade effects evaluated at the average increase of trade exposure in the respective period. The left panel shows the results for workers with very specific skills ($Spec_0 = 1$), and the right panel shows the results for workers with very general skills ($Spec_0 = -1$).

—Table 4 and Figure 4 about here—

The dashed blue lines represent the predictions for import exposure and the dashed red lines those for export exposure. The light gray bars represent the average increases in exports throughout the respective periods, and the dark gray bars the average increases of imports. For example, between 1990 and 1991 (first sub-period) export exposure increased by approximately 440 Euros per worker (first light gray bar in the left panel). As a result, export exposure increased the earnings of workers with very specific skills on average by approximately 1.6 percent (of the base-year earnings; $0.062 \cdot 0.44 + 0.01 \cdot 0.44 \approx 0.016$) throughout the first year after 1990. In contrast, throughout the entire period between 1990 and 2000 exports increased by approximately 2,675 Euros per worker (last light gray bar in the left penal of Figure 3) such that the cumulated earnings effect of export exposure amounts to approximately 58 percent (of the base year earnings; $0.145 \cdot 2.675 + 0.07 \cdot 2.675 \approx 0.575$) over the entire observation period of 10 years (or on average 5.8 percent per year).

Figure 4 reveals two important insights: first, the cumulated earnings effects presented in Table 3 are not a consequence of short-term transitory earnings losses. Instead, the earnings effects appear to have evolved over time with a particularly strong increase in the mid-1990s. Second, in the early 1990s, differences of trade effects between workers with specific and general skills were modest but increased substantially afterwards. These two results suggest that adjustment processes evolved rather slowly over time—at least, for the incumbent workers in our sample. However, the next subsection sheds additional light on these adjustment processes by analyzing the heterogonous effects of trade for long- and short-tenured workers and for young and old workers.

D. Tenure, age, and adjustment processes

If workers' skill specificity indeed determines the heterogeneity of trade effects, we should find stronger effects for workers with long tenure than for those with short tenure. Long-tenured workers who had more time to invest in the specific (idiosyncratic) skill-bundles required by their current job should be more productive in performing these skills. As a result, long-tenured workers with specific skills should become more valuable for firms that demand similar skill bundles when exports increase. On one hand, specific skills are by definition scarce such that employers can hire fewer comparable workers on the labor market. On the other hand, retraining low-tenured workers so that they achieve the productivity level of the long-tenured workers is costly and time-intensive. Thus, long-tenured workers with larger investments in specific skills should gain larger returns from increasing exports, because, as predicted by our model, their outside options should improve relatively more. However, long-tenured workers with specific skills should also suffer more from negative demand shocks, because their outside options decline relatively more with increasing imports. Moreover, long-tenured workers should lose larger rents to investments in specific skills when they are laid off in response to increasing import competition.

—Table 5 about here—

To analyze this argument, the first two columns of Table 5 replicate our main estimations from regression equation (6) for workers who had at least five years of tenure in the base year (first column) and for workers who had less than five years of tenure (second column). For long-tenured workers, the results reveal large and significant coefficient estimates for the two interaction terms between workers' skill specificity and the trade exposure variables. The absolute values of both coefficient estimates are even slightly larger than in Table 3. In contrast, for workers with less than five years of tenure, the interaction terms have small coefficient estimates that are not significantly different from zero. These results are consistent with a model in which workers' skill specificity determines the magnitude of returns from positive, and penalties from negative demand shocks. If we would not have found such a relationship between workers' tenure and the trade effects, our main results would have been likely to reflect other industry or worker-specific effects that are unrelated to their level of skill-specificity.

The third and the fourth column of Table 5 replicate our main estimations for older workers, at least 40 years old, and for younger workers, younger than 40 years. For older workers the results reveal precisely estimated coefficient estimates for the interaction terms between workers' skill specificity and trade exposure that are consistent with our main results. In contrast, the results for younger workers reveal only a small and insignificant negative coefficient estimate for the interaction term between workers' skill specificity and import exposure, but a positive significant coefficient estimate for the interaction term between skill specificity and increasing export exposure. These results suggest that older workers have higher adjustment costs than younger ones. On average, younger workers with specific skills even appear to be able to collect the increasing returns from increasing exports without suffering from the losses from increasing import exposure.

Overall, the results from Table 5 not only validate our main results, but they also suggest that the relationship between workers' skill specificity and increasing international trade should vanish in the long run. On one hand, more and more old and long-tenured workers with high adjustment costs will leave the labor market. On the other hand, more and more young and short-tenured workers will enter the market, driving the relationship between workers' skill-specificity and trade exposure towards zero.

To analyze this argument, the fifth column of Table 5 replicates our main specification for the period between 2000 and 2010. In more detail, the sample for column five contains workers who were between 22 and 54 and held a stable full-time job in 2000. We follow these workers until 2010. Thus the sample contains workers who have either experienced the consequences of increasing international trade with low-wage countries (Eastern Europe) for a decade or have entered the labor market throughout a period when these consequences were already visible to them.

As a result, we should expect that the relationship between workers' skill specificity and the labor market effects of trade is weaker than in our main specification. Indeed, the results for the period between 2000 and 2010 (column 5) reveal much smaller interaction terms than the results of our main specification. While the interaction term between export exposure and workers' skill specificity is not significantly different from zero, the interaction term between import exposure and workers' skill specificity is even positive and marginally significant. This result is consistent with a model in which low ability workers select out of jobs that are exposed to rising import competition.

