

Globalization, Labor Markets and the Role of Human Capital

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Abstract

This paper investigates the interaction between international trade and specific human capital in order to better understand the costs associated with globalization. Using a combination of rich and unique datasets from Germany, we find evidence that the costs of trade-related displacements are associated with loss of industry- and occupation-specific human capital. Additionally, we find that trade-related displacements are associated with workers having to move to “distant” occupations and being unable to transfer existing task skills. These preliminary results have potentially significant implications for how we think about the net returns to worker specialization in a world of “kaleidoscope” or knife-edge comparative advantage.

I. Introduction

"[W]hat we are facing now is a new and steadily encroaching economic universe in which the nature of comparative advantage is becoming thin, volatile, and kaleidoscopic and is creating vulnerabilities for industries, firms and workers...The margins of competitive advantage have, therefore, become thinner: a small shift in costs somewhere can now be deadly to your competitiveness. We used to call such industries 'footloose'...In the old days, few considered such industries to be the norm. Today, they are the norm."

Bhagwati (1998), p20-21

The last several decades have witnessed dramatic increases in international trade flows, following reductions in policy barriers to trade and improvements in transportation and communication technologies. International trade in goods and services clearly brings important economic benefits. Countries are able to specialize production in those goods in which they have comparative advantage, thereby improving their allocation of productive resources. In addition, the rationalization of industry structure caused by trade may lead to increases in aggregate productivity, as more productive firms displace their less efficient counterparts. Ultimately, international trade allows consumers to access a greater variety of goods. While these benefits of trade are well understood (see, for instance Bhagwati (2007), Krugman (1979), Melitz (2003)), it is also true that a movement towards greater trade openness will cause a reallocation of workers across different industries, and across different firms and occupations within an industries. This process may be disorderly, costly and long-lasting. Underlying much of the public concern regarding globalization is the apprehension that greater trade may expose workers to income losses, income variability and unemployment, resulting potentially in significant social and economic costs (see, for instance, Rodrik (1997), Stiglitz (2002)). Moreover, workers may be affected to varying extents depending on their levels of education and skill, with these unequal effects leading to a further erosion of support for the process of globalization itself.

In this paper, we seek to better understand the costs and who bears the burdens of these costs associated with international trade. To investigate these issues, we undertake a detailed analysis of the mechanisms through which globalization impacts different segments of the labor market, placing particular emphasis on the differences in the *extent* and *nature* of human capital possessed by different workers. Our proposed research is also related to several hypotheses concerning the evolution of labor markets that have been advanced in theoretical and policy discussions. For instance, it has been suggested that while many generations of workers have operated under a paradigm where specialization – in one occupation, one firm, and one industry – was the key to success, such thinking is outdated in our era of unprecedented globalization. In fact, there may be significant costs to specialization (see Ljungqvist and Sargent (1998); Lamo, Messina, and Wasmer

(2006); Kambourov and Manovskii (2009)). An alternative and better strategy in this new environment may be to invest in a more diversified portfolio of skills that are portable across jobs, in order to reduce income and employment risk. Separately, it has been suggested that the structure of the labor market itself affects the incentives to acquire different types of skills. Countries with rigid labor markets may see workers over-specialize in education and skills necessary for their particular occupations and jobs, while countries with flexible markets and significant turnover in jobs may see an inefficient lack of acquisition of specialized skills and over-acquisition of merely those skills that are readily portable across jobs (see Wasmer (2006); Davidson and Matusz (2000)).

The interaction between human capital specialization and globalization is the core of our research project. Several papers have analyzed this interaction with regards to industry-specific human capital (see Artuc, Chaduri, and McLaren (2010); Dix-Carneiro (2010); Cosar (2011)). These theoretical papers argue that the adjustment costs of international trade disproportionately fall on workers with industry-specific human capital. In related empirical work, Kletzer (2001) and Krishna and Senses (2009) find that trade-related displacements are costlier for workers who switch industries.

We plan to extend these previous works, by taking advantage of incredibly rich, new data sources, to empirically analyze the interactions between international trade and more nuanced dimensions of specific and general human capital. Through this investigation, we hope to shed some light on these important questions and provide analytical support for the design of suitable labor market and educational policies to better manage the effects of globalization.

