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Explaining the training disadvantage of less-educated workers: The role of labor market allocation in international comparison

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Abstract: Less-educated workers have the lowest participation rates in job-related further training across the industrialized world, but the extent of their disadvantage varies. Using data on 28 high- and middle-income countries, we assess different explanations for less-educated workers' training disadvantage relative to intermediate-educated workers, with a focus on the role of labor market allocation (i.e., job tasks, other job features, and firm characteristics). Shapley decompositions reveal a broadly similar pattern for all countries: differences in labor market allocation between less- and intermediate-educated workers are more important for explaining the training gap than differences in individual learning disposition (i.e., cognitive skills and motivation to learn). Our analysis further suggests that the training gap is related to educational and labor market institutions and that labor market allocation processes play a key role in mediating any institutional 'effects'. Strong conclusions regarding the role of institutions are hampered by the small country-level sample, however.

Running head: Country comparison of training disadvantage

Keywords: inequality in adult training, skills, labor market allocation, Shapley decomposition, labor market institutions, education systems

JEL Classification: I24 Education and Inequality; J24 human capital, skills, occupational choice, labor productivity; J5 labor–management relations, trade unions, and collective bargaining

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1. Introduction

Research consistently shows that less-educated adults (i.e., those who have not completed upper secondary education) are severely disadvantaged on the labor market in terms of earnings, job security, and career development (e.g., Abrassart, 2013; Gebel and Giesecke, 2011; Heisig *et al.*, 2019). These disadvantages are compounded by the fact that less-educated adults are less likely to participate in job-related further training than workers with higher levels of education (Bassanini *et al.*, 2005; OECD, 2019a). As training opportunities arguably constitute a major ‘job perk’ (Bills and Hodson, 2007, p. 261), training inequalities can be considered an important dimension of labor market inequality in their own right. Furthermore, since job-related further training is crucial for acquiring, maintaining, and enhancing skills (Cedefop, 2015; Desjardins and Rubenson, 2013), a lack of training opportunities likely contributes to less-educated workers’ elevated risks of precarious employment, unemployment, and even social exclusion (Dieckhoff *et al.*, 2007). A reduction of inequalities in further training participation therefore has the potential to strengthen both economic competitiveness and social cohesion (European Commission, 2000). But despite resurgent political interest in equalizing access to continuing skill formation, training inequalities as well as country differences in their extent persist (Dieckhoff *et al.*, 2007).

In this article, we seek to improve our understanding of less-educated workers’ training disadvantage through a comparative analysis of survey data from the *Programme for the International Assessment of Adult Competencies* (PIAAC; OECD, 2016). We focus on job-related non-formal training (hereafter job-related NFT), the predominant form of adult education and training (Cedefop, 2015; Desjardins and Ioannidou, 2020). Job-related NFT refers to intentional, job-related training activities that are typically provided in the form of classroom instruction, lectures, theoretical and practical courses, seminars, or workshops. It is often certified but does not lead to qualifications recognized by national or sub-national education authorities.¹

Recent work on training participation suggests that *labor market allocation* plays a decisive role in determining access to job-related NFT: Job- and firm-related characteristics—including job tasks, use of technologies, type of work contract, and firm environment—appear to trump any (residual) influences of socio-demographic or attainment-related worker characteristics such as age, education, or work experience (Ehlert, 2020; Görlitz and Tamm, 2016; Mohr *et al.*,

2016; Saar and Räis, 2017; Schindler *et al.*, 2011). Our contribution departs from these findings and seeks to extend them in three main respects.

First, our focus on the training disadvantage of less-educated workers puts *inequalities in training participation* at the center of the analysis, whereas most previous studies focus on overall access to training and do not explicitly differentiate by level of education. By the same token, previous work also fails to provide clear evidence on the contributions of differences in labor market allocation and worker characteristics to training inequalities between educational groups.

Second, our data provide a set of high-quality measures capturing workers' *individual learning disposition*, most importantly cognitive skills and overall motivation to learn. We thus account for an alternative explanation of training inequalities that is not modeled adequately in previous work. While this is mostly due to data limitations, it does raise concerns that the decisive role of labor market allocation might be an artifact of omitting these alternative factors.

Third, we take a *comparative perspective* and thus go beyond existing research on the role of labor market allocation for training participation, which has been largely confined to Germany. This focus on a single country raises obvious questions about generalizability, especially given Germany's rather unique firm-based vocational education and training system and its occupation-specific, highly credentialized labor market (Elbers *et al.*, 2021; Protsch and Solga, 2016). We also complement the comparative literature on training participation and skill formation systems more broadly which has paid considerable attention to the role of educational and labor market institutions but has largely abstracted away from underlying mechanisms at the level of individual workers (Desjardins and Ioannidou, 2020; Desjardins and Rubenson, 2013; Estevez-Abe *et al.*, 2011; Roosmaa and Saar, 2012; Saar *et al.*, 2013; Vogtenhuber, 2015). Therefore, we do not know *how* educational and labor market institutions contribute to country differences in training inequalities: Do they do so by shaping the labor market allocation of less-educated vis-à-vis better-educated workers? Or do they rather operate through cognitive skills and learning dispositions more broadly, an alternative that seems plausible for education system characteristics in particular?

In summary, we seek to answer the following two sets of research questions: 1) Does labor market allocation explain the training disadvantage of less-educated workers? Does the

finding that labor market allocation is decisive for training participation generalize to countries other than Germany, and is it robust to controlling for differences in individual learning disposition? 2) Does the size of less-educated workers' training disadvantage vary according to educational and labor market institutions? And to what extent can such institutional 'effects' be attributed to differences in the labor market allocation of less- and better-educated workers?

Our analysis is based on PIAAC data for 33,523 adults in 28 high- and middle-income countries. PIAAC provides high-quality and internationally comparable data on job-related NFT and key explanatory variables, including job tasks, motivation to learn, and general cognitive competencies (numeracy and literacy skills). The latter are based on an extensive assessment component rather than the kinds of self-reports or very short tests included in other surveys. They arguably provide the best internationally comparable data on adult skills so far.

We focus on the training disadvantage of less-educated workers (who did not complete upper secondary education) relative to intermediate-educated workers (who hold an upper-secondary or non-tertiary post-secondary degree). This focus on low-intermediate differences is motivated by the fact that intermediate-educated workers are the main competitors of less-educated workers when it comes to hiring and training opportunities. Higher education graduates, by contrast, tend to be employed in very different labor market segments (OECD, 2019a, b).

Our empirical analysis proceeds in two main steps. In the first, we provide a Shapley decomposition of the training disadvantage of less-educated workers for each country. Our goal here is to quantify the contribution of differences in labor market allocation and learning disposition to the overall training gap. The second step focuses on country-level regressions that relate the training disadvantage of less-educated workers to several labor market and education systems institutions. We again combine these regressions with Shapley decompositions to investigate whether institutional 'effects' can be attributed to differences in the labor market allocation and learning disposition of less-educated relative to intermediate-educated workers.

Our main findings are a) that the training gap between less- and intermediate-educated workers is very substantial in most countries and b) that differences in labor market allocation are an important driver of these training inequalities in all countries (while workers' learning disposition tends to matter less). We also find c) that labor market and educational institutions appear to moderate the magnitude of less-educated training disadvantage, although strong

conclusions are hampered by the small country-level sample. Finally, d) differences in the labor market allocation of less- and intermediate-educated seem to be a major mechanism underlying the associations between institutional characteristics and training inequalities.

2. Theoretical considerations and literature review

Figure 1 presents our stylized model of the interplay between education, labor market allocation, and participation in job-related NFT—and of how it might depend on institutional context. In Section 2.1, we first discuss why we expect labor market allocation to mediate the education-training relationship in all countries (*paths a and b*), before turning to the potential moderating role of educational and labor market institutions in Section 2.2 (*paths 1 and 2*). Section 2.3 then provides a shorter discussion of workers’ learning disposition as an alternative explanation of training inequalities. Section 2.4 distills the theoretical discussion into two broad empirical expectations.

[FIGURE 1]

2.1 The role of labor market allocation

As job-related NFT is mostly employer-sponsored (Cedefop, 2015; Desjardins and Ioannidou, 2020), differences in training opportunities and participation are often attributed to differences in employers’ expected returns to training investments (Acemoglu and Pischke, 1998; Dieckhoff *et al.*, 2007).² For reasons described below, these expected returns likely depend on the types of work people do (i.e., job tasks), other features of the job and employment relationship (e.g., work hours, type of contract), and various organizational/firm characteristics (e.g., public vs. private ownership, firm size). Together, these sets of factors describe what a person does on her job, on what (contractual) terms she does it, and where she does it (i.e., the work context). We subsume them under the umbrella term ‘labor market allocation’ because they can be understood as the current endpoints of a dynamic (allocation) process of labor market positioning and matching. For each of the three sets of factors—*job tasks*, *other job characteristics*, and *firm characteristics*—we now discuss how and why they are plausibly linked to training opportunities.