The isolated coefficient estimates of export and import exposure point in the same direction as the isolated coefficient estimates of our main specification and are precisely estimated at conventional levels. However, they are much smaller than those for our main specification. This result is consistent with the employment results of Dauth et al. (2014) who found that China's entry to the WTO in 2001 only had a modest impact on the German labor market, because Germany already imported labor intensive goods from Eastern European countries throughout the 1990s that were only gradually replaced by Chinese imports throughout the 2000s. This result stays in sharp contrast to the evidence from the U.S. where China's entry to the WTO had a substantial impact on the labor market.

E. Subsamples: 2SLS estimates

This subsection shows the results of four different subsamples to address four concerns that might arise when interpreting our main results. First, following previous studies such as Autor et al. (2013) our main regressions included all workers—in particular, also those workers who do not work in the manufacturing sector. However, our trade measures only capture the trade of tangible goods from the manufacturing sector and set trade for other sectors to zero. Thus, our trade measures may have by construction a lower direct effect on workers outside the manufacturing sector than on workers inside the manufacturing sector. One concern may be that workers who do not work in the manufacturing sector are also less likely to work in occupations with a high demand for specific skills. If this were true, our results might capture that trade has a lower impact on workers outside the manufacturing sector who simply happen to have fewer specific skills. Therefore, the first specification of Table 6 shows the results for a sample that only includes workers in the manufacturing industry. The results remain very similar to our main results in Table 3. However, as a result of the smaller sample size the coefficient estimates are somewhat less precisely estimated.

—Table 6 about here—

Second, Table 1 reveals that workers with specific skills are better educated than workers with general skills, such that our results may capture unobserved ability differences—even after accounting for detailed worker and firm characteristics. Therefore, the second specification presents results from a subsample that only includes workers whose highest degree is an apprenticeship degree. Apprenticeship graduates are a very homogeneous group of workers, because very few of them have obtained their permission to study in a university or dropped out of school (Dustmann & Meghir, 2005). Moreover, apprenticeship training curricula precisely define the training content for apprenticeship training programs in Germany, and firms and vocational schools have to obey these training curricula to receive their training permission. Thus, apprenticeship graduates possess similar skills within occupations. As our information from the BERUFENET largely stems from these training curricula, our measure for workers' skill specificity is less likely to suffer from measurement error for apprenticeship graduates than for other workers. The third specification shows that the results for the sample of apprenticeship graduates remain very similar to our main results. Thus, apprenticeship graduates do not seem to be more or less affected by international trade than workers with other types of education.

Third, our main estimations are based on a sample of only men. Running a separate regression for women may be informative for proving the robustness of our results. Therefore, the third specification shows the results for a subsample of women. Again, the results remain similar to those of our main specification for men, although for women, the negative effects of import exposure seem to be somewhat larger—and the positive effect of export exposure somewhat smaller. This could be explained by the fact that women are less likely to choose the most specific occupations.

Fourth, for our main regression sample, we assigned zeros to missing values in our earnings data—unless workers died or left the country. Although most of these missing values are likely to correspond to periods of non- or unemployment, workers may also have missing data if they become self-employed or civil servants. In other words, assigning zero earnings to missing values introduces some measurement error. Therefore, the last specification only includes workers for whom we have earnings information throughout the entire period between

1990 and 2000.[28] As expected, the coefficient estimates of this last specification are much more precisely estimated than the coefficient estimates from our main specification. However, the results remain qualitatively the same, suggesting that international trade has not led to long periods of non- or unemployment in Germany.

VI. Conclusions

This paper analyses how increasing international trade has influenced the labor market careers of workers with specific and general skills. Accelerating globalization and increasing international trade has led to a substantial reallocation of jobs. Studies showing that workers with specific skills experience larger earnings losses and longer periods of unemployment might thus suggest that investments in specific human capital have become a dangerous endeavor in a globalized world—particularly, as workers and firms commonly share the investments into specific skills with their employers.

Although this paper shows that workers with specific skills experience larger earnings losses from negative demand shocks induced by increasing import competition, workers with specific skills also appear to profit more from positive demand shocks from rising exports. Indeed, in Germany, workers with specific skills experience on average larger positive net effects than those with general skills, because the returns to increasing exports overcompensate their losses from increasing import competition. However, international trade appears to produce more inequality among workers with specific skills than among those with general skills.

[28] We emphasize here that this is a selective sample of workers who manage to remain employed throughout the entire period.

Overall, our results demonstrate that workers' skill specificity is an important determinant for the labor market consequences of increasing international trade and that the relationship between increasing international trade and workers' skill specificity appears to contribute to the rising inequality within education groups observed in many developed countries throughout the last decades.

Moreover, our results provide important insights for policy makers who want to reform education policies to face future challenges of a globalized world. Our findings suggest that the combination of single skills in training programs, i.e., the skill bundles prescribed by educational curricula, should be an important consideration when designing any training curriculum, vocational or academic. Holding a specific skill bundle appears to be riskier than having a general skill bundle, but it can also turn out to be an advantage and shield workers in export-oriented industries from labor market competition.