II. The Role of Human Capital

Central to our investigation of the impacts of changes in the international economic environment on workers is the analysis of the role played by different dimensions of “human capital” (or skill) possessed by these workers. Human capital can be understood broadly as the stock of embodied competences, knowledge and personality attributes that enable an individual to generate economic value. In characterizing labor market skills, Becker (1964) distinguishes between general skills that are fully portable between jobs and, (firm) specific skills that increase the productivity of the worker only at the current job. The initial literature focused on the importance of firm-specific human capital for productivity (and hence wages) until Neal (1995) and Parent (2000) argued that those initial results were spurious and that industry-specific human capital was more important. More recently, there has been increasing evidence on the importance of occupation-specific human capital.¹

¹ While Shaw (1984, 1987) argued long back on the importance of occupation-specific human capital, the literature is surprisingly quiet on this topic. Recently, Kambourov and Manovskii (2009a, 2009b) have re-

However, even more nuance is essential when thinking of the transferability of human capital across jobs. While some skills accumulated in an occupation are specific to that particular occupation (occupation-specific skills) and will be lost when the worker moves to a different occupation, other skills acquired by performing tasks in a given occupation can also be valuable in other occupations that require skills similar to the current one. Such task-based skills are transferable between occupations and are important in understanding the costs of occupational mobility. For example, imagine a baker who becomes chef at a hotel compared to a baker who becomes a professor. The example, while ostensibly extreme, serves to highlight the previous point. Upon their respective job switches, both bakers lose all of their industry, firm, and occupational human capital. However, there is clearly a difference between the two moves. The former baker can transfer some of his/her task skills the new job, whereas the latter baker most likely cannot. To handle this extra precision, the literature has recently moved towards a more refined conceptualization of human capital by incorporating tasks.

One way to measure the transferability of skills is by studying the association between occupations and tasks and calculating how “distant” different occupations are from each other based on the differences in tasks performed in each occupation (see Poletaev and Robinson (2008); Gathmann and Schoenberg (2010); Nedelkoska and Neffke (2011)). Following Gathmann and Schoenberg (2010) we are able to define occupations as a 17-dimensional vector of tasks. Then, using either a Euclidian measure or angular separation measure, we can find the “distance” between occupational vectors. In either measure, the distance between any two occupations is the dissimilarity of the tasks used in the two occupations: Occupations that have few (or no) tasks in common are more ‘distant’ compared to occupations that require a similar set of tasks to be performed.² The distance between any two occupations is bounded below by 0 for identical occupations and above by 1 for orthogonal occupations. Having calculated distances between occupations, we follow Gathmann and Schoenberg (2006) in constructing a continuous measure of task specific human capital – task tenure. At any given point in time, task tenure is calculated as the weighted (by tenure) average of the distances between all previous occupations and the current occupation. When a worker switches jobs and occupations, he/she loses all occupation-specific human capital, potentially preserves some task-based skills (task tenure) and maintains all of their experience. Hence, the task tenure measure is bounded above by experience and bounded below by occupation tenure. Then, controlling for experience, we can interpret higher task-tenure to capture a higher degree of (task) specialization and lower task-tenure to capture lower (task) specialization.

focused on occupation-specific human capital.

² For instance, imagine a guard/watchman who contemplates becoming a police officer as opposed to a teacher. In this approach, the former move shares more tasks in common and hence is a “closer” move, enabling the worker to transfer more skills to his/her new occupation.

To summarize, human capital can then be differentiated between specific skills that are useful only in a single industry (industry-specific skills), or a single firm (firm-specific skills), or a single occupation (occupation-specific skills), versus more general skills that can be partly transferred (task-based skills). These measures capture the different dimensions of the specific nature of skills as well as the transferability of certain skills across jobs. As we discuss in the next section, globalization can result in greater variability in wages, employment, and job turnover. Distinguishing between different dimensions of human capital is important for gaining a deeper understanding of the differential labor market costs borne by workers and the underlying mechanisms of those costs.

