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Lack of skills or formal qualifications? New evidence on cross-country differences in the labor market disadvantage of less-educated adults

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Abstract

We use PIAAC data on the literacy and numeracy skills of 49,366 25-to-54-year-olds in 27 countries to shed new light on cross-national variation in the labor market disadvantage of less-educated adults (i.e., those who have not completed upper secondary education). Our empirical analysis focuses on the occupational status gap between less-educated adults and those with a degree at the upper secondary level and yields three main findings. First, individual-level differences in literacy and numeracy skills are an important source of cross-national variation in labor market inequalities by educational attainment, but substantial gaps in occupational status remain even after accounting for individuals' actual skills and further socio-demographics. Second, this remaining occupational status gap rises with a country's level of "skills transparency" (i.e., the extent to which formal qualifications are more informative about actual skills): labor market gaps increase as the skills gap between the two educational groups increases and as the within-group distribution of skills becomes more homogeneous. Third, country differences in skills transparency seem to be the primary mediating channel for the inequality-enhancing effect of tracking in secondary education found in previous research.

Keywords: Education; Inequality; Social Stratification; International Comparison; Skills; PIAAC

1 INTRODUCTION

It is well-established that educational degrees are positively associated with labor market outcomes such as employment rates, occupational status, or wages. Less-educated adults, that is, adults who did not complete upper-secondary education, bear particularly high risks of labor market marginalization (e.g., Abrassart, 2013; Gesthuizen et al., 2011). While the less educated are facing difficulties throughout the industrialized world, the extent of their labor market disadvantage varies considerably across countries (Abrassart, 2013; Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011; Gesthuizen et al., 2011; Shavit and Müller, 1998).

Several influential theories (e.g., human capital theory; Becker 1964) suggest that skills differentials are a major driver of labor market inequalities by educational attainment and empirical evidence is generally consistent with this (Hanushek and Woessmann, 2008). The role of skills as a source of cross-national variation in the labor market disadvantage of the less educated is not well understood, however. While the relationship between skills and educational attainment has received some theoretical attention in previous research (e.g., Andersen and van de Werfhorst, 2010), empirical evidence remains very limited. The latter is mainly because of a shortage of cross-nationally comparable data on the actual skills of working-age adults. In this paper, we analyze data from the most ambitious cross-national survey of adult skills so far, the first and second rounds of the *Programme for the International Assessment of Adult Competencies* (PIAAC). PIAAC is a unique data set that provides high-quality and comparable data on the literacy and numeracy skills of adults for a large set of advanced economies.

We use these data to assess two explanations that have not been clearly disentangled in previous research. First, the levels of skills achieved by less- and more-educated workers vary across countries (Park and Kyei, 2011; Heisig and Solga, 2015). Thus, if employers reward skills, as suggested by human capital theory (Becker 1964), these differences should more or less directly translate into differences in labor market attainment (e.g., Gesthuizen et al., 2011; Murnane et al., 1995). The second explanation is closely related to signaling and screening theories of labor market inequalities (Spence, 1973; Weiss, 1995) and argues that the "skills transparency" of educational certificates varies across countries (Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011). If the relationship between (easily observable) formal qualifications and (hard-to-observe) skills is closer—that is, if formal qualifications are more "skills transparent"—in some countries than in others, then this might affect labor market inequalities by exacerbating statistical discrimination against less-educated workers because of their (lack of) formal qualifications. Recent research has indeed found that the relationship between formal qualifications and skills differs markedly across countries, both in terms of the extent of skills differentials among educational groups and in terms of the variability of skills within educational groups (Heisig, 2018; Heisig and Solga, 2015). In this paper, we investigate whether these country differences help account for cross-national variation in the labor market disadvantage of the less educated.

The main contribution of our paper is to test the skills transparency explanation more directly than previous research. To this end, we use two *novel country-level measures of skills transparency*: the *skills gap* (the adjusted differential in mean literacy and numeracy competencies between adults with low and intermediate formal qualifications) and the *index of internal homogeneity* (which measures the residual skills variation within these educational groups). In countries where the skills gap is large and where educational groups are internally homogeneous, educational credentials are highly informative about an individual's actual skills (Heisig, 2018). In such settings, formal qualifications should play a particularly important role as screening devices on the labor market—and we should find greater labor market inequalities among educational groups even after accounting for the direct effect of (individual-level) differences in skills.