Figures in the text

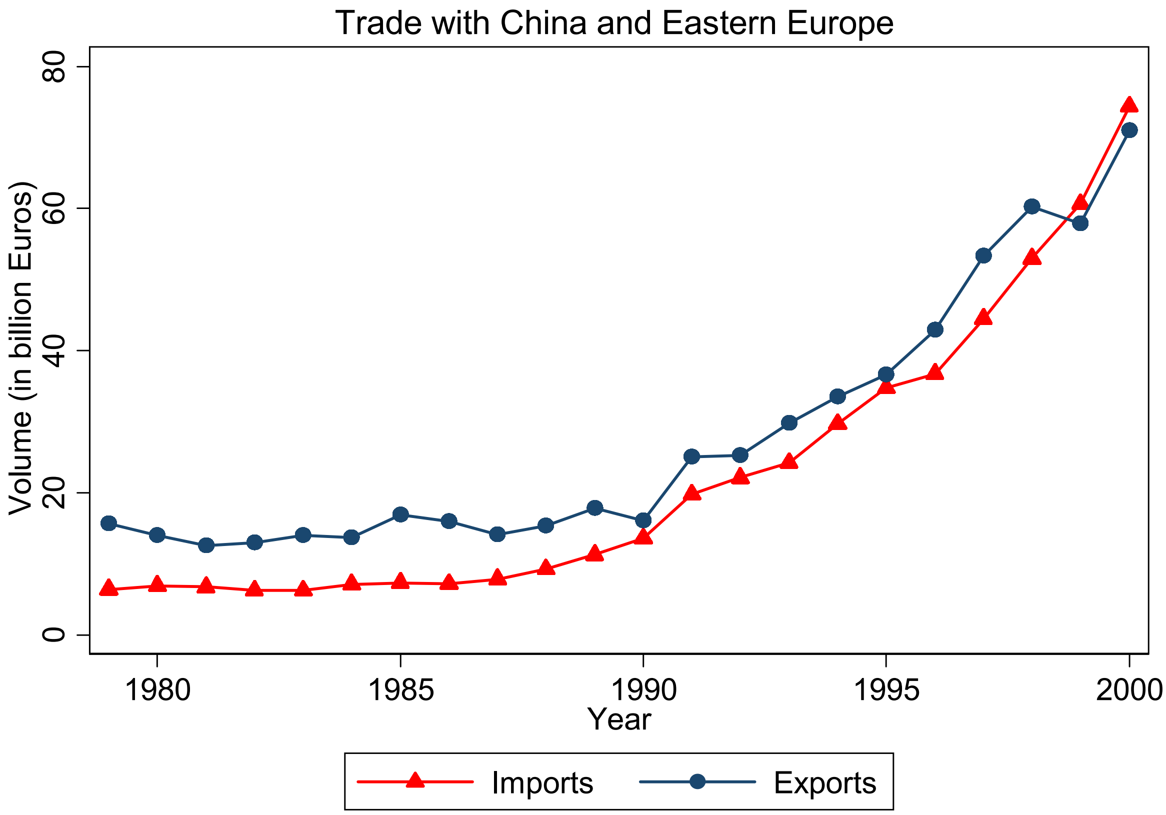

Figure 1: German trade volumes in billion Euros

Notes: The figures show the development of imports and exports in commodities from Germany to Eastern Europe and China (excluding goods assigned to the primary sector)