II. Data

This section briefly describes the three main data sources that will be used for this project. We have already invested considerable time and effort in gaining access to a combination of confidential datasets from Germany and have linked them together. Our main dataset is the Sample of Integrated Labor Market Biographies (SIAB), which contains a 2% representative sample of administrative social security records in Germany. SIAB is particularly suited for our purposes thanks to the detailed information on a very large sample of workers (approximately 1.6 million individuals) over a very long period of time (1975-2008). This confidential dataset contains detailed information on the full labor market experience of workers in the sample. In addition to detailed information on worker characteristics such as gender, age, education level, occupation etc, SIAB includes information on each employer of the worker (such as industry, size, average wage and location) throughout the worker's tenure in the job market. Note that each unit of observation in the dataset ("spell") represents the employment condition for a worker. The worker could be employed or unemployed in any given spell. If the worker is employed, then employment information such as wages, firm, occupation, etc is provided for that employment spell. If the worker is unemployed, then benefits information will be provided for that unemployment spell.

Importantly, from this data, we are able to construct full employment histories of workers including job switches and any unemployment spells starting from the point of entry to the job market. The ability to construct full employment histories and detailed wage and firm-level information for each job is crucial for us to construct measures of industry-, firm-, occupation-, and task-specific human capital for each worker. By allowing us to follow workers across jobs and in and out of employment, the dataset enables us to cleanly identify job displacements.

In constructing the task-based measure of human capital, we will use data from the German Qualification and Career Survey, which is a repeated cross-section that tracks skill requirements and task usage for occupations. There are five waves for the years 1979, 1985, 1991/92, 1998/99, and 2006 containing information on

approximately 20-30,000 workers and 250 occupations in each wave.³ In the surveys, workers are asked the frequency with which they perform 17 different tasks (such as operating machines, research and development, cleaning/waste disposal, consulting/advising, healing/taking care etc.) in their job. We use this information to code a 17-dimensional task vector for each occupation and calculate the distance between two occupations (calculated as the distance between the vectors). The distance is defined in terms of similarity of tasks performed in each occupation; the more dissimilar are the tasks performed in each occupation the more distant are the two occupations. We then link these measures with the aforementioned worker-level data and use it to construct each worker's task-based human capital.

We complement these two datasets with publicly available industry level measures of trade exposure for Germany from the OECD's database.

IV. Research Questions, Methodology, and Preliminary Results

Table 1 starts by providing some basic summary statistics of our data sample. Industry, occupation, and firm tenure variables capture the specific human capital that the worker has attained at their current job along each of these dimensions. On average, a worker has been at their current industry, firm, and occupation for 4.8, 3.7, and 5.0 years, respectively and has been in the labor market for 8.3 years. We also provide summary statistics for the sample of involuntary job displacements. The sample of involuntary job displacements will be particularly useful in our empirical estimations detailed below. It is not possible to perfectly identify the cause of a job displacement as voluntary or involuntary but following existing literature, we identify involuntary job displacements as ones where a displacement was followed by an unemployment spell of at least 90 days.⁴ From table 1 we see that the average involuntary displacement involves a younger worker, with less experience and less tenure, and earning lower wages compared to the full sample.

We start our analysis by estimating a simple Mincer-type wage regression, where we estimate the returns to the different measures of human capital:

$$(1) \quad w_{it} = \alpha_1 X_{it} + \alpha_2 IT_{it} + \alpha_3 OT_{it} + \alpha_4 FT_{it} + \alpha_5 TT_{it} + \alpha_6 Exp_{it} + FE + \varepsilon_{it}$$

The dependent variable is log wages. The human capital variables IT , OT , FT , and TT represent industry tenure, occupation tenure, firm tenure, and task tenure,

³ Currently, we are using only the 2006 wave for constructing out task-based occupational vectors. However, we plan to eventually incorporate all waves to deal with the fact that certain occupations may have changed over time in their task intensities.