Job tasks are constitutive of what it means to do a certain job—in fact, jobs have even been *defined* as ‘bundles of task’ (Autor and Handel, 2013, p. 64). They refer to what people actually do when they perform their work, with standard taxonomies separating job tasks into manual *vs.* cognitive tasks on the one hand and into routine *vs.* non-routine tasks on the other (Autor *et al.*, 2003). Effective job performance requires that workers possess the skills needed to perform their job tasks, which in turn suggests that job task profiles play a key role in determining access to training opportunities (Schindler *et al.*, 2011). A potential mechanism linking job tasks to demand for continuing skills investments refers to the pace at which job-relevant skills depreciate. Previous research suggests that skills required to perform abstract (i.e. non-routine cognitive) tasks change more rapidly than those needed for manual tasks (Arthur *et al.*, 1998; Blechinger and Pfeiffer, 2000). From the employer’s perspective, expected returns to training should therefore be higher for workers who perform high shares of non-routine cognitive tasks than for workers who mostly perform routine and/or manual tasks (Ehlert, 2020; Görlitz and Tamm, 2016; Mohr *et al.*, 2016; Schindler *et al.*, 2011). As less-educated workers predominantly hold low-skilled jobs (Bassanini *et al.*, 2005; Heisig *et al.*, 2019; Nedelkoska and Quintini, 2018) characterized by higher shares of routine and manual tasks (Autor and Handel, 2013; Autor *et al.*, 2003), job tasks likely mediate the education-training relationship (*path a* and *b* in Figure 1).

Besides job tasks, there are a number of *other job characteristics* that might explain the low training participation of less-educated workers. For example, less-educated workers are more often employed in fixed-term or part-time work, in lower-status occupations, and less likely to use computers at work (*path a*; OECD, 2019b). All of these job characteristics are empirically associated with lower participation in job-related NFT (Bassanini *et al.*, 2005; Görlitz and Tamm, 2016; Nedelkoska and Quintini, 2018; Schindler *et al.*, 2011). As with job tasks, these associations can be linked to expected-returns-to-training considerations on the employer’s side (*path b*). For example, both part-time work and fixed-term contracts should reduce the total number of work hours that an employer can expect to receive from an employee after the completion of a training measure.

Similar rationales apply to *firm characteristics*. Less-educated workers are overrepresented in smaller firms and less training-intensive economic sectors (*path a*). Small firms have fewer financial resources for training investments and usually lack human resources

departments to organize them. Furthermore, firms in the growing service economy invest less in training because of higher labor turnover and weaker collective bargaining power than, for example, in the public sector (*path b*; Mohr *et al.*, 2016; Schindler *et al.*, 2011; Wotschack, 2020).

2.2 The roles of educational and labor market institutions

The above considerations suggest that differences in the labor market allocation of less-educated vis-à-vis intermediate-educated workers will be an important source of education-related training inequalities in most or even all countries (Figure 1, *paths a* and *b*). At the same time, we would expect the magnitude of less-educated workers' training disadvantage to depend on the national context, particularly in terms of labor market and educational institutions. Given the likely importance of labor market allocation for training inequalities, we would further expect such institutional 'effects' to partly operate through two (mutually non-exclusive) channels: First, national institutional factors might strengthen or weaken the relationship between educational attainment and labor market allocation (Figure 1, *path 1*: institutions as moderators of *path a*). Second, they might strengthen or weaken the link between labor market allocation and training participation (Figure 1, *path 2*: institutions as moderators of *path b*). We now discuss each of these paths for a variety of labor market and educational institutions.

As for possible effects of labor market institutions through *path 1*, strict *employment protection legislation* (EPL) has been argued to nurture a labor market dualism between core workers with permanent contracts and 'secondary' workers with temporary contracts (see the overview in Bentolila *et al.*, 2019). Less-educated adults are prototypical secondary workers, suggesting that strict EPL reinforces training inequalities by pushing them into unstable and low-quality 'dead-end' jobs (Biegert, 2019). Strong *trade unions*, by contrast, might weaken the link between formal qualifications and labor market allocation by pursuing a broadly egalitarian agenda that includes quality jobs for less-educated workers, particularly in the context of larger firms (Brunello, 2001; Wotschack, 2020).

Concerning educational institutions, stratified education systems with *early tracking* have been argued to reinforce the link between formal qualifications and actual skills, for example, in the form of larger *skills gaps* between less- and intermediate-educated adults (Andersen and van de Werfhorst, 2010; Heisig, 2018; Heisig *et al.*, 2019; Heisig and Solga, 2015). Stronger links

between formal qualifications and skills—or greater ‘skills transparency’ (Andersen and van de Werfhorst, 2010)—should in turn raise the importance of formal qualifications for labor market positioning. This suggests that less-educated workers in countries with early tracking and high skill transparency will often be relegated to low-skilled jobs (Heisig *et al.*, 2019; see also Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2013; Shavit and Müller, 2000)—and thus jobs that provide fewer incentives and opportunities for further training (see Section 2.1). A strong *vocational orientation* of upper secondary education may further amplify this boundary between skilled and low-skilled jobs: As employers can rely on occupationally trained workers for skilled jobs, less-educated workers (who have not completed a certified vocational training) tend to be sorted into low-skilled labor market segments (Bol *et al.*, 2019; Elbers *et al.*, 2021; Shavit and Müller, 2000).

Turning to *path 2* in Figure 1 (moderation of *path b*), the above institutions might also shape training inequalities by strengthening or weakening the link between labor market allocation and opportunities for job-related NFT. Strict *EPL* raises hiring and firing costs, and therefore provides employers with an incentive to rely on the training of their employees rather than external recruitment. Less-educated workers may benefit less from this than intermediate-educated workers, however. Training opportunities may be focused on core workers, while less-educated adults are more often employed on fixed-term contracts. Strong *trade unions*, by contrast, might weaken the link between labor market positioning and access to training by negotiating inclusive collective agreements that ensure training opportunities also for workers in low-skilled jobs, especially in larger firms (Wotschack, 2020). In addition, strong unions and collective bargaining might have an indirect effect by lowering *wage inequality*: Previous research indicates that low wage inequality increases employers’ incentive to invest in their workforces, including those in low-skilled jobs, because it allows them to reap a greater portion of the resulting productivity increases (Acemoglu and Pischke, 1999; Bassanini *et al.*, 2005).

Turning to the key features of secondary education systems, *early tracking* and the *skills transparency* of educational degrees do not seem to have obvious implications for the link between labor market allocation and training opportunities. As for *vocational orientation*, the Varieties of Capitalism approach (Hall and Soskice, 2001) highlights that most coordinated market economies are strongly reliant on occupational skills for their high-skill equilibrium. These skills are ensured not only through initial vocational education and training (VET) but also

through continued job-related NFT after labor market entry (Sorge and Streeck, 2018). However, given the dualistic nature of labor markets in many of these countries, these investments in further training might be focused on workers in skilled positions and thereby strengthen rather than weaken the link between labor market allocation and training opportunities.

Taken together, these considerations suggest that less-educated workers' training disadvantage should be larger in countries with lower union density, stricter EPL, higher wage inequality, greater skills transparency, earlier tracking, and a stronger vocational orientation of upper secondary education.

2.3 The role of workers' learning disposition

Differences in workers' learning disposition—that is, in their (cognitive) skills and motivation to learn—are another common explanation for the training disadvantage of less-educated workers (Becker, 1964). Employers might be reluctant to invest in workers that seem to lack the skills or motivation needed for a successful learning experience (Brunello, 2001). For similar reasons, less-educated workers might not expect to gain much from attending a training course (Acemoglu and Pischke, 1999; Siebert, 2006). These explanations for training inequalities have an empirical basis in that less-educated adults actually tend to have substantially lower cognitive skills than their higher-educated counterparts (Heisig and Solga, 2015). Their general motivation to learn tends to be lower as well, in part because it is an important predictor of educational attainment in the first place (e.g., Doll, 2010).

The role of differences in workers disposition might again depend on national institutional context. For example, Heisig and Solga (2015) show that the skills gap between less- and intermediate-educated workers is larger in countries with early-tracking education systems, which suggests that skills differentials will be an important source of training inequalities in these countries. A full discussion of plausible institutional moderation is beyond the scope of this paper, however, and we consider the corresponding parts of the analysis as explorative.

That being said, our ability to account for workers' individual learning disposition—facilitated by the unique assessment component of the PIAAC survey (see Section 3 below)—is important. Confounding of the relationship between labor market allocation and training by differences in learning dispositions (e.g., more learning-motivated workers sorting into more

skilled jobs) is a plausible concern that previous studies cannot account for due to data limitations. The potentials of our data should not be overstated, however. Our cross-sectional data do not allow us to model potential feedback effects between labor market allocation and workers' learning disposition. For example, workers' levels of cognitive skills might be affected by the nature of their job tasks. In such a scenario, skill differentials would partly be a consequence (and mediator) of differences in labor market allocation, rather than a pure confounder. While our results thus need to be interpreted cautiously, we nonetheless consider them important for assessing the robustness of prior findings on the important role of labor market allocation.

2.4 Empirical expectations

The above considerations can be condensed into two general expectations, the first of which relates to the role of labor market allocation in explaining training inequalities within countries:

Expectation 1: We expect labor market allocation in terms of job tasks, other job features, and firm characteristics to play an important role in accounting for less-educated workers' training disadvantage in all countries, above and beyond workers' learning disposition (i.e., their skills and motivation to learn).