We also shed new light on the finding that tracking (or "external differentiation") in secondary education is associated with greater labor market returns to formal qualifications (e.g., Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011; Shavit and Müller, 1998). One prominent interpretation of this result is that external differentiation strengthens the skills transparency of educational certificates (Andersen and van de Werfhorst, 2010). Consistent with this argument, recent studies have already shown that tracking is positively associated with the two direct measures of skills transparency mentioned above: the skills gap between less- and intermediate-educated adults (Heisig and Solga, 2015) and with the internal homogeneity of educational groups (Heisig, 2018). In this paper, we turn to labor market inequalities and use these measures to provide direct empirical evidence on the claim that skills transparency is an important mediating channel for the role of tracking in upper secondary education.

Our empirical analysis covers 49,366 adults in 27 countries and focuses on the occupational status gap between less-educated adults (who have less than upper secondary education) and intermediate-educated adults (who have a degree at the upper-secondary or non-tertiary postsecondary level). We exclude adults with tertiary education because they are unlikely to be direct competitors of the less educated on the labor market.

Country-specific Kitagawa-Oaxaca-Blinder decompositions reveal that individual-level differences in literacy and numeracy skills are an important source of labor market inequalities between the less-educated and the intermediate-educated group, but substantial gaps in occupational status remain even after accounting for individuals' actual skills and socio-demographic controls. Country-level regressions then show that the size of the remaining gap is related to the aggregate skills gap between less- and intermediate-educated adults and to the internal homogeneity of these groups, thus supporting the skills transparency explanation. Further regressions suggest that the country-level relationship between tracking and the occupational status gap between less- and intermediate-educated adults is indeed largely mediated by country differences in skills transparency. We can replicate the finding of previous studies that tracking in secondary education is associated with larger labor market inequalities between less- and intermediate-educated adults. However, once we include the skills gap and the internal homogeneity measure in the regression, the coefficient on the tracking measure essentially drops to zero.

2 EXPLAINING THE LABOR MARKET DISADVANTAGE OF LESS-EDUCATED ADULTS

Skills are not homogeneous. They comprise a diverse set of capabilities that differ in their transferability across different types of jobs (Becker, 1964). One important distinction in this respect is between general and occupation-specific skills (e.g., Müller and Jacob, 2008). Whereas general skills such as literacy and mathematical skills are useful in a wide variety of jobs, occupation-specific skills (e.g., an auto mechanic's understanding of how to repair a car engine) are, by definition, valuable only in a narrow set of particular occupations. The PIAAC data used in our empirical analysis provide measures of individuals' general (literacy and numeracy) skills, but no direct measures of occupation-specific skills. This limitation is important to keep in mind in the following (see also Section 2.2 below).

We now review previous research and theoretical considerations on the role of skills for labor market returns to education and the labor market disadvantage of less-educated adults, with a particular focus on comparative work. We close the section with a discussion of complementary and alternative explanations.

2.1 Individual-level skills vs. aggregate-level skills transparency

A common explanation for the labor market disadvantage of less-educated workers is based on human capital theory (Becker, 1964). It is argued that skills enhance productivity and are therefore rewarded by employers (e.g., by higher wages or job placements). Accordingly, because less-educated adults gain on average lower levels of skills than intermediate-educated workers (Heisig and Solga, 2015; Park and Kyei, 2011), they should have poorer occupational attainment in all countries (Bills, 1990, 2003; Solga, 2002, 2008). While this argument is straightforward, empirical tests with direct measures of cognitive skills remain rare. A major reason for this has been a shortage of direct skills measures, especially in cross-national surveys. A few studies have used data from the mid-1990s *International Adult Literacy Survey* (Gesthuizen et al., 2011; Hanushek and Woessmann, 2008; van de Werfhorst, 2011), but they must be viewed with caution because severe problems with this data set have been detected in recent years (see Solga, 2014, for further details). PIAAC's high-quality measures of general skills allow us to (re-)assess the empirical relevance of this argument for a large set of advanced economies.

This argument about the importance of *individual* skills also suggests a first and straightforward explanation for cross-national variation in the labor market disadvantage of the less educated. Previous research has documented large country differences in the mean skills levels of less-educated workers (see, for example, Figure 1 in Heisig and Solga's, 2015, analysis of PIAAC data). This finding suggests that, in some countries, less-educated adults might attain higher occupational status simply because they are, on average, better equipped with skills. This argument motivates the following hypothesis:

Hypothesis 1: Accounting for differences in literacy and numeracy skills at the individual level reduces cross-national variation in the occupational status gap between less- and intermediate-educated adults.