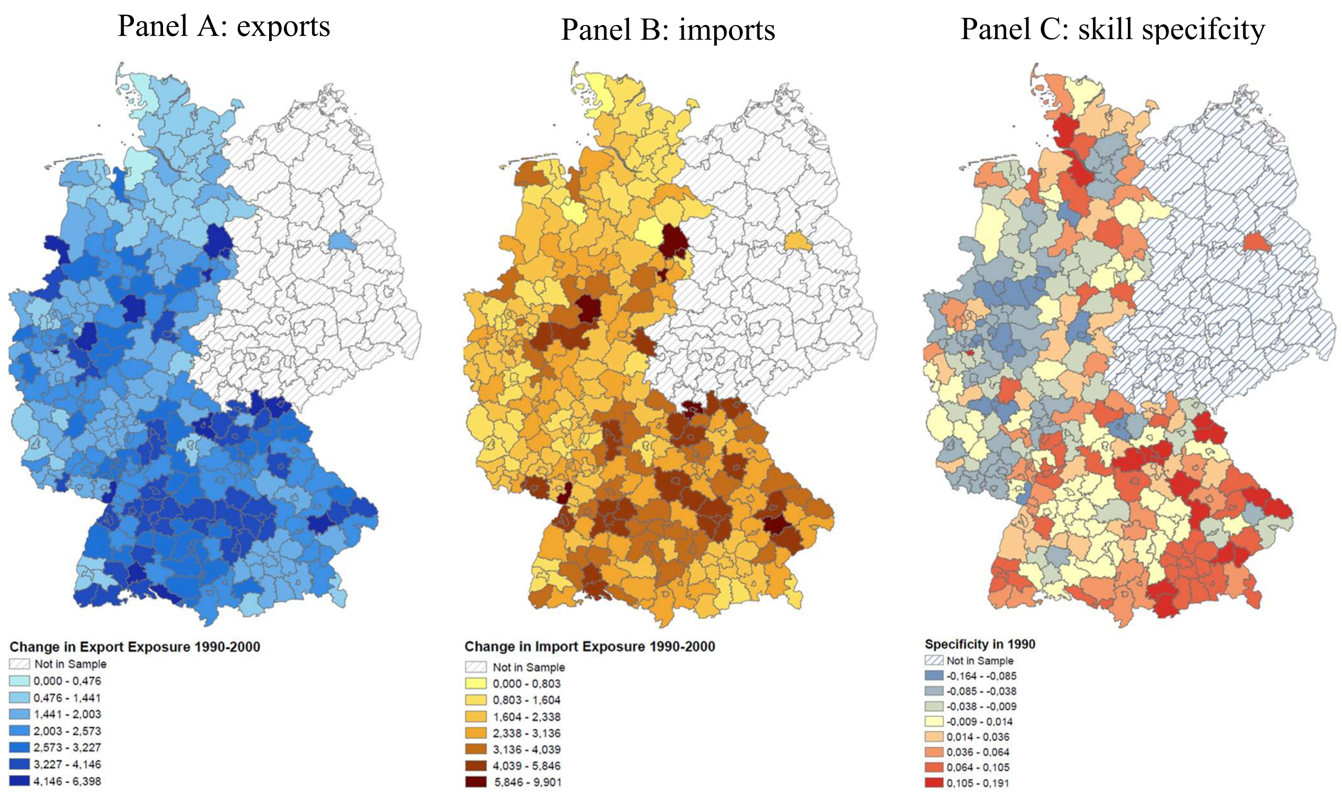

Figure 2: Change in regional import and export exposures per worker (1990-2000)

Notes: Increase in imports (Panel A) and exports (Panel B) from China and Eastern Europe, 1990-2000 in 1000€ per worker. Panel C: distribution of average occupational specificity (standardized).

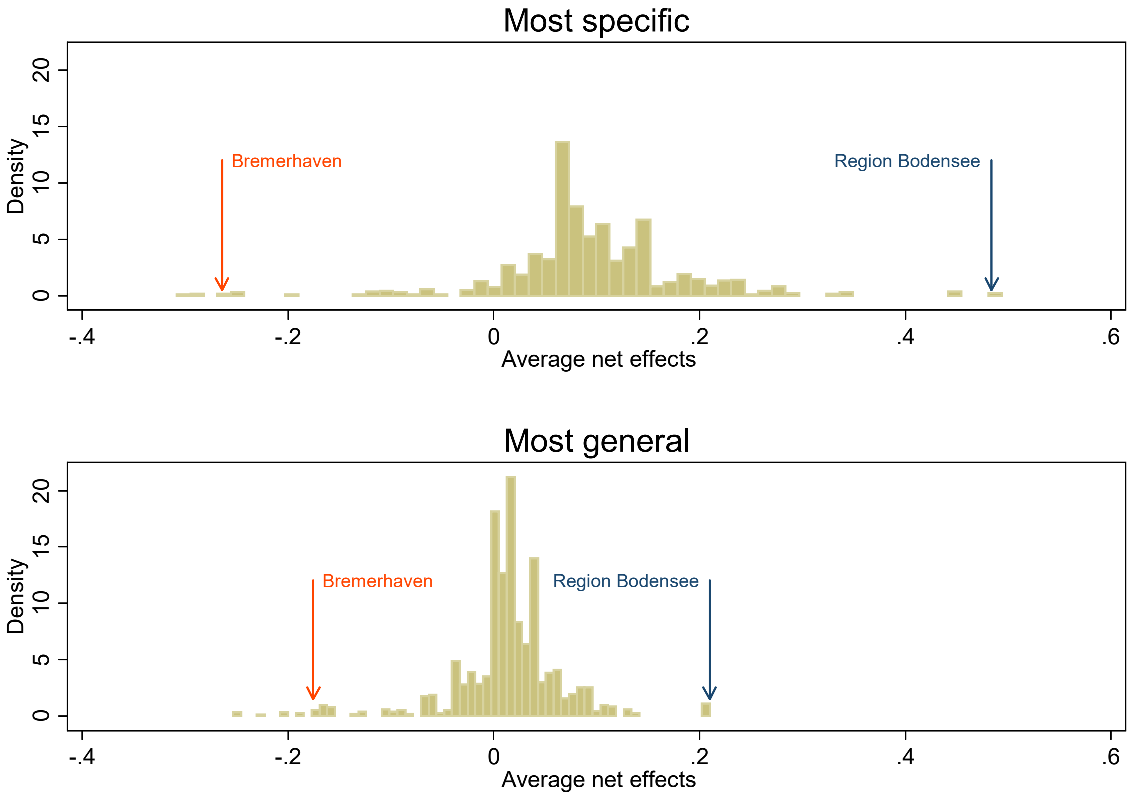

Figure 3: Distribution of conditional average net earnings effects of trade exposure

Notes: The figures show distribution of German labor market regions with average conditional net earnings effects of trade exposure. The upper panel shows the effects for workers with specific skills (i.e., a standardized specificity of plus one) and the lower panel the effects for workers with general skills (i.e., a standardized specificity of minus one).