At the same time, the magnitude of this disadvantage is likely to depend on several education system characteristics and labor market institutions, in part because they shape the role of labor market allocation itself. Institutions likely influence both how important formal qualifications are for securing skilled and stable jobs that tend to come with good training opportunities and how important being in such a job (as opposed to a low-skilled, unstable one) is for getting access to training opportunities:

Expectation 2: We expect that country-level associations between (educational/labor market) institutions and the low-intermediate training gap are largely attributable to differences in the labor market allocation of less- relative to intermediate-educated workers. Controlling for labor market allocation at the individual level should thus account for a large portion of any institutional 'effects' on the training gap that we may find.

3. Data and methods

3.1 Data and sample

We use data from PIAAC, the *Programme for the International Assessment of Adult Competencies*, conducted for 24 countries in 2011/12 and for another 9 countries in 2014/15 (OECD, 2013, 2016). Of these, we exclude Australia and Indonesia because they do not provide public use files, Cyprus and Russia because of low data quality, and Singapore because of missing country-level variables. Our country sample comprises the remaining 28 high- and middle-income countries, most of which are members of the OECD (for a list, see Table 2 below).

We restrict the sample to 25-to-54-year-old³ wage and salary workers who have, a), not completed upper secondary education or, b), completed upper secondary (including non-tertiary post-secondary) education but no tertiary-level program. We refer to the former group as ‘less-educated’ and to the latter as ‘intermediate-educated’. Employees with a tertiary-level degree are not part of the analysis as they tend to work in very different labor market segments than less-educated workers. We also drop workers who had worked in their current job for less than a year.⁴ This ensures that labor market allocation characteristics at the time of interview match the reference period of the training participation measures, which refer to the 12 months before the interview (see below). Finally, we exclude so-called ‘literacy-related non-respondents’ (OECD, 2013) and 157 cases with incomplete information on sample-defining variables (i.e., age, highest educational degree, employment status, job tenure).

33,956 cases meet the above sample restrictions. 1,605 of these (4.7 %) have missing information on at least one variable included in the analysis. Our primary missing data approach is to use multiple imputation through chained equations with ten imputations, one for each ‘plausible value’ of the PIAAC numeracy score (see Section 3.2 below). However, we had to drop 433 incomplete cases with missing information on economic sector or foreign-birth/foreign-language status. This was due to persistent convergence problems with the multinomial logistic regressions required to impute these variables. Our final sample consists of 33,523 cases.⁵ Section G in the Online Supplement provides further details on the imputation procedure.

3.2 Individual-level measures

The *outcome variable* is *training participation*, measured as attendance of job-related non-formal training (NFT) in the 12 months before the interview. Figure A1 (in the Appendix) shows that job-related NFT is the dominant form of adult training participation for both less- and intermediate-educated workers. We do not consider training intensity in terms of training hours because this information is not available for all countries and would likely lead to similar results (Bassanini *et al.*, 2005).⁶

Our central *independent variable* is an indicator for being *less educated*. We follow standard practice and define this as ‘not having completed upper secondary education’. More technically, less-educated workers have formal qualifications corresponding to levels 0 to 2 in the 1997 revision of the International Standard Classification of Education (ISCED-97). Intermediate-educated workers, the comparison group, have qualifications at ISCED-97 levels 3 and 4.

We operationalize *labor market allocation* with three sets of variables: *job tasks*, *other job characteristics*, and *firm characteristics*. Our measures of *job tasks* build on Ehlert’s (2020) PIAAC-based study and differentiate between *abstract* (i.e., non-routine cognitive), *routine* (i.e. routine cognitive), and *manual* (i.e., routine and non-routine manual) tasks. We use factor analysis with the principal component method (FA-PC)⁷ to measure abstract tasks and routine tasks (see Online Supplement, Section A, for items and factor loadings). To capture manual tasks, we include two measures without dimension reduction through factor analysis: the frequency of working physically and the frequency of using hand and finger accuracy.

The set of *other job characteristics* includes three variables: computer use at work (yes/no), part-time employment (yes/no), and ISEI scores as an indicator of occupational status (International Socio-Economic Index of Occupational Status; Ganzeboom and Treiman, 1996). We use ISEI scores based on one-digit 2008 International Standard Classification of Occupation codes because more fine-grained categories are not available for all countries.

The set of *firm characteristics* includes firm size in terms of the number of employees (five categories), public vs. private firm ownership (dummy variable), and eight broad economic sectors following the International Standard Industrial Classification of All Economic Activities (ISIC; United Nations, 2008).

We use two measures to capture differences in the *learning disposition* of workers. For *cognitive skills*, we use the PIAAC numeracy proficiency scores. They are based on standardized and internationally comparable test items, a unique feature of the survey. Since the PIAAC testing component is more sophisticated and elaborate than in almost any other population-based survey of adults, its length had to be limited in order not to overburden respondents. PIAAC therefore provides ten so-called plausible values (PVs) whose variability reflects remaining uncertainty about individual proficiency levels (OECD, 2013). We account for these PVs by running all analyses ten times and combining the PV-specific estimates according to the appropriate rules (Little and Rubin, 2002; for further details, see Section 3.5 below). To assess workers' *motivation to learn*, we again use FA-PC to construct an indicator based on four items that express intrinsic motivation for several learning behaviors, as proposed by Gorges *et al.* (2016; see Online Supplement, Section A, for items and factor loadings).

Table 1 presents an overview of the variables used for the five predictor sets (for descriptive statistics see Online Supplement, Section A). In addition to these focal individual-level variables, our analysis uses several straightforward measures of key demographic characteristics such as age or gender (see Section 3.4).

[TABLE 1]

3.3 Country-level variables

To measure cross-national differences in *education systems*, we use the *external differentiation index* as an indicator of *early tracking* (Bol and van de Werfhorst, 2013), the percentage of students attending vocational programs in upper secondary education as a measure of *vocational orientation* (ibid.), and the *skills gap* between less- and intermediate-educated adults—calculated from the PIAAC data—as a direct measure of the skills transparency of educational degrees (Heisig and Solga 2015; Heisig 2018).

Labor market institutions are measured with the OECD indicator of *employment protection legislation* (EPL) governing the dismissal of workers on regular contracts, *union density* rates, and the ratio of gross earnings at the 50th and 10th percentiles (P50/P10) of full-

time employees as an indicator of *wage inequality* in the lower half of the wage distribution (i.e., where intermediate- and especially less-educated workers are primarily located).⁸

Depending on the time of PIAAC data collection (see Section 3.1 above), the country variables refer to 2011/12 or 2014/15, or to the closest year available. More information on the country-level variables, including scores, sources, and a correlation matrix, is provided in Tables A1 and A2 in the Appendix.

3.4 Analytic strategy

This section summarizes the main elements of our empirical strategy. A more detailed, algorithmic description of our approach is provided in Section H in the Online Supplement.

A first challenge that we need to address is the different demographic composition of the two educational groups. While we have no substantive interest in the role of demographic factors, they might nevertheless confound our results. Throughout the analysis, and for each country separately, we therefore reweight intermediate-educated workers to have the same demographic profile as the less-educated group in terms of gender, age, living with partner, having children (<age 13), foreign degree, and foreign-birth/foreign-language status (for descriptive statistics, see Online Supplement, Section A). We rely on the entropy balancing method by Hainmueller (2012) to obtain the weights for this compositional adjustment.

Concerning Expectation 1, our goal is to estimate, for each of the 28 countries, a), the magnitude of the training disadvantage of less-educated workers and, b), the extent to which it can be attributed to different aspects of labor market allocation and workers' learning disposition. Our approach is based on country-specific linear probability models (LPM) that regress the binary measure of job-related NFT participation on the indicator variable for belonging to the less-educated group and all possible combinations of the five sets of explanatory variables identified above (see Table 1). Education coefficients from 'empty' LPM specifications that include only the education indicator (and apply the demographic adjustment weights described above) provide estimates of the *demographically-adjusted* training disadvantage.⁹ Education coefficients from 'full' LPM specifications that include all five sets of explanatory variables provide estimates of the *fully-adjusted* training disadvantage.

The fully-adjusted estimate will typically be smaller (in absolute terms) than the demographically-adjusted one because group differences in labor market allocation and learning disposition partly account for the training disadvantage of the less educated. To quantify the unique contribution of each of the five sets of explanatory factors, we use a *Shapley decomposition* (Shorrocks, 2013). In this framework, the contribution of a set of predictors (e.g., job tasks) to the training disadvantage is estimated as the average marginal change in the estimated training gap (i.e., the coefficient on the low education indicator) associated with removing that set of predictors across all possible elimination sequences leading from the full LPM to the empty LPM specification. With five sets of predictors, there are a total of 120 (=5!) elimination sequences.