What about cross-national variation in the remaining occupational status gap, that is, in labor market inequalities that remain after accounting for individual-level differences in literacy and numeracy skills? Previous research (e.g., Abrassart, 2013; Andersen and van de Werfhorst, 2010; Solga, 2002, 2008) has already stated that the *aggregate* relationship between formal qualifications and skills might affect the labor market disadvantage of less-educated workers—above and beyond the direct individual-level effect of skills that underlies Hypothesis 1. This research has mainly relied on signaling and screening accounts for theoretical justification.[1] In their weak versions, these accounts do not dispute the aforementioned argument that higher qualifications are rewarded by employers because qualifications are positively related to skills (Bills, 2003). However, the signaling approach emphasizes that skills are very difficult to observe and that employers therefore heavily rely on more readily observable proxies for skills and "trainability" in hiring, job placement, and promotion decisions (Spence, 1973; Thurow, 1979). Degrees and other indicators of educational success such as grades therefore serve as crucial sources of information (Arrow, 1973; Hirsch, 1977; Thurow, 1979; Weiss, 1995).

When employers assess the skills of applicants based on beliefs about how well educational certificates indicate (i.e., "signal") an applicant's skills level, they effectively apply so-called statistical discrimination (Aigner and Cain, 1977; Phelps, 1972). Employers should be particularly likely to statistically discriminate on the basis of educational credentials when the latter are strongly predictive of an individual's actual skills—in other words, when "skills transparency" is high (Andersen and van de Werfhorst, 2010). Hence, even after accounting for skills at the individual level, the labor market disadvantage of less-educated adults should still increase with a country's level of skills transparency—reflecting stronger statistical discrimination against all less-educated adults, independent of their individual skills, in more skill-transparent contexts.

[1] We treat signaling and screening theories as one general approach in this article. While some scholars view the two approaches as distinct, we concur with Bills' (2003) reading of Weiss (1995) that the two approaches are conceptually very similar and that the primary "difference between screening and signaling models is that, in the former, firms move first and, in the latter, students move first" (Bills, 2003, p. 447).

Measuring skills transparency is not trivial, however, and previous studies have mostly proxied it using education system indicators. Andersen and van de Werfhorst (2010), for example, tried to capture a country's level of skills transparency using an index based on several education system characteristics, including the extent of tracking, the prevalence of vocational enrollment, and participation in tertiary education. Based on this operationalization, and not accounting for skills at the individual level, they concluded that skills transparency seems to be "the primary moderator" explaining country differences in the relationship between educational degrees and occupational status (Andersen and van de Werfhorst, 2010, p. 336).

Bol and van de Werfhorst (2011) included self-reported years of schooling as a proxy for individuals' skills and found similar results. Instead of using a summary index, they analyzed the moderating role of external differentiation and vocational enrollment separately. Their main findings were that higher levels of external differentiation and vocational orientation are both associated with higher returns to formal qualifications in terms of occupational status. In line with the above argument, they speculated that this was due to the signaling value of educational degrees being higher in countries with stronger tracking and vocational orientation.

Some studies have used data from the mid-1990s *International Adult Literacy Survey* (IALS), the most important cross-national survey with direct measures of individual skills before PIAAC. Van de Werfhorst (2011) found that earnings returns to educational degrees are positively related to external differentiation and vocational orientation, even after controlling for individuals' skills. Abrassart (2013) employed a more direct measure of skills transparency: the skills differential (or "skills gap") between less- and intermediate-educated workers at the country level. He found that the labor market disadvantage of less-educated adults (with respect to employment rates) increases with the aggregate skills differential. However, he did not include skills at the individual level, so it remains unclear if the effect of the aggregate skills gap in his study simply picked up the direct, individual-level effect of skills motivating hypothesis 1. Finally, Gesthuizen, Solga, and Künster (2011) found that, net of individual general skills, the skills mean of the less-educated group is positively related to their average occupational status. Yet, the skills mean alone is a poor measure of skills transparency. This is because an educational degree can only function as a useful signal to the extent that it indicates differences in the likely skills of a person relative to another one with a different degree. In this sense, the notion of skills transparency involves a comparative or relational element that cannot be captured by the skill mean of a single educational group. Furthermore, using only average skills levels neglects another important element of skills transparency, that is, the extent to which individuals *within* an educational group are alike in terms of their skills.