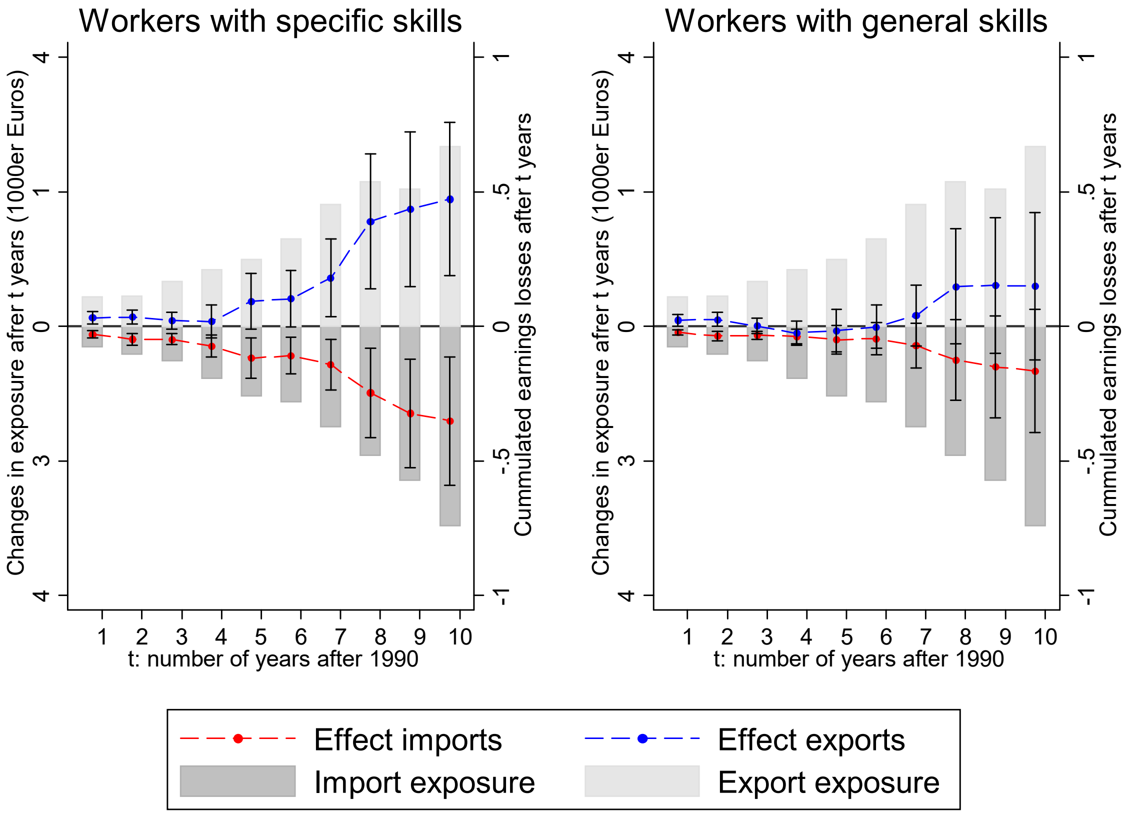

Figure 4: Dynamic of conditional net earnings effects of trade exposure over time for workers with specific and general skills

Notes: The gray bars show the increase in the average trade exposure per worker between 1990 (the base-year) and the year 1990 + t (dark gray: imports, light gray: exports). The red and blue dots represent the cumulated earnings losses due to the trade increase (red: imports; blue: exports) on workers earnings, calculated as the change in the trade exposure up to year t (represented by the gray bars) times the estimated marginal effect from Table 4. The left panel shows the effects for a worker with specific skills (i.e., a standardized specificity of plus one) and the right panel the effects for a worker with general skills (i.e., a standardized specificity of minus one).

Tables in the text

Table 1: Descriptive Statistics Base Year 1990, by Specificity

	Base Year 1990			
	(1) Most Specific	(2) Least Specific	(3) Difference (2)-(3)	(4) All Workers
Earnings base year (in EUR)	48,834.5	45,165.2	3669.233***	45,380.5
	(32,077.6)	(25,896.4)	(64.276)	(27,534.9)
Apprentice (dummy)	0.712	0.814	-0.102***	0.780
	(0.453)	(0.389)	(0.001)	(0.414)
German (dummy)	0.918	0.916	0.002***	0.909
	(0.274)	(0.278)	(0.001)	(0.287)
Age (years)	38.27	37.88	0.395***	37.93
	(9.301)	(9.465)	(0.021)	(9.428)
N	432,876	398,489		1,291,210

Notes: The table summarizes observed characteristics of the workers in the sample in the base year 1990, separately for the 33 percent of workers who work in the occupations with the most specific skill demand and the 33 percent of workers who work in the occupations with the least specific skill demand. The third column reports the differences between both groups, along with t-tests. The last column reports the statistics for all workers in our main sample. Levels of significance: *** p<0.01.

Table 2: Workers' skill specificity and instrumental variables

	(1)	(2)	(3)	(4)
Instrument: imports	0.001	-0.001		
	(0.001)	(0.001)		
Instrument: exports	0.005	0.007		
	(0.004)	(0.005)		
Import exposure			0.009	0.007
			(0.006)	(0.006)
Export exposure			-0.012	-0.010
			(0.010)	(0.010)
Base year earnings	No	Yes	No	Yes
Federal states	No	Yes	No	Yes
Firm characteristics	No	Yes	No	Yes
Individual-level controls	No	Yes	No	Yes
R-squared	0.000	0.023	0.000	0.023
Clusters	205	205	205	205
Number of observations	1291210	1291210	1291210	1291210

Notes: Dependent variable is the standardized measure of workers skill specificity. Results report coefficients from OLS regressions. Individual control variables include dummies for gender, nationality, three tenure groups, and seven age groups. Controls for firm characteristics include five plant size groups and four broad industry groups. Regional controls include fixed effects for federal states. Robust standard errors (in parenthesis) are clustered on start-of-period labor market region.