To assess Expectation 2 on the moderating role of education systems and labor market institutions, we use a two-step approach that connects the country-specific individual-level LPMs described above with linear regressions at the country level. In the first step of the estimation procedure, the LPMs provide us with country-specific estimates of the training disadvantage. In the second step, these estimates then become the dependent variable in a country-level regression with 28 cases. Given this small number of cases, we entered the institutional explanatory variables one at a time. The country-level regressions are fitted by Feasible Generalized Least Squared to account for the fact that the dependent variables are estimated with (sampling) error and therefore heteroscedastic (Lewis and Linzer, 2005). We additionally use HC3 robust standard errors to adjust for any remaining heteroskedasticity (Long and Ervin, 2000). As discussed in Lewis and Linzer (2005) and Heisig *et al.* (2017), the two-step approach is a flexible alternative to more widely used mixed-effects (multilevel) models.

If the institutional ‘effects’ on the training disadvantage are attributable to the labor market allocation of less- relative to intermediate-educated workers, controlling for the latter in the country-specific (first-step) regressions should lead to a reduction of the coefficients on institutional variables in the country-level (second-step) regressions. For example, if high rates of union density reduce the training disadvantage by reducing education-related inequalities in job tasks, we would expect controlling for job tasks in the first-step regressions to result in a reduction of the union density coefficient in the second-step regression. To explore this possibility, we again conducted Shapley decompositions—where we now decomposed, for each institutional predictor, the difference between the predictor’s coefficient for the demographically-

adjusted gap and its coefficient for the fully-adjusted gap. In so doing, we answer the following question: By how much does removing a set of (individual-level) predictors (e.g., job tasks) from the country-specific (first-step) regressions change the coefficient of an institutional predictor (e.g., union density) in the country-level (second-step) regressions, again averaging across all possible elimination sequences?

3.5 Weighting and variance estimation

Finally, we provide a short summary of our approach to weighting and variance estimation (for further details, see the algorithmic description in the Online Supplement, Section H). The PIAAC survey comes with sample weights that correct for unequal selection probabilities and selective non-response. We take these weights into account, a), by applying the unmodified sample weights for less-educated workers and, b), by supplying the sample weights as base weights for the reweighting of the socio-demographic composition of intermediate-educated workers through the entropy balancing procedure (see Section 3.4 above).

In addition to the final sample weights, PIAAC provides replicate weights that implement (jackknife) approaches to variance estimation to account for PIAAC's complex survey design (OECD, 2016). We use these replicate weights to obtain standard errors and confidence intervals for the Shapley-based contributions of the different variable sets in the country-specific regressions.¹⁰ To account for the uncertainty of the imputed missing values and the ten plausible values for workers' numeracy proficiency, we repeat this procedure for each completed data set and subsequently obtain final point and variance estimates using 'Rubin's rules' (Little and Rubin, 2002).

The above steps account for statistical uncertainty arising from (complex) sampling of individuals within countries and from (imputation) uncertainty in the imputed values and competency scores. When looking at country-level relationships to assess Expectation 2, we additionally need to account for uncertainty introduced by the finite country-level sample. In this step of the analysis, we therefore combine the above procedures with a non-parametric bootstrap with 999 replications. Bootstrap samples are drawn by sampling with replacement from the 28 countries in our analysis.

4. Results

Figure 2 shows the training disadvantage of less-educated relative to intermediate-educated workers before and after adjustment for differences in labor market allocation (job tasks, other job characteristics, firm characteristics) and workers' learning disposition (numeracy skills, motivation to learn). While the estimated demographically-adjusted training disadvantage (left panel) is negative in all countries and statistically significant in all but three, its magnitude varies considerably—ranging from -26 percentage points in the Slovak Republic to only -3 percentage points in Japan.¹¹ The fully-adjusted training disadvantage (right panel) is considerably smaller in all countries and statistically insignificant in most. In a few cases, the point estimate even becomes positive, indicating a training advantage of less-educated workers over observationally similar workers with intermediate levels of education (none of the positive point estimates are statistically significant, however). Estimates for the fully-adjusted gap range from -17 percentage points in Lithuania to 9 percentage points in Greece. Labor market allocation and learning disposition combined thus explain large parts of the education-training relationship.

[FIGURE 2]

But what is the role of the individual variable sets? Does labor market allocation really turn out to be important for less-educated workers' training disadvantage above and beyond individual learning disposition (Expectation 1)? Table 2 provides an answer to this question based on the Shapley approach (see Section 3.4 above). The total explained part is equal to the difference between the demographically-adjusted and the fully-adjusted gaps presented in Figure 2. The last two columns of the table decompose the total explained part into the combined contributions of the three sets of the labor market allocation measures (job tasks, other job characteristics, firm characteristics) and of the two learning disposition measures (numeracy skills, motivation to learn). Figure 3 depicts the individual contributions of the five sets of predictors (for the exact values, see Online Supplement, Section B). Negative values mean that compositional differences with respect to the given set of predictors *contribute* to less-educated workers' training disadvantage (i.e., they partly explain the gap). Positive values indicate that compositional differences in a given domain *reduce* the training disadvantage (i.e., the latter would be even larger in the absence of these compositional differences).

Table 2 shows that differences in labor market allocation generally make a substantial contribution to less-educated workers' training disadvantage, above and beyond workers' learning disposition, in all 28 countries—supporting Expectation 1. In fact, labor market allocation accounts for a larger part of the training gap than workers' learning disposition in all countries, despite marked institutional differences.

[TABLE 2]

The more detailed decomposition in Figure 3 shows that job characteristics (i.e., computer use, occupational status, and part-time employment) tend to be the most important factor in the majority of countries. Only in Lithuania, Slovenia, Austria, Poland, Finland, and Belgium differences in job tasks make the largest contribution to the training gap. Firm characteristics are the most important aspect of labor market allocation in only three countries (South Korea, Ireland, and Turkey), and there are several countries where they play essentially no role.

Turning to workers' learning disposition, motivation to learn seems to be at most a minor factor, except in Poland. The contribution of workers' numeracy skills is small in many countries as well, but there are a few exceptions where these skills do play a substantial and statistically significant role, most importantly Slovak Republic, Germany, and the U.S.

[FIGURE 3]

We now examine the role of educational and labor market institutions (Expectation 2). Figure 4 graphically summarizes the results (for exact values, see Online Supplement, Section D). Panel A shows, for each institutional predictor, the coefficient from a country-level regression for the demographically-adjusted gap (squares) and from a similar regression for the fully-adjusted gap (circles), along with 90 and 95% confidence intervals. Predictors were entered one at a time and are all z-standardized, so coefficient estimates can be interpreted as the predicted percentage point change in the training disadvantage associated with a standard deviation increase in the respective institutional characteristic. Negative (positive) coefficient estimates imply that the training disadvantage tends to increase (decrease) as the respective institutional predictor increases.

Starting with results for the demographically-adjusted training gap and taking the coefficient estimates at face value, a standard deviation increase in union density reduces the training disadvantage of less-educated workers by 1.3 percentage points, while standard deviation increases in EPL and wage inequality raise the training disadvantage by 1.5 and 1.4 percentage points, respectively. Turning to educational institutions, the training disadvantage of less-educated workers increases with the level of skills transparency (2.2 percentage points), external differentiation (2.2 percentage points), and vocational orientation of upper secondary education (1.4 percentage points). These coefficient estimates generally have the expected sign (see Section 2.2 above), and their magnitude is quite substantial relative to the average demographically-adjusted training disadvantage (-15.5 percentage points) and its cross-country standard deviation (5.7 percentage points; see Appendix, Table A1). However, despite these relatively large effect sizes, only the union density and skills transparency coefficients approach conventional levels of statistical significance ($p < .1$, as indicated by the 90% confidence intervals not including zero). When excluding the United States, the most problematic country case according to the outlier analysis in Online Supplement, Section E, both of these coefficients increase in absolute size and become statistically significant at the five percent level (union density: $b = 1.5$; wage inequality: $b = -2.2$).

Turning to the fully-adjusted training gap, all country-level relationships are weaker (i.e., closer to zero) than for the demographically-adjusted training gap and also far from reaching statistical significance. Generally speaking, this indicates that individual-level differences in labor market allocation and learning disposition largely account for any institutional ‘effects’ on the demographically-adjusted gap. Panel B in Figure 4 depicts the size of this attenuation and shows that it is statistically significant in four cases: union density, wage inequality, skills transparency, and external differentiation (for details on the bootstrapping procedure for assessing statistical significance, see Online Supplement, Section H).

Which specific individual-level factors play the most important role here? Or to put it differently: Through which individual-level channels do the effects of the institutional predictors operate? To answer these questions, we conducted another set of Shapley decompositions whose results are also reported in Figure 4, Panel B. We now highlight the main insights from this exercise.

When it comes to labor market institutions, the inequality-reducing effects of higher union density and lower wage inequality appear to stem from less-educated workers' allocation to more training-active workplaces in terms of firm and other job characteristics (e.g., larger firms, more frequent computer use). For EPL, we find a substantial and statistically significant contribution of job tasks, which appears consistent with the dualization thesis: Less-educated workers seem to more often end up in secondary labor market jobs with low skill requirements when EPL is strict.

Turning to educational institutions, any effects of skills transparency and external differentiation on the training disadvantage appear to operate through workers' skills (which is quite intuitive) but also through job tasks (external differentiation only) and other job characteristics. The coefficient of vocational orientation changes relatively little when differences in labor market allocation and workers' skills are accounted for, and the detailed decomposition suggests that this is due to offsetting effects of job tasks on the hand and firm characteristics on the other.