Taken together, the aforementioned studies provide meaningful hints that country differences in skills transparency might be an important part of the explanation why less-educated adults face greater labor market disadvantages in some countries than in others. But they leave important questions unanswered. Some studies only look at the moderating role of education system characteristics and argue on theoretical grounds that the latter are related to the skills transparency of educational degrees (Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011). Other studies attempt to measure skills transparency more directly, but do not control for skills differences at the individual level (Abrassart, 2011) or use a suboptimal measure of skills transparency (Gesthuizen et al., 2011).

In the present paper, we use a more sophisticated approach to measuring skills transparency. We understand skills transparency as the extent to which formal qualifications are predictive of actual skills and focus on two aspects of the distribution of skills conditional on formal qualifications (Heisig, 2018). The first is the difference in the average skills levels of different educational groups, adjusted for other readily observable factors such as age or gender. We refer to this igner and as the *skills gap*. Formal qualifications should become more informative about the actual skills a person has (i.e., they should become more skills transparent) as the skills gap increases (Aigner and Cain, 1977). The less educated should therefore face stronger statistical discrimination and consequently also greater labor market disadvantages in countries where the skills gap is large. The second aspect of skills transparency is the *internal skills homogeneity* of educational groups: Other things being equal, including the skills gap, degrees are a less noisy proxy of actual individual skills (and therefore send a stronger signal about them) when educational groups are internally more homogeneous (Aigner and Cain, 1977). Based on these considerations, we formulate the following hypotheses, both of which we expect to hold after controlling for literacy and numeracy skills at the individual level:

Hypothesis 2: The occupational status gap between less-educated and intermediate-educated adults is larger in countries where the skills gap (with respect to numeracy and literacy skills) between the two groups is larger.

Hypothesis 3: The occupational status gap between less-educated and intermediate-educated adults is larger in countries where the distribution of literacy and numeracy skills within the two groups is more homogeneous (i.e., has lower variance).

Our fourth and last hypothesis is concerned with the role of external differentiation (or "tracking") in secondary education, that is, the extent to which students are allocated to different educational programs (i.e., tracks) depending on their academic achievements. Previous studies have found that the labor market disadvantage of less-educated adults and returns to educational attainment more broadly, are higher in countries with stronger tracking (e.g., Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011; Shavit and Müller, 1998; van de Werfhorst, 2011) . Some authors (Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011) explicitly attribute this pattern to a positive link between external differentiation and skills transparency: By channeling students into different programs based on their academic potential, tracking supposedly makes educational degrees more informative about actual skills. Consistent with this argument, recent country comparisons based on PIAAC show that the extent of tracking in secondary association is positively associated with the skills gap between less-and intermediate-educated adults (Heisig and Solga, 2015) and with the internal homogeneity of educational groups (Heisig, 2018). These patterns might be attributable to selective assignment to different tracks (in terms of prior achievement), differences in the pace of skill acquisition across tracks, or a combination of both. Unfortunately, it is not possible to disentangle these alternative explanations with the cross-sectional PIAAC data (for further discussion, see Heisig and Solga, 2015, and Heisig, 2018).

Irrespective of these questions about the underlying mechanisms, skills transparency is often taken to be a primary pathway mediating the effect of tracking on labor market inequalities. Due to the data constraints discussed above this possibility has not been investigated empirically, however. Our direct measures of skills transparency allow us to do exactly this by testing the following hypothesis:

Hypothesis 4: The effect of the index of external differentiation of secondary education on the occupational status gap between less-educated and intermediate-educated adults is mediated by the skills transparency of educational degrees. Including direct measures of skills transparency (i.e., of the skills gap and the internal homogeneity of educational groups) in the regression will therefore substantially reduce the estimated effect of external differentiation on the occupational status gap.

2.2 Further explanations

We now discuss some complementary or alternative explanations for cross-national variation in the occupational status gap between less-educated and intermediate-educated adults. In our empirical analysis below, we will take them into account by including appropriate control variables.

The studies by Bol and van de Werfhorst (2011) and van de Werfhorst (2011) both find that the labor market disadvantage of less-educated adults is larger in countries with a stronger *vocational orientation of upper secondary education*. Earlier work by Shavit and Müller (1998) reached similar conclusions. Moreover, Andersen and Werfhorst (2010) also included indicators of vocational orientation in their summary index of skills transparency. A straightforward argument for this inequality-enhancing role of vocational orientation builds on the two explanations discussed above (individual-level differences in skills and in skills transparency): In countries with a strong vocational orientation, most adults with an upper secondary degree have completed a program that focuses on occupation-specific skills, which likely ensures that "more job-relevant skills are acquired that are directly applicable in the workplace" (van de Werfhorst, 2011, p. 1080). This suggests that these countries are characterized by greater differences in occupational skills between less- and more-educated workers. Other things being equal, these greater skills differentials should translate into greater labor market inequalities, either because of the direct relationship between (occupational) skills and labor market attainment emphasized by human capital theory (e.g., van de Werfhorst, 2011), or because formal qualifications are more transparent with respect to occupational skills when the education system emphasizes vocational programs (e.g., Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011).[2] For our purposes, it is important to acknowledge that, unlike for (general) literacy and numeracy skills,