⁴ It is also common in the literature to define involuntary displacements as ones that occur as part of mass layoffs, where mass layoffs are defined as a 30% fall in year-over-year employment at that firm. However, since our data is worker based and not firm based, we cannot accurately calculate involuntary displacements in this manner.

respectively. Task tenure, as we discussed in the previous section, captures the degree to which the worker has been able to transfer skills across their history of occupational moves. Exp_{it} is the total duration of the worker's labor market experience. X_{it} are all other observable characteristics of the worker. FE represents all the fixed effects in this regression, which include industry-, year-, occupation-, firm-state-, and worker- fixed effects.

The two left columns from table 2 present the estimation results for equation (1) with and without worker fixed effects. Consistent with earlier literature, all the tenure measures are positive and significant, and interestingly task tenure has the largest effect. We interpret the strong positive coefficient on task tenure as higher returns to specialized task skills. More specifically, an increase in task tenure of 1 year, holding all other variables constant, would increase wages by approximately 3.2%.⁵

Next, we consider the sample of involuntary displacements in order to understand the impact of human capital on the costs of involuntary displacement (i.e. wage loss):

$$(2) \quad \Delta w_{it} = \alpha_1 X_{it} + \alpha_2 IT_{it} + \alpha_3 OT_{it} + \alpha_4 FT_{it} + \alpha_5 TT_{it} + \alpha_6 Exp_{it} + FE + \varepsilon_{it}$$

The two right columns from table 2 present the estimation results for equation (2) with and without worker fixed effects. Here, we see that having more tenure within an industry or occupation can be costly following an involuntary job displacement. Interestingly, the same does not apply to firm tenure. Moreover, specialization in task skills proved especially costly following a job displacement: an additional year of task tenure would lead to an extra loss of 3.8% in real wages following an involuntary job displacement.

The result that acquired industry and occupation tenure is costly for post-displacement outcomes could be a result of multiple reasons. First, it could be that switching industries and occupation is itself costly because of the loss of industry- and occupation-specific human capital and naturally this cost would be higher for workers with more tenure. Or it could be that workers with more tenure are more likely to switch industry and occupations after an involuntary displacement. To try and answer this question, we again look at the sample of involuntary displacements and estimate the following equation:

(3)

$$\Delta w_{it} = \beta_1 X_{it-1} + \beta_2 Ind_switch_{it} + \beta_3 Occ_switch_{it} + \beta_4 IT_{it-1} + \beta_5 OT_{it-1} + \beta_6 FT_{it-1} + \beta_7 TT_{it-1} + \beta_8 Exp_{it-1} + FE + \varepsilon_{it}$$

⁵ We get to this number by multiplying the coefficient on task tenure by 100 (since the dependent variable is log wages) and then multiplying again by 12 since task tenure is measured in months.

Equation (3) is similar to equation (2) except now we are also controlling for whether the worker switched industries and occupations after the involuntary displacement. Indeed, from columns 1 and 4 in table 3, we see that industry and occupation switchers suffered larger wage losses even conditioning on their initial human capital, consistent with the former channel proposed above.

Next, we would like to incorporate trade in analyzing the costs of involuntary displacements. Here we extend equation (3) in two ways. First, in equation (4) below, we add import penetration (ratio of imports to total production) of the industry of the worker's current job as an explanatory variable.

(4)

$$\Delta w_{ijt} = \beta_1 X_{ijt-1} + \beta_2 Ind_switch_{ijt} + \beta_3 Occ_switch_{ijt} + \beta_4 IT_{ijt-1} + \beta_5 OT_{ijt-1} + \beta_6 FT_{ijt-1} + \beta_7 TT_{ijt-1} + \beta_8 Exp_{ijt-1} + \beta_9 IMP_Pen_{jt-1} + FE + \varepsilon_{ijt}$$

We interpret the coefficient β_9 as the marginal effect of being in a slightly more trade-affected industry on post-displacement wages. Again, in table 3, we see that the OLS estimates (column 2) for β_9 are negative and significant and the FE estimates (column 5) are negative but statistically insignificant. This is interesting because previous studies have demonstrated clearly that trade-related displacements are more costly. However, we hypothesize that perhaps trade-related displacements are more costly *because* they lead to industry and occupation switches, which are absorbing the negative effect in equation (4). To test this interaction more clearly, we estimate the following equation:

(5)

$$\Delta w_{ijt} = \beta_1 X_{ijt-1} + \beta_2 Ind_switch_{ijt} + \beta_3 Occ_switch_{ijt} + \beta_4 IT_{ijt-1} + \beta_5 OT_{ijt-1} + \beta_6 FT_{ijt-1} + \beta_7 TT_{ijt-1} + \beta_8 Exp_{ijt-1} + \beta_9 IMP_Pen_{jt-1} + \beta_{10} Ind_switch_{ijt} * IMP_Pen_{jt-1} + \beta_{11} Occ_switch_{ijt} * IMP_Pen_{jt-1} + FE + \varepsilon_{ijt}$$

Equation (5) is similar to equation (4) except now we have added interaction terms between industry/occupation switches and import penetration. The results in columns 3 and 6 of table 3 are consistent with the above hypothesis. The coefficients on the interaction terms are indeed negative, implying that trade-related displacements are more costly for workers who switch industries and occupations. Trade-related displacements not associated with industry/occupation switches are not costly as we see from the coefficient on import penetration in columns 3 and 6.

To summarize our findings this far, it seems that:

- (i) Being more specialized (higher task tenure) is more costly for post-displacement outcomes

- (ii) Industry and occupational switches are more costly for post-displacement outcomes
- (i) Trade-related displacements are more costly if the displacement is associated with industry and/or occupational switches

Clearly industry and occupation switches are important in understanding the costs of displacement and especially the costs of trade-related displacements. However, is their importance due entirely to the direct loss of industry- and occupation-specific human capital? Or could industry and occupation switches be correlated with more distant occupational moves, which is the costly channel? To begin a test of these issues, we first want to identify whether trade-related shocks are associated with more distant moves. To that end, we estimate the following equation, again on the sample of involuntary displacements:

(6)

$$\Delta TT_{it} = \beta_1 X_{it-1} + \beta_2 IT_{it-1} + \beta_3 OT_{it-1} + \beta_4 FT_{it-1} + \beta_5 TT_{it-1} + \beta_6 Exp_{it-1} + \beta_7 IMP - Pen_{it-1} + FE + \varepsilon_{it}$$

Now the left hand side is change in task tenure. Remember, a larger (smaller) change in task tenure denotes transferring more (less) task skills by moving to a closer (further) occupation. From table 4, we see that $\beta_7 < 0$, indicating that trade-related displacements are associated with workers having to move to further occupations. Hence, our preliminary results indicate that trade-related displacement are more costly because they are more likely to lead to industry-switches (loss in industry-specific human capital), occupational switches (loss in occupation-specific human capital) and further occupational moves (inability to transfer tasks skills to new job). While these initial regressions have uncovered some interesting stylized facts, we hope to push this empirical analysis further in investigating the channels between trade, specificity of human capital, and the costs of displacement.

V. Conclusion

In sum, we are investigating the interaction between an environment of increased exposure to trade, and the extent and nature of the specificity of human capital that workers possess. In particular, we seek to analyze whether this interaction has implications for the costs of adjustment from trade. Understanding these implications allows us to tackle broader issues related to the effects of globalization. For instance, economists acknowledge the importance of job re-training as a means of mitigating some of the costs related to globalization. However, numerous studies have documented the ineffectiveness of job re-training programs for trade-displaced workers. One reason, potentially highlighted by our research, could be the poor compatibility between workers' existing and new skills.⁶

⁶ Decker and Corson (1995) suggest that training provided to participants of the trade-adjustment assistance program (TAA) in the US "was aimed at developing specific job-related skills in new occupations." Perhaps, minimizing the distance of occupational switches could be more effective by allowing workers to

Additionally, our initial results portend a potentially interesting implication for the net returns to specific human capital. In particular, in a world of dynamic, kaleidoscope comparative advantage (Bhagwati (1998)), where comparative advantage in industries, firms, occupations, and tasks comes and goes, the costs of specialization may drastically increase. Then, a combination of governmental action through education reform and incentive structures through markets could push away from an equilibrium where workers invest in specialized skills to a new equilibrium where workers acquire more general skills. These examples provide a glimpse of the broad and profound range of implications from this research.

transfer some of their human capital to their new job?