[FIGURE 4]

Overall, the decomposition results are consistent with Expectation 2 that any effects of educational and labor market institutions on the training disadvantage of less-educated workers operate, to a good extent, through labor market allocation (although, perhaps unsurprisingly, differences in individual learning disposition also seem to play a role in mediating the effects of external differentiation and skills transparency). It bears repeating, however, that these results are based on a small sample and need to be interpreted cautiously. In particular, the associations of the various institutional measures with the demographically-adjusted training gap, while meaningful in size, do not attain conventional levels of statistical significance.

5. Supplementary analyses

We conducted several supplementary analyses to extend the main results and to assess the robustness, especially of the country-level findings. As a first check, we reran our analyses using literacy instead of numeracy proficiency. The results (available upon request) were very similar to the main analyses presented above.

Second, we conducted influence diagnostics for the country-level regressions presented in Figure 4 above. This analysis revealed that the results are not driven by a single country, although—as noted in the previous section—the U.S. emerged as a somewhat influential case (see Online Supplement, Section E).

Third, we included two potential confounding factors into our country-level regressions (results available upon request): the *share of less-educated among the adult population*—because higher shares might decrease less-educated workers’ risk of stigmatization and improve their labor market placement (Gesthuizen *et al.*, 2011)—and the *share of unemployed less-educated adults* to control for potential cross-national differences in the selectivity of the employed group (our analytic sample). Neither indicator led to substantial changes in the country-level regression results.

Fourth, we explored the country-level correlation between the low-intermediate and the intermediate-tertiary training gap, which turns out to be zero (Pearson’s r of 0.03; see Online Supplement, Section A). The low-intermediate training gap is thus largely independent of training inequalities at the upper end. This suggests that cross-national variation in the low-intermediate gap is not primarily driven by variation in intermediate-educated workers’ access to training (if this were the case, we should see a negative correlation between the low-intermediate and intermediate-tertiary gaps).

In a final supplementary analysis, we considered a typology-based approach, as commonly used in comparative training research (Desjardins and Rubenson, 2013; Roosmaa and Saar, 2012) and the political economy literature more broadly (Estevez-Abe *et al.*, 2001; Hall and Soskice, 2001). More specifically, we explored country variation across a limited set of ‘institutional configurations’ as an alternative to our main analysis, which looks at institutional characteristics one at a time (see Online Supplement, Section F). We identified configurations by running a cluster analysis on the institutional features considered in our country-level regressions. This inductive approach is more practicable than a theory-guided one because the classification of several countries in our sample is uncertain or contested. A four-cluster solution seemed most appropriate and aligns quite well with standard welfare regime typologies and the Varieties of Capitalism framework (Hall and Soskice, 2001). Country-level regressions revealed that less-educated workers’ (demographically-adjusted) training disadvantage is smallest in social-

democratic coordinated market economies (CMEs), largest in conservative CMEs, and somewhere in between in the remaining two groups, European and North American liberal market economies (LMEs). Shapley decompositions confirmed that labor market allocation remains more important than learning disposition when it comes to explaining cross-national differences in the training gap (here: across clusters) . These results (reported in the Online Supplement, Table F3) are qualitatively consistent with those in Figure 4. They also suggest that training disadvantages do not map neatly onto standard political economy classifications in that we find the smallest training inequalities in one type of coordinated market economies (social-democratic CMEs) and the largest in another (conservative CMEs).

6. Conclusions

Job-related further training is considered important for improving workers' productivity, employment outcomes and career prospects in an ever-changing world of work. The training disadvantage of less-educated workers thus constitutes an important dimension of labor market inequalities and appears to cement rather than counteract labor market inequalities by level of formal education. Better understanding the nature and sources of training inequalities is therefore of high interest, both theoretically and policy-wise.

In this article, we have examined the training disadvantage of less-educated relative to intermediate-educated workers across 28 countries, focusing on job-related non-formal training as the dominant form of continued training in advanced economies. Our analysis generalizes and extends previous results that labor market allocation is decisive in determining workers' access to training (Ehlert, 2020; Görlitz and Tamm, 2016; Mohr *et al.*, 2016; Saar and Räis, 2017; Schindler *et al.*, 2011). Despite salient institutional differences, labor market allocation emerges as the key proximate factor shaping the training disadvantage of less-educated workers in all 28 countries under study. In particular, it turns out to be more important for understanding training inequalities than workers' learning disposition. As for the different dimension of labor market allocation, what we referred to as 'other job characteristics' (computer use, occupational status, and part-time employment) emerged as the most important domain, but job tasks (routine, abstract, and manual tasks) and firm characteristics (firm size, economic sector, public vs. private ownership) are relevant factors, too, with some variation across countries.

Country-level regressions suggest that the magnitude of less-educated workers' training disadvantage depends on educational and labor market institutions, although strong conclusions are hampered by the limited sample size. That being said, strong unions appear to be associated with smaller training inequalities, while high skills transparency (i.e., a strong association between formal qualifications and actual skills) appears to amplify them, resembling findings for other dimensions of labor market attainment such as occupational status (Abrassart, 2013; Andersen and van de Werfhorst, 2010; Gebel and Giesecke, 2011; Heisig *et al.*, 2019). Results for other institutional characteristics do not reach statistical significance, although coefficient estimates generally point in the expected direction. Importantly, decomposition results indicate that labor market allocation again is a key channel through which any institutional 'effects' operate.

This explanatory salience of labor market allocation carries important insights for the political economy literature on production and skill regimes (Busemeyer, 2009; Estevez-Abe *et al.*, 2001). While this literature points to differences in overall training participation across skill formation regimes, it has paid little attention to training *inequalities*—especially at the very bottom of the educational ladder, the focus of our study. Our results are consistent with a key tenet of the Varieties of Capitalism literature in that the workplace (i.e., labor market allocation) emerges as the main source of these inequalities. At the same time, our analysis suggests that prominent taxonomies of skill and production regimes are of limited use for understanding how inequalities in adult further training vary across countries. A likely reason is that '[adult learning systems] are in general not only less regulated but also less homogeneous than the regular cycle of formal education regarding their institutional structure, function and target groups' (Desjardins and Ioannidou, 2020, p. 146). Thus, our study may inspire the political economy literature to not only focus on initial skill formation but also to deepen the theoretical consideration of further training and of training inequalities between educational groups.

While our study significantly advances our understanding of the factors driving less-educated workers' training disadvantage, it will not be the final word on the issue. Our cross-sectional, conditioning-on-observables approach does not justify strong causal claims, and the moderate size of our country sample further limits our ability to draw robust conclusions. However, the unique skills assessment component of the PIAAC survey enabled us to control for a potentially important confounder that is not accounted for in most previous studies.

Despite this key strength, our individual-level data also have some weaknesses. A major one is the relative shortage of information on the firm context. We had to rely on respondent reports of some very general firm characteristics (number of employees, broad economic sector, public vs. private ownership). The fact that firm characteristics account for a substantial portion of the training disadvantage in at least some countries, despite the relative crudeness of these measures, attests to the importance of the organizational context. Linked employer-employee data providing detailed information on training policies, training infrastructures, recruitment strategies, or the structure of internal labor markets have clear potential to move the literature forward. Unfortunately, such data continue to remain rare—and virtually non-existent when it comes to data sets that are well-suited for cross-national comparisons.

Policy-wise, our findings highlight a vicious cycle: Less-educated workers are more likely to be exposed to work situations that require fewer skills investments and provide fewer job-related learning opportunities, which cements and reinforces their poor labor market prospects in the long run. Policies aiming to reduce inequalities in training participation should therefore target training barriers related to job and firm characteristics—while taking into account country-specific patterns in the relevance of individual labor market allocation characteristics. Promising measures include the reduction of training costs (e.g., through subsidies), provision of information on expected productivity returns, or the promotion of collective agreements in workplaces with limited incentives and infrastructures to train, such as smaller firms.

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¹ Examples of job-related NFT are type-writing courses or introductory courses on information technologies. In contrast to NFT, formal training leads to a recognized certificate such as a university degree or a vocational qualification, whereas informal training is also intentional but less organized, occurring in the workplace or the family, for example (Eurostat, 2006).

² The following discussion adopts this perspective in that we focus on employer-based explanations for (not) training workers. This is mostly for parsimony, and we do not mean to imply that workers’ agency does not matter. Employer- and worker-focused explanations usually point in the same direction, however, and we cannot disentangle the two sides of the process empirically. For example, longer expected (remaining) tenure with a firm increases incentives to invest in firm-specific skills for both employers and workers.

³ The age bounds increase cross-national comparability by reducing country differences due to age of labor market entry and retirement.

⁴ Further analyses (available upon request) show that less-educated workers are somewhat more likely to be short tenured and that they are also more likely to be employed on a fixed-term/non-standard contract in the 26 countries where this information is available (all except Canada and the U.S.). This suggests that our estimates of the training gap may be somewhat conservative because fixed-term employees may be less likely to be included in training measures.

⁵ Our sample of *employed* less-educated adults is positively selected in terms of job-related NFT participation (see Appendix, Figure A1) or skills (see Online Supplement, Section A). This selectivity indicates that our estimates of training gaps and potential explanations may be somewhat conservative, even though intermediate-educated workers show qualitatively similar selectivity when compared with their non-employed counterparts.