[2] Another prominent explanation why less-educated workers are more disadvantaged in countries with strong vocational education systems is *credentialism* (e.g., Collins, 1979), which suggests that the benefits of holding a vocational certificate might derive from occupational licensing and closure (e.g., Bol and Weeden, 2014; see also Sørensen's, 2000, theory of rent generation). In its weaker versions, it states that "the relation between education and productivity is smaller than that between education and rewards" (Bills, 2003, p. 452). Empirical support for hypotheses 1 to 3 would be compatible with this weaker form of credentialism.

we have no direct, individual-level measures of occupation-specific skills, because they were not assessed in PIAAC. However, we can include a country-level measure of the vocational orientation of upper secondary education in our analyses, similar to what has been done in previous research.

A second reason for including a measure of vocational orientation in the regressions is that there might be a trade-off between investments in general and occupation-specific skills. In countries with a strong vocational education systems young people tend to invest more in occupation-specific skills in upper secondary education—and these investments may come at the cost of investments in general skills (e.g., Muja et al, 2019). This suggests that vocational orientation might be negatively related to skills transparency with respect to *general* skills by lowering the general skills achievements of intermediate-educated adults with a vocational degree, and thereby the (general) skills gap between the less and the intermediate-educated group. We indeed find that the gap in literacy and numeracy skills between less- and intermediate-educated adults is smaller in countries with a stronger vocational orientation (see Table 3 in Section 3.3 below). However, as Heisig and Solga (2015) have shown, this is not because the mean skills levels of intermediate-educated adults are lower in countries with a strong vocational orientation but rather because the mean skills levels of less-educated adults are higher. Nonetheless, the association between the vocational orientation and the size of the skills gap provides further reason to control for country differences in vocational orientation in our analyses.

Differences in industrial and job structures are another possible source of country variation in labor market inequalities. The relative position of less-educated adults in a country might not primarily be a matter of their relative skill endowments; it might rather be a function of the structure of labor demand, that is, of the availability of "good" and "bad" jobs (Kalleberg et al. 2000; Kallegerg 2009). One influential account suggesting such an explanation is the theory of labor market segmentation. While heterogeneous in their details, segmentalist theories generally view the labor market as divided into a small number of segments, with many positing an essentially dualistic structure consisting of a primary and a secondary sector (e.g., Doeringer and Piore, 1971; Piore, 1994). Jobs in the primary sector are characterized by good career opportunities (on internal labor markets), high levels of job security, high remuneration, and good overall job quality, whereas jobs in the secondary sector tend to be rather low skilled, insecure, badly paid, and unattractive in other respects. Segmentation theory breaks with the supply-side orientation of mainstream economic theories, and of human capital theory in particular, and sees demand-side factors as the primary determinants of job quality (Leontaridi, 1998). Country differences in the degree of deindustrialization, deskilling, and technological change might result in differences in the job structure that eventually translate into differences job opportunities for less-educated workers and thereby affect their labor attainment. The industry and job structure might also be related to the skills gap between less- and intermediate educated adults, for example, by shaping opportunities for informal learning on the job. All of these considerations suggest that differences in the industry and job structure might confound our focal country-level relationships. We will therefore investigate whether the latter are robust to the inclusion of appropriate controls.

A final concern could be that our data were collected during the first half of the 2010s, when the countries in our sample were characterized by very *different labor market conditions*. Some countries such as Spain and Greece were still in the midst of the deep recessions that unfolded in the years after the 2007 financial crisis. Other countries such as Austria or Germany were faring much better. Because the labor market prospects of less-educated adults are particularly sensitive to the business cycle (Farber, 1997), these cross-national differences might affect our results. We account for this possibility in two ways. First, we measure labor market attainment in terms of occupational status in the *current or last* job (up to five years before the interview). Thus, we also observe the outcome for respondents who lost their job in the wake of the financial crisis. Second, we explore whether our focal country-level relationships are robust to controlling for the national unemployment rate.