Table 3: Main results: trade exposure and individual earnings

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) OLS	(5) Reduced form
Import exposure	-0.067*	-0.067	-0.087**	-0.032	
	(0.039)	(0.046)	(0.039)	(0.025)	
Export exposure	0.142***	0.090*	0.116**	0.023	
	(0.054)	(0.054)	(0.050)	(0.039)	
Import × specificity	-0.046***	-0.050***	-0.031***	-0.002	
	(0.016)	(0.016)	(0.012)	(0.008)	
Export × specificity	0.081***	0.087***	0.061***	0.024*	
	(0.025)	(0.025)	(0.017)	(0.013)	
Instruments					
Imports					-0.013**
					(0.006)
Exports					0.024
					(0.015)
Imports × specificity					-0.004**
					(0.002)
Exports × specificity					0.020***
					(0.007)
Base year earnings	Yes	Yes	Yes	Yes	Yes
Federal states	No	Yes	Yes	Yes	Yes
Firm characteristics	No	Yes	Yes	Yes	Yes
Individual controls	No	No	Yes	Yes	Yes
Sanderson Windmeijer F-stat					
Import	137.905	121.145	121.179		
Export	126.182	132.470	132.057		
Imports × specificty	171.844	163.622	163.522		
Imports × specificty	129.920	133.034	133.004		
P-val. of joint sig.					
Imports	0.013	0.004	0.003	0.429	0.008
Exports	0.003	0.001	0.000	0.192	0.005
R-square	0.018	0.002	0.003	0.141	0.141
Clusters	205	205	205	205	205

Notes: Dependent variable: Cumulated earnings (normalized by base year income). Cumulated earnings are defined as the sum of total income from employment during the decade divided by the base year income. Individual control variables include dummies for gender, nationality, three tenure groups, and seven age groups. Controls for firm characteristics include five plant size groups and four broad industry groups. Regional controls include fixed effects for federal states. All first stage regressions include the same set of control variables as the corresponding second stage. Robust standard errors (in parenthesis) are clustered on start-of-period labor market region. Levels of significance: * p<0.1; ** p<0.05; *** p<0.01.

Table 4: Dynamic effects - expanding panel estimations

	(1) 90-91	(2) 90-92	(3) 90-93	(4) 90-94	(5) 90-95	(6) 90-96	(7) 90-97	(8) 90-98	(9) 90-99	(10) 90-00
Import exposure	-0.087***	-0.101***	-0.080***	-0.071***	-0.082***	-0.069**	-0.072**	-0.097**	-0.104**	-0.087**
	(0.019)	(0.024)	(0.017)	(0.020)	(0.028)	(0.027)	(0.028)	(0.040)	(0.042)	(0.039)
Export exposure	0.062**	0.066**	0.017	-0.004	0.039	0.039	0.061*	0.125**	0.145**	0.116**
	(0.026)	(0.029)	(0.021)	(0.029)	(0.043)	(0.033)	(0.033)	(0.052)	(0.064)	(0.050)
Import × specificity	-0.012***	-0.015**	-0.015**	-0.023**	-0.033**	-0.028**	-0.024**	-0.032**	-0.038***	-0.031***
	(0.004)	(0.006)	(0.007)	(0.011)	(0.016)	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)
Export × specificity	0.010**	0.010	0.015*	0.026**	0.054***	0.040**	0.039**	0.056***	0.070***	0.061***
	(0.004)	(0.008)	(0.008)	(0.013)	(0.020)	(0.016)	(0.016)	(0.019)	(0.023)	(0.017)
Base year earnings	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Federal states	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sanderson-Windmeijer F-stat										
Import	29.894	28.962	43.706	55.434	30.118	89.241	135.287	104.942	82.259	121.179
Export	9.918	39.846	51.926	67.662	39.978	107.919	127.729	73.626	74.284	132.057
Imports × Specificity	15.195	21.343	29.445	40.220	17.631	76.328	126.934	118.362	117.373	163.522
Imports × Specificity	8.853	62.105	37.237	77.131	27.897	211.045	222.004	95.528	90.934	133.004
P-value of joint significance										
Imports	0.000	0.000	0.000	0.002	0.008	0.005	0.010	0.007	0.001	0.003
Exports	0.007	0.033	0.168	0.094	0.024	0.037	0.026	0.003	0.002	0.000
R-square	-0.000	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.003	0.003
Clusters	205	205	205	205	205	205	205	205	205	205
Number of observations	1291210	1291210	1291210	1291210	1291210	1291210	1291210	1291210	1291210	1291210

Notes: The table repeats our main estimation for different time periods (all starting in 1990), i.e., 1990-1991, 1990-1992 and so on. Dependent variable: Cumulated earnings (normalized by base year income). Cumulated earnings are defined as the sum of total income from employment during the respective time period divided by the base year income. 2SLS Regressions. Individual control variables include dummies for gender, nationality, three tenure groups, and seven age groups. Controls for firm characteristics include five plant size groups and four broad industry groups. Regional controls include fixed effects for federal states. All first stage regressions include the same set of control variables as the corresponding second stage. Robust standard errors (in parenthesis) are clustered on start-of-period labor market region. Levels of significance: * p<0.1; ** p<0.05; *** p<0.01.