⁶ Among the 26 countries that do provide training hours information, training participation rates and average training hours are highly correlated, with (country-level) Pearson correlations of 0.77 for the less-educated and 0.81 for the intermediate-educated group (see Online Supplement, Section A).

⁷ With the principal component method, we follow Ehlert (2020). Robustness checks with other methods, such as the principal factor method (FA-PF) or a principal component analysis (PCA), produce almost identical factor scores with Pearson correlations above 0.99.

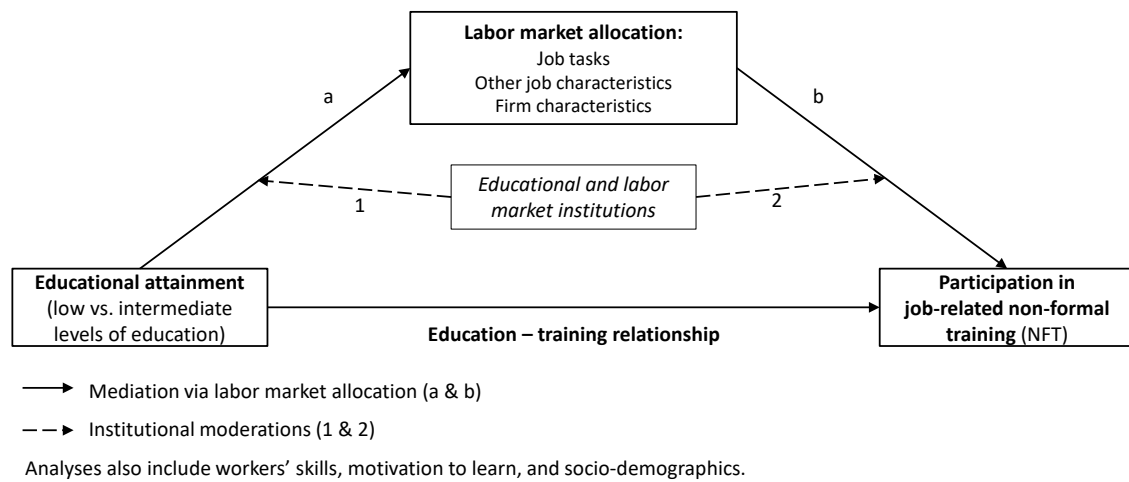
⁸ Due to data limitations, the wage inequality data are not fully comparable and refer to weekly and monthly earnings in 24 countries, to hourly earnings in two countries, and to annual earnings in another two.

⁹ For a comparison to the unadjusted training disadvantage (i.e., before accounting for demographic composition), see Online Supplement, Section A.

¹⁰ This means that the entropy balancing procedure is not only carried out for the final sample weights but also for all replicate weights. The resulting demographically-adjusted final sample and replicate weights are then used to calculate final point and variance estimates (OECD, 2016).

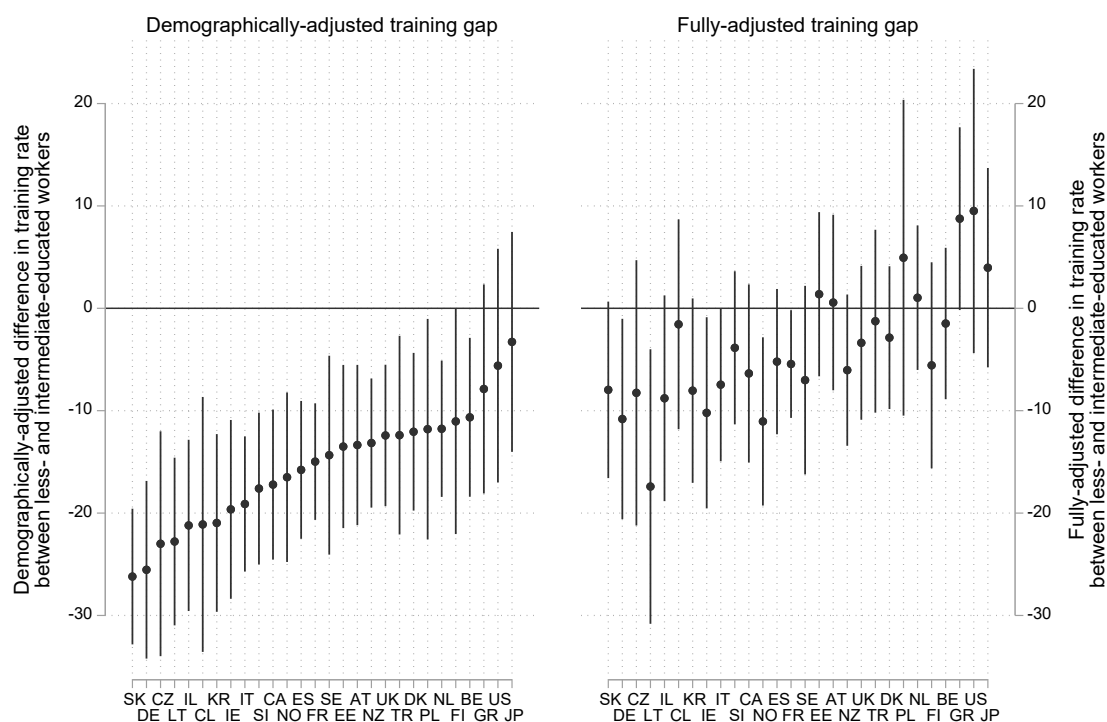
¹¹ For the absolute training participation rates of less- and intermediate-educated workers, see Figure A1 in the Appendix.

Figure 1: The education-training relationship and the role of labor market allocation



Note: authors' elaboration.

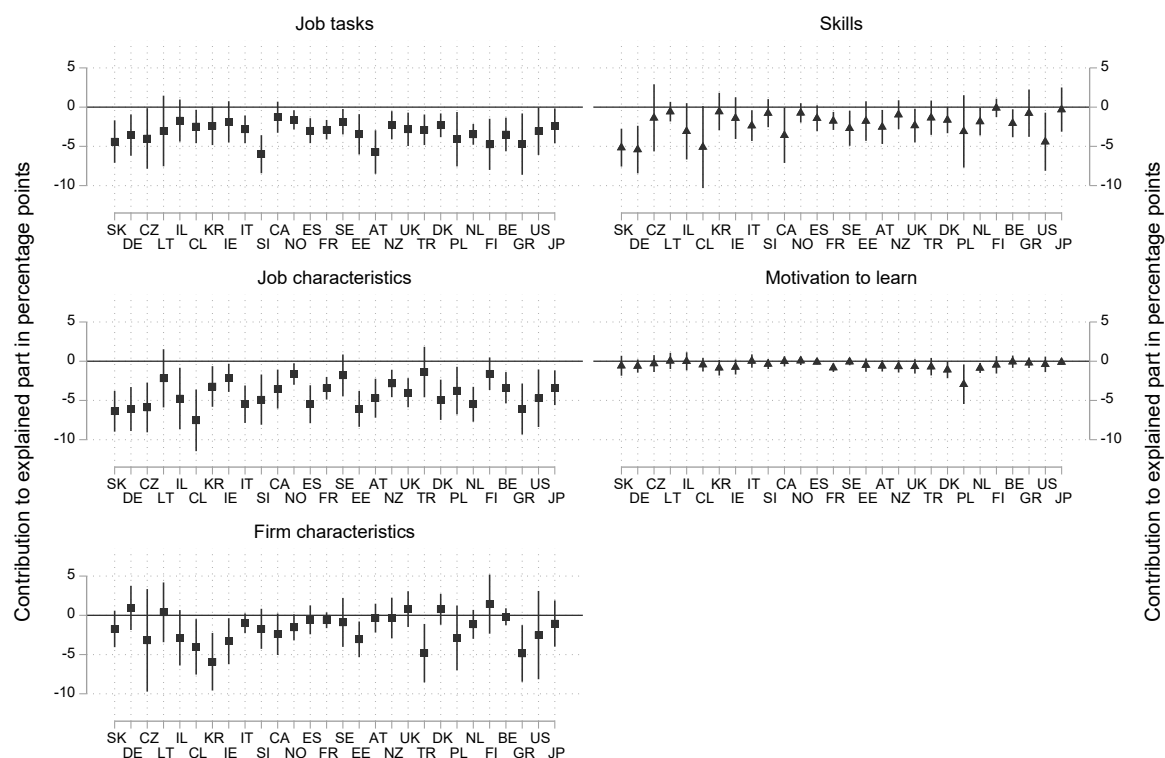
Figure 2: Training disadvantage of less-educated workers relative to intermediate-educated workers in 28 countries (% points)



Notes: Ordered by size of the demographically-adjusted training disadvantage. Demographically-adjusted gap is adjusted for gender, age, living with partner, having children (< age 13), foreign degree, and foreign-birth/foreign-language status. Fully-adjusted training disadvantage additionally accounts for differences in labor market allocation and learning disposition (see Table 1). Vertical lines indicate 95% confidence intervals. For country abbreviations and sample sizes see Table 2 below.

Source: PIAAC, authors' own calculations.