VI. Tables

TABLE 1 – Summary Statistics

	Full Sample	Sample of Involuntary Displacements
Age	33.2	29.4
Industry Tenure	4.8	2.0
Firm Tenure	3.7	1.4
Occupation Tenure	5.0	2.2
Task Tenure	7.8	4.1
Experience	8.3	4.7
Male	52%	54%
Daily Real Wages	54 euros	35 euros

TABLE 2 – Real Wages and Changes in Real Wages

	log(Wages)		Change in log(Wages)	
Experience	0.0007*** (0.000)	0.0085*** (0.000)	0.0011*** (0.000)	-0.0006 (0.001)
Gender	-0.2731*** (0.001)		-0.0831*** (0.003)	
Industry Tenure	0.0003*** (0.000)	0.0002*** (0.000)	-0.0003*** (0.000)	-0.0004*** (0.000)
Occupation Tenure	0.0006*** (0.000)	0.0003*** (0.000)	-0.0004*** (0.000)	-0.0007*** (0.000)
Firm Tenure	0.0002*** (0.000)	0.0001*** (0.000)	0.0001** (0.000)	0.0006*** (0.000)
Task Tenure	0.0057*** (0.000)	0.0027*** (0.000)	-0.0011*** (0.000)	-0.0032*** (0.001)
Worker fixed effects	NO	YES	NO	YES
Other fixed effects	YES	YES	YES	YES
R-squared	0.48	0.49	0.05	0.02
N	1,913,216	1,913,216	290,838	290,838

TABLE 3 – Change in Real Wages after an Involuntary Displacement

	OLS			Worker FE		
	I	II	III	IV	V	VI
Ind_switch	-0.072*** (0.006)	-0.072*** (0.006)	-0.050*** (0.007)	-0.078*** (0.013)	-0.078*** (0.013)	-0.049*** (0.015)
Ind_switch* Imp_penetration			-0.002*** (0.000)			-0.002*** (0.001)
Occ_switch	-0.110*** (0.006)	-0.110*** (0.006)	-0.063*** (0.007)	-0.071*** (0.012)	-0.071*** (0.012)	-0.037** (0.015)
Occ_switch* Imp_penetration			-0.003*** (0.000)			-0.002*** (0.001)
Industry Tenure	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
Occupation Tenure	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.001** (0.000)	-0.001** (0.000)
Firm Tenure	-0.0005*** (0.000)	-0.0005*** (0.000)	-0.001*** (0.000)	0.0001 (0.000)	0.0001 (0.000)	0.000 (0.000)
Task Tenure	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
Experience	0.001** (0.001)	0.001** (0.001)	0.001** (0.001)	-0.0003 (0.002)	-0.0003 (0.002)	-0.000*** (0.002)
Gender	-0.125*** (0.005)	-0.125*** (0.005)	-0.126*** (0.005)			
Imp_penetration		-0.001** (0.001)	0.002*** (0.001)		-0.0002 (0.002)	0.004** (0.002)
R-squared	0.10	0.10	0.10	0.09	0.09	0.10
N	112,877	112,877	112,877	112,877	112,877	112,877

TABLE 4 – Change in Task Tenure after an Involuntary Displacement

	I	II
Experience	0.483*** (0.015)	1.034*** (0.047)
Gender	-0.754*** (0.050)	
Industry Tenure	0.002*** (0.002)	-0.004*** (0.006)
Occupation Tenure	-0.002 (0.002)	0.004 (0.004)
Firm Tenure	-0.008*** (0.003)	0.011** (0.006)
Task Tenure	-0.515*** (0.016)	-1.103*** (0.048)
Imp_penetration	-0.015** (0.007)	-0.026* (0.015)
Worker Fixed Effects	NO	YES
Other fixed effects	YES	YES
R-squared	0.14	0.11
N	109,037	109,037

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