Table 5: Subsamples by age, tenure and period 2000-2010

	(1) Tenure >= 5	(2) Tenure < 5	(3) Age >= 40	(4) Age < 40	(5) Period 2000-2010
Import exposure	-0.091**	-0.083	-0.019	-0.147***	-0.025**
	(0.040)	(0.053)	(0.049)	(0.043)	(0.013)
Export exposure	0.121**	0.101	0.039	0.198***	0.034***
	(0.051)	(0.070)	(0.070)	(0.053)	(0.011)
Import × specificity	-0.035***	0.007	-0.040***	-0.015	0.015*
	(0.012)	(0.037)	(0.014)	(0.015)	(0.008)
Export × specificity	0.062***	0.032	0.054**	0.059***	0.003
	(0.018)	(0.050)	(0.023)	(0.020)	(0.006)
Base year earnings	Yes	Yes	Yes	Yes	Yes
Federal states	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Sanderson-Windmeijer F-stat					
Import	120.113	168.899	116.383	125.188	75.263
Export	133.578	122.806	131.319	131.215	45.624
Imports × Specificity	162.867	188.760	164.501	162.310	46.497
Imports × Specificity	132.493	156.538	133.020	133.724	42.485
P-value of joint significance					
Imports	0.002	0.294	0.011	0.003	0.002
Exports	0.000	0.254	0.012	0.000	0.009
R-square	0.003	0.004	0.001	0.004	0.003
Clusters	205	205	205	205	205
Number of observations	1174428	116782	526307	764903	1504375

Notes: Dependent variable: Cumulated earnings (normalized by base year income). Cumulated earnings are defined as the sum of total income from employment during the decade divided by the base year income. 2SLS Regressions. Individual control variables include dummies for gender, nationality, three tenure groups, and seven age groups. Controls for firm characteristics include five plant size groups and four broad industry groups. Regional controls include fixed effects for federal states. All first stage regressions include the same set of control variables as the corresponding second stage. Robust standard errors (in parenthesis) are clustered on start-of-period labor market region. Levels of significance: * p<0.1; ** p<0.05; *** p<0.01.

Table 6: Trade exposure and individual earnings (subsample analysis)

	(1) Manufacturing	(2) Apprenticeship	(3) Women	(4) Non-zeros
Import exposure	-0.094*	-0.049	-0.120***	-0.206***
	(0.054)	(0.032)	(0.041)	(0.056)
Export exposure	0.151**	0.067	0.066	0.239***
	(0.069)	(0.044)	(0.045)	(0.065)
Import × specificity	-0.032	-0.033***	-0.049***	-0.031***
	(0.022)	(0.010)	(0.016)	(0.012)
Export × specificity	0.068***	0.054***	0.056**	0.061***
	(0.026)	(0.017)	(0.023)	(0.016)
Base year earnings	Yes	Yes	Yes	Yes
Federal states	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Individual-level controls	Yes	Yes	Yes	Yes
Sanderson-Windmeijer F-stat				
Import	100.575	120.328	175.017	175.017
Export	155.882	129.291	142.449	142.449
Imports × Specificity	97.879	162.722	186.127	186.127
Imports × Specificity	127.971	130.481	153.923	153.923
P-value of joint significance				
Imports	0.100	0.001	0.000	0.000
Exports	0.001	0.001	0.036	0.000
R-square	0.000	0.004	0.005	0.003
Clusters	205	205	205	205
Number of observations	549’947	1’006’903	663’765	949’809

Notes: Dependent variable: Cumulated earnings (normalized by base year income). Cumulated earnings are defined as the sum of total income from employment during the decade divided by the base year income. 2SLS Regressions. Individual control variables include dummies for gender, nationality, three tenure groups, and seven age groups. Controls for firm characteristics include five plant size groups and four broad industry groups. Regional controls include fixed effects for federal states. All first stage regressions include the same set of control variables as the corresponding second stage. Robust standard errors (in parenthesis) are clustered on start-of-period labor market region. Levels of significance: * p<0.1; ** p<0.05; *** p<0.01.

Additional Figures and Tables

Table A1: Skill bundles, examples (simplified)

Skill	Tool mechanic	Precision mechanic	Construction Carpenter
Work according to technical drawings	x	x	
CNC-programming	x		
Precision engineering	x	x	
Mold making	x		
Machine guidance	x	x	x
Metrology	x	x	
Fixture construction	x		
Thermal treatment	x		
Tool making	x		
Mechanical engineering		x	
Calibrating		x	
Mounting			x
Planning			x
Carpentry			x
Timbering			x
Sawing			x
Sound insulation			x
Stair construction			x
Plastering			x

Notes: Examples of skills (core competencies) listed in BERUFENET.

Table A2: Top 5 most specific and general occupations (1990)

Most General		
Job description	KldB	Specificity
Commercial employee	714-2	0.8540
Sales assistant for retail services	621-2	0.9224
Management assistant	612-2	0.9283
Mechanical engineering occupations	251-2	0.9313
Metalworking occupations	242-2	0.9355
Most Specific		
Job description	KldB	Specificity
Fishing	114-2	0.9999
Acting, dance and movement art	942-3	0.9996
Equine manager	113-2	0.9995
Vehicle guidance in air traffic	523-3	0.9994
Animal husbandry professions	833-4	0.9993

Notes: The table shows the five most general and the five most specific occupations, along with their KldB 2010 identifier and the (non-standardized) specificity measure.

Appendix A: Expected value of λ

In this section, we derive an expression for the highest expected value of λ with N independent draws, which we use in section II.