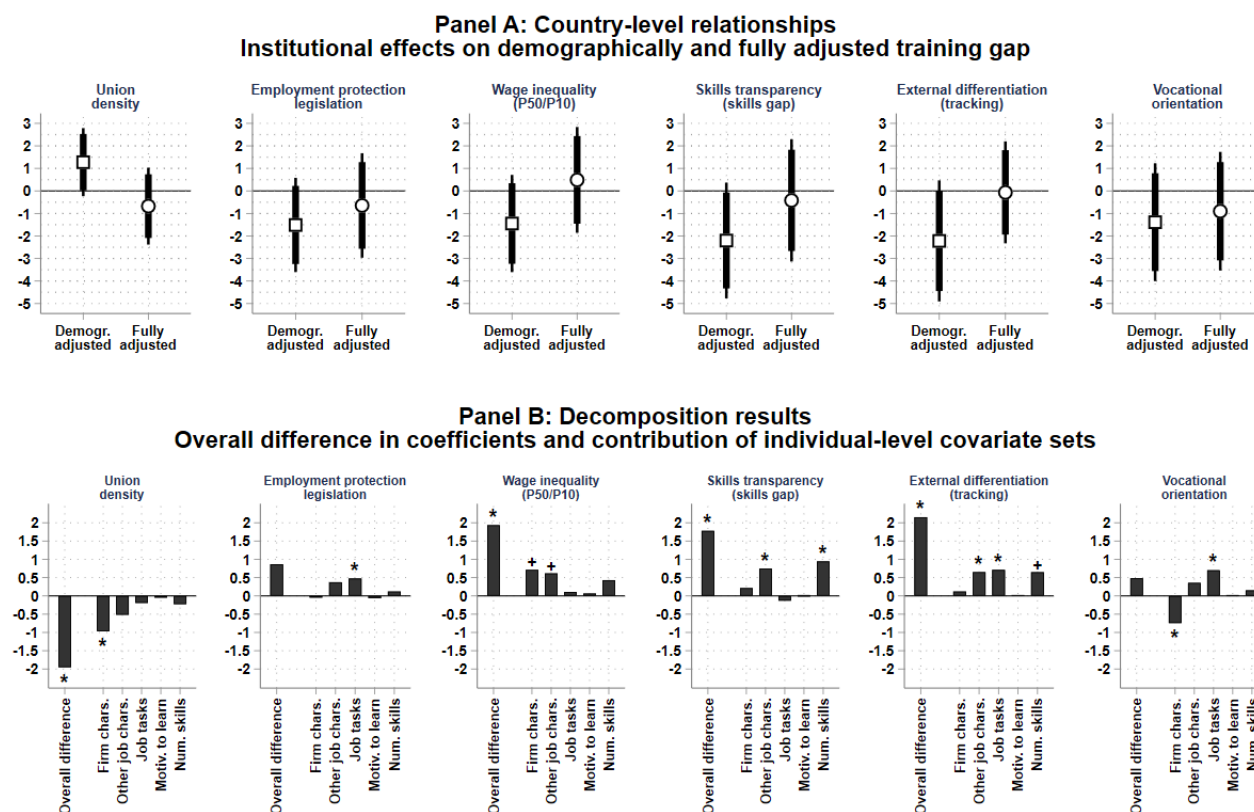
Figure 3: Country-specific Shapley decompositions of less-educated workers' training disadvantage for the five sets of predictors (% points)



Notes: Ordered by size of the demographically-adjusted training disadvantage (see Figure 2). Vertical lines indicate 95% confidence intervals based on jackknife replicate weights. Shapley decomposition: contributions of each set are equal to the average marginal contribution to the training disadvantage over all possible elimination sequences leading from the fully-adjusted to the demographically-adjusted training gap (for variables see Table 1). For exact values, see Online Supplement, Section B.

Source: PIAAC, authors' calculations.

Figure 4: Country-level regressions of the training disadvantage of less-educated workers and Shapley decomposition results (% points)



Notes: N = 28 countries; for external differentiation N = 26 (w/o Estonia, Lithuania). *Panel A* shows coefficient estimates from country-level feasible generalized least squares regressions of the demographically-adjusted and fully-adjusted training gap on the country-level predictors (Lewis and Linzer, 2005). Country-specific (first-step) regressions for the fully-adjusted training gap are reported in the Online Supplement, Section C. Country-level predictors are z-standardized (mean of 0, standard deviation of 1) and entered one at a time (i.e., other country characteristics are not controlled). Thick lines indicate two-sided 90% and thinner extensions indicate two-sided 95% confidence intervals based on heteroskedasticity-consistent (HC3) standard errors (Long and Ervin, 2000). *Panel B* shows the total difference in coefficient estimates for the demographically-adjusted and for the fully-adjusted gap and uses a Shapley approach to decompose this difference into the contributions of the five sets of individual-level predictors. These contributions are estimated as the average marginal change in the institutional coefficient associated with eliminating a given set of individual-level predictors from the country-specific (first-step) regressions, averaged over all possible elimination sequences leading from the fully-adjusted to the demographically-adjusted gap. Symbols indicate two-tailed p -values based on a non-parametric cluster bootstrap: + $p < 0.10$; * $p < 0.05$. See Section “Data and Methods” and Online Supplement, Section H, for further details.

Source: PIAAC, authors’ calculations.

Table 1: Overview of the five sets of individual-level predictors

Constructs	Variables
<i>Labor market allocation</i>	
Job tasks	Factor of abstract tasks (based on five items) Factor of routine tasks (based on four items) Single-item indicator for manual tasks Single-item indicator for manual accuracy tasks
(Other) Job characteristics	Part-time employment (yes/no) Respondent's occupational status (ISEI) Computer use at work (yes/no)
Firm characteristics	Firm size (five categories) Public (vs. private) firm ownership Economic sectors (eight ISIC groups)
<i>Learning disposition</i>	
Workers' skills	Numeracy proficiency
Workers' motivation to learn	Factor of motivation to learn (based on four items)

Table 2: Country-specific Shapley decompositions of less-educated workers' training disadvantage (% points)

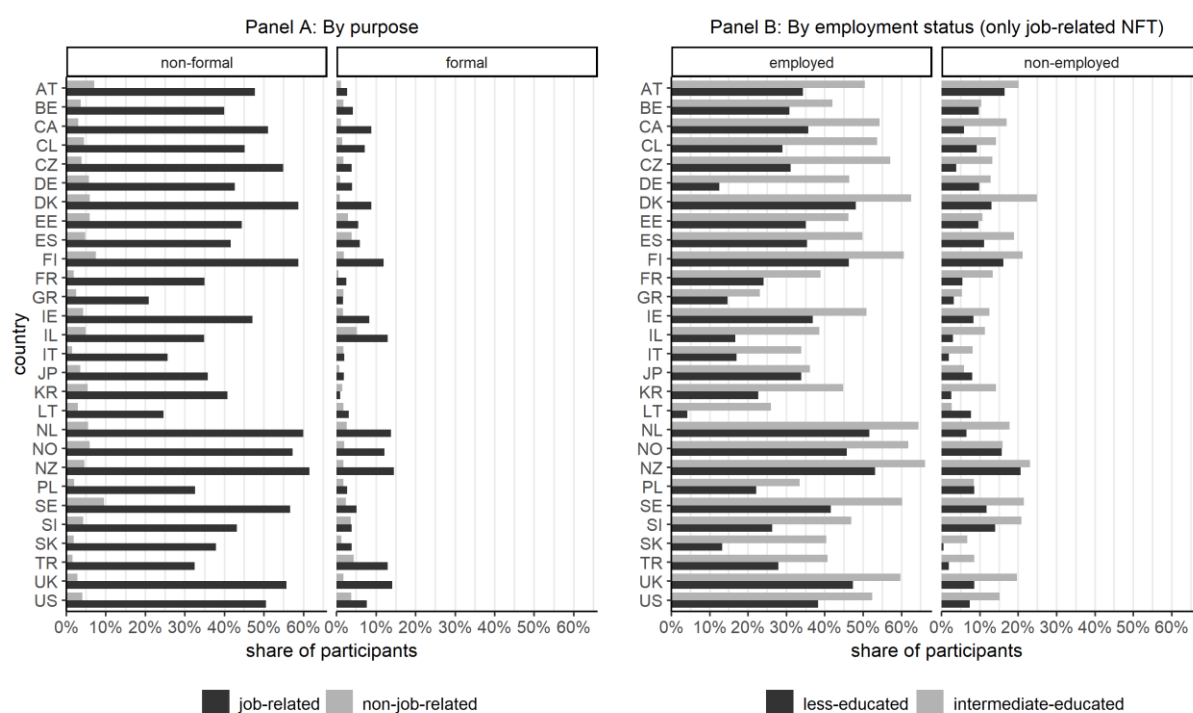
Country	Country code	N	Demographically-adjusted training disadvantage	Total explained part of the training disadvantage	Explained part attributable to sets of predictors	
					Labor market allocation	Learning disposition
Slovak Rep.	SK	1,419	-26.2***	-18.2***	-12.3***	-6.0***
Germany	DE	1,517	-25.5***	-14.7***	-8.1**	-6.7***
Czech Rep.	CZ	1,308	-23.0***	-14.7***	-12.8***	-1.9
Lithuania	LT	1,046	-22.8***	-5.4	-4.7	-0.7
Israel	IL	692	-21.2***	-12.4***	-9.1**	-3.3+
Chile	CL	876	-21.1**	-19.5***	-13.7***	-5.9*
South Korea	KR	845	-21.0***	-12.9***	-11.3***	-1.6
Ireland	IE	974	-19.6***	-9.4***	-7.0**	-2.5
Italy	IT	1,300	-19.1***	-11.7***	-8.9***	-2.7*
Slovenia	SI	1,327	-17.6***	-13.7***	-12.3***	-1.4
Canada	CA	3,497	-17.2***	-10.9***	-6.9**	-3.9*
Norway	NO	1,000	-16.5***	-5.5***	-4.6***	-0.9
Spain	ES	1,086	-15.8***	-10.6***	-8.8***	-1.8*
France	FR	1,594	-15.0***	-9.5***	-6.6***	-3.0***
Sweden	SE	940	-14.3**	-7.3**	-4.2+	-3.1*
Estonia	EE	1,419	-13.5**	-14.9***	-12.1***	-2.8*
Austria	AT	1,330	-13.3**	-13.9***	-10.1***	-3.8**
New Zealand	NZ	1,120	-13.2***	-7.1**	-5.2**	-1.9+
United Kingdom	UK	1,642	-12.4***	-9.0***	-5.7**	-3.3**
Turkey	TR	682	-12.4*	-11.1***	-9.0***	-2.1
Denmark	DK	1,134	-12.1**	-9.2***	-6.0***	-3.2**
Poland	PL	1,093	-11.8*	-16.7***	-10.5**	-6.3*
Netherlands	NL	1,241	-11.8***	-12.8***	-9.7***	-3.1**
Finland	FI	871	-11.0*	-5.5+	-4.7+	-0.8
Belgium	BE	1,106	-10.6**	-9.2***	-6.6***	-2.5*
Greece	GR	658	-7.9	-16.6***	-15.6***	-1.1
United States	US	902	-5.6	-15.1***	-9.9*	-5.2*
Japan	JP	904	-3.3	-7.2**	-6.6**	-0.7

Notes: Ordered by size of the demographically-adjusted training disadvantage (see Figure 2). Negative values indicate lower (adjusted) training participation rates for less-educated workers compared to the intermediate-educated group (percentage point difference). Correspondingly, negative (positive) values of the explained part indicate that compositional differences in labor market allocation or learning disposition contribute to (reduce) the training disadvantage. Contributions are estimated as the combined average marginal contribution of the sets of labor market allocation/learning disposition measures over all possible elimination sequences leading from the fully-adjusted to the demographically-adjusted training disadvantage (Shapley decomposition). For subsets see Figure 3 and Online Supplement, Section B. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests).

Source: PIAAC, authors' calculations.

Appendix

Figure A1: Training participation in adult training (in the last 12 months) of less- and intermediate-educated adults



Notes: N = 33,523 for the employed sample (Panel A/left column in Panel B), N=18,512 for the non-employed sample (right column in Panel B). Ordered by country code. Survey weights applied.

Source: PIAAC, authors' own calculations.

Table A1: Descriptive statistics of the country-level variables used

	Country code	Dem.- adjusted disad- vantage	Fully- adjusted disad- vantage	Union density	Employ- ment protection legislation	Wage inequality (P50/P10)	Skills gap	Index of external differen- tiation	Prevalence of vocational enrolment	% of less- educated adults	% of non- employed among less-educated adults
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Austria	AT	-13.4	0.6	28.1	2.4	1.7	24.9	1.8	78.3	17.4	8.2
Belgium	BE	-10.6	-1.5	54.1	2.8	1.4	23.1	1.0	61.8	28.5	12.1
Canada	CA	-17.2	-6.4	27.1	1.3	1.9	42.7	-1.3	2.8	11.2	11.1
Chile*	CL	-21.1	-1.6	14.9	1.8	1.6	35.9	0.3	37.0	36.9	5.5
Czech Rep.	CZ	-23.0	-8.3	15.1	2.9	1.9	26.0	1.6	79.2	7.6	23.5
Denmark	DK	-12.1	-2.9	68.8	1.8	1.4	23.1	-0.9	50.6	21.6	9.8
Estonia	EE	-13.5	1.4	6.5	2.1	2.0	28.1	Not avail.	31.0	10.5	23.6
Finland	FI	-11.0	-5.6	69.4	2.1	1.5	14.5	-0.9	57.1	15.7	11.4
France	FR	-15.0	-5.4	10.8	2.8	1.4	27.0	-0.5	49.6	27.9	13.3
Germany	DE	-25.5	-10.8	18.3	2.8	1.8	42.6	1.9	60.3	13.7	13.4
Greece*	GR	-7.9	8.8	23.1	2.5	1.8	23.6	-0.5	33.9	30.8	27.0
Ireland	IE	-19.6	-10.2	30.9	1.9	1.9	31.5	-0.3	32.9	25.9	22.5
Israel	IL	-21.2	-8.8	22.8	2.4	2.0	32.0	-0.1	34.8	14.6	7.0
Italy	IT	-19.1	-7.5	35.4	3.2	1.5	33.5	0.2	61.7	43.4	10.8
Japan	JP	-3.3	4.0	18.5	2.1	1.6	22.5	-0.5	24.6	Not avail.	Not avail.
Lithuania*	LT	-22.8	-17.4	8.0	2.5	1.8	18.5	Not avail.	28.2	8.7	24.2
Netherlands	NL	-11.8	1.0	19.0	3.2	1.6	27.1	0.9	68.5	27.1	5.5
New Zealand*	NZ	-13.2	-6.0	18.3	1.1	1.6	30.9	-0.4	24.3	25.6	5.7
Norway	NO	-16.5	-11.0	49.9	2.3	1.4	14.2	-1.0	60.2	18.0	4.6
Poland	PL	-11.8	4.9	16.9	2.4	2.0	22.5	-0.1	47.3	10.7	17.3
Slovak Rep.	SK	-26.2	-8.0	14.5	2.8	1.8	35.8	1.6	73.6	8.5	40.4
Slovenia	SI	-17.6	-3.9	26.6	2.4	1.7	34.7	0.1	64.1	13.7	14.5
South Korea	KR	-21.0	-8.0	9.8	2.2	2.0	26.1	0.1	28.6	18.0	2.6
Spain	ES	-15.8	-5.2	17.8	2.4	1.6	26.8	-1.0	40.6	45.7	28.7
Sweden	SE	-14.3	-7.0	67.5	2.6	1.3	22.5	-0.9	55.8	12.7	11.5
Turkey*	TR	-12.4	-1.3	7.5	2.7	1.2	29.9	1.2	37.6	63.7	8.8
United Kingdom	UK	-12.4	-3.4	26.1	1.8	1.8	26.4	-1.0	36.6	22.5	10.8
United States	US	-5.6	9.5	11.1	1.0	2.1	35.1	-1.3	0.0	10.7	15.2
Mean		-15.5	-3.9	26.3	2.3	1.7	27.9	0.0	45.0	21.9	14.4
Standard dev.		5.7	6.1	18.7	0.6	0.2	7.1	1.0	20.5	13.3	8.9

Notes: Alphabetical order. * Second PIAAC round. Training gap estimates are controlled for socio-demographics by including entropy balancing weights. For the country-level regressions all predictors were z-standardized to have a mean of 0 and a standard deviation of 1.

Sources: 1-2, 6: PIAAC (rounds 1 and 2), authors' calculations; 3-5, 9-10: OECD online database (<https://stats.oecd.org/>), measured at time of survey (2011/12 for round 1 and 2014/15 for round 2); 7: Educational Systems Database, version 4 (Bol and van de Werfhorst, 2013); 8: OECD (2006: Table C2.5) and UNESCO online database (<http://data.uis.unesco.org/>).

Table A2: Correlation matrix of country-level variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Demographically-adjusted disadvantage	1.00									
(2) Fully-adjusted disadvantage	0.78***	1.00								
(3) Union density	0.20	-0.12	1.00							
(4) Employment protection legislation	-0.31	-0.22	0.01	1.00						
(5) Wage inequality (P50/P10)	-0.20	0.13	-0.53**	-0.32	1.00					
(6) Skills gap	-0.39*	-0.01	-0.42*	-0.17	0.37*	1.00				
(7) Index of external differentiation	-0.45*	-0.13	-0.31	0.61**	0.01	0.24	1.00			
(8) Prevalence of vocational enrolment	-0.29	-0.21	0.32	0.72***	-0.36	-0.23	0.61***	1.00		
(9) % of less-educated adults	0.21	0.15	-0.08	0.21	-0.56**	0.04	0.04	-0.03	1.00	
(10) % unemployed among less-educated adults	-0.22	-0.00	-0.26	0.19	0.31	0.06	0.14	0.07	-0.18	1.00

Notes: N=28. For pairwise correlations (7) N=26 because the index is not available for Estonia and Lithuania, (9) and (10) N=27 because the shares are not available for Japan. * p < 0.05, ** p < 0.01, *** p < 0.001.

Sources: See Table A1.