Let $f_\lambda(\lambda)$ denote the probability density function and $F_\lambda(\lambda)$ the cumulative density function of the random variable λ. Consider N independent draws of λ and let *Y* denote the highest of these N draws, i.e., $Y = \max(\lambda_1, \lambda_2, \ldots, \lambda_N)$. The max of these N independent draws can be written as (see e.g., Paarsch & Golyaec, 2016):

$$E(Y) = \int_{-\infty}^{+\infty} y f_y(y)\, dy \tag{A1}$$

The cumulative density function of *Y*, i.e., $F_Y(y)$ can be written as:

$$\begin{aligned}\Pr(Y \leq y) = F_Y(y) &= \Pr[(\lambda_1 \leq y) \cap (\lambda_2 \leq y) \cap \ldots \cap (\lambda_N \leq y)] \\ &= \prod_{n=1}^{N} \Pr(\lambda_n \leq y) = F_\lambda(y)^N\end{aligned} \tag{A2}$$

As in our case $f_\lambda(\lambda)$ is a continuous function with support [0,1] we can write:

$$E(Y) = \int_0^1 y F_y{}'(y)\ dy \tag{A3}$$

Integrating by parts, we get:

$$E(Y) = yF_y(y)\Big|_0^1 - \int_0^1 F_y(y)\, dy \tag{A4}$$

Since $F(0) = 0$ and $F(1) = 1$, we get:

$$E(Y) = 1 - \int_0^1 F_y(y)\, dy \tag{A5}$$

Finally, replacing $F_y(y)$ by its equivalent expression from above:

$$E(Y) = 1 - \int_0^1 F_\lambda(y)^N \, dy = \int_0^1 1 - F_\lambda(y)^N \, dy. \tag{A6}$$

Appendix B: Identification in an IV estimation with interaction terms

This section provides more intuition on our identification assumption by clarifying our approach with an example of a regression equation with only one interaction term. Therefore, we depart from the following regression equation:

$$y_i = \beta_0 + \beta_x x_i + \beta_{xw} x_i w_i + \beta_w w_i + \varepsilon_i \tag{B1}$$

where y_i represents the dependent variable and ε_i is the error term. x_i and w_i are two endogenous variables with $cov(x_i, \varepsilon_i) \neq 0$ and $cov(w_i, \varepsilon_i) \neq 0$. Furthermore, let z_i be an instrument for x_i with $cov(z_i, \varepsilon_i) = 0$ and $cov(z_i, x_i) \neq 0$.

The first stages of this model are

$$x_i = \pi_{11} + \pi_{12} z_i + \pi_{13} z_i w_i + \pi_{14} w_i + \epsilon_1 \tag{B2}$$

$$x_i w_i = \pi_{21} + \pi_{22} z_i + \pi_{23} z_i w_i + \pi_{24} w_i + \epsilon_2 \tag{B3}$$

and the reduced form is

$$y_i = \pi_{31} + \pi_{32} z_i + \pi_{33} z_i w_i + \pi_{34} w_i + \epsilon_3 \tag{B4}$$

As z_i is exogeneous ($cov(z_i, \varepsilon_i) = 0$), $cov(z_i, \epsilon_1) = cov(z_i, \epsilon_2) = cov(z_i, \epsilon_3) = 0$, and we are able to identify π_{12}, π_{22}, and π_{32}. Moreover, we know from Nizalova and Murtazashvili (2016) that we can also identify π_{13}, π_{23}, and π_{33} if z_i and (w_i, ε_i) are conditionally independent—even if w_i is endogenous. In our specific case, w_i represents the workers skill specificity that needs to be independent of our instruments for international trade. Our approach satisfies this assumption by restricting our sample to only include workers who have chosen their jobs before the fall of the Iron Curtain. These workers were unable to have foreseen the consequences of international trade after the fall of the Iron Curtain. Thus, that these workers have made their investments in specific and general skills in anticipation of the consequences of international trade is unlikely.

Following Angrist and Pischke (2009) we can substitute the first stage expressions (B2) and (B3) into the relation of interest in equation (B1) and rearrange the equation so that follows

$$y_i = \beta_0 + [\beta_x \pi_{12} + \beta_{xw} \pi_{22}] z_i + [\beta_x \pi_{13} + \beta_{xw} \pi_{23}] z_i w_i + [\beta_x \pi_{14} + \beta_{xw} \pi_{24} + \beta_w] w_i + [\beta_x \epsilon_1 + \beta_{xw} \epsilon_2] + \varepsilon_i \tag{B5}$$

with $[\beta_x \pi_{12} + \beta_{xw} \pi_{22}] = \pi_{32}$, $[\beta_x \pi_{13} + \beta_{xw} \pi_{23}] = \pi_{33}$, $[\beta_x \pi_{14} + \beta_{xw} \pi_{24} + \beta_w] = \pi_{34}$, and $[\beta_x \epsilon_1 + \beta_{xw} \epsilon_2] + \varepsilon_i = \epsilon_3$.

Thus, $\beta_x = \frac{\pi_{32}\pi_{23} - \pi_{33}\pi_{12}}{\pi_{23}\pi_{12} - \pi_{22}\pi_{13}}$ and $\beta_{xw} = \frac{\pi_{33}\pi_{12} - \pi_{32}\pi_{13}}{\pi_{23}\pi_{12} - \pi_{22}\pi_{13}}$ are combinations of coefficients that we can identify given that the assumptions discussed in Section III hold.

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