3 DATA AND METHODS

3.1 Individual-level data and sample

Our individual-level data are from the first and second round of PIAAC, which was conducted in 33 countries in 2011/12 and 2014/15, respectively (OECD, 2013, 2016).[3] The PIAAC data are

[3] For all countries except Germany and the United States, we use the latest version of the public use files (PUFs) released on June 28, 2016, and available at http://www.oecd.org/skills/piaac/publicdataandanalysis/. For the United States, we use the Combined 2012/2014 U.S. International PUF, which is available under the same address and includes additional cases from a second round of data collection. In the German case, we use version 1.1.0 of the so-

representative of the noninstitutionalized 16-to-65-year-old population. The OECD requested a minimum sample size of 4,500 or 5,000 cases per country[4] and a minimum response rate of 50 percent. All countries were required to provide a non-response bias analysis after data collection, and the results of this analysis were taken into account in the construction of the final survey weights, which were used in all analyses reported in this article. We also use the replicate weights provided by PIAAC to correct the standard errors for the complex survey design (for further details, see OECD, 2016).

PIAAC was conducted in 33 countries. Two of these, Australia and Indonesia, provide no public use files. We decided to exclude two further cases, Cyprus and Russia, because of concerns about data quality.[5] Influence diagnostics for the remaining 29 countries revealed that the inclusion of Israel and Slovenia has a dramatic impact on the main regression results reported below (as indicated by the DFBETA and Cook's D statistics; see Fox, 1991). We therefore chose to drop these two cases, resulting in a sample of 27 countries for the main analysis (see Table 1 below for the individual countries). We provide a detailed account of the influence diagnostics in Section D of the Online Supplement, including the main regression results when Israel and Slovenia are included. A brief summary is provided in Section 4.4 below.

Our goal is to explain the labor market disadvantage of less-educated workers. We therefore compare the occupational status attainment of less-educated workers—defined as those with the highest degree below the upper secondary level—to those with upper secondary education degrees. We exclude respondents with a tertiary degree[6] from the analysis, as they rarely compete for the same kinds of jobs as less-educated adults. We restrict the analysis to prime-working-age men and women (aged 25 to 54) who, a), worked for pay at the time of interview or within the last five years before the interview, b), were not enrolled in full-time education at the time of

called "Prime Age" data, which include more fine-grained information than the German PUF and additional cases from an oversample of East German respondents (Solga and Heisig, 2015). All analyses are weighted to correct for the oversampling.

[4] The higher sample size was required if respondents were also tested in the optional "problem solving in technology-rich environments" (PS-TRE) domain, in addition to the (mandatory) literacy and numeracy domains. We ignore PS-TRE skills because they are not available for all countries.

[5] Cyprus has a very high share (almost 18%) of so-called literacy-related non-respondents, that is, of sampled respondents who did not complete the survey because of language difficulties (OECD, 2013). The country with the second-highest share is Belgium (5.2%). Among several concerns about the quality of the Russian data, a major one is that the Moscow municipal region was not included in the survey (OECD, 2016, p.21).

[6] That is, those with levels 5 and 6 according to the 1997 revision of the International Standard Classification of Education (ISCED).

interview, and, c), had obtained their highest educational degree in the country where they were surveyed.

A total of 49,685 cases meet the sample restrictions, after excluding 1,304 so-called literacy-related non-respondents (OECD, 2013) and 32 cases with missing values on at least one of the variables defining the sample.[7] The only variables with non-negligible proportions of missing data are parental education and occupational status, which are unavailable for 3,479 and 443 cases, respectively. We use multiple imputation via chained equations to fill in missing values on these two measures. All other variables have very low proportions of missing data. To simplify the imputation procedure, we drop the 319 cases that are incomplete with respect to these variables. We generate ten imputations, one for each of the so-called plausible values for the skills measures (see Section 3.2). The final sample comprises 49,366 (= 49,685 – 319) respondents, with country-specific sample sizes ranging from 976 cases in Singapore to 6,095 cases in Canada (see Table 1 below).

3.2 Individual-level variables

PIAAC provides information on the respondent's highest educational degree in terms of the 1997 revision of the International Standard Classification of Education (ISCED). We differentiate between less-educated (ISCED levels 0–2) and intermediate-educated (ISCED levels 3–4) adults. This corresponds to the highest degree being at the lower secondary level or below and at the upper secondary or non-tertiary post-secondary level, respectively.

We operationalize the labor market disadvantage of less-educated adults by the *occupational status gap* between less- and intermediate-educated adults. *Occupational status* is measured using the International Socio-Economic Index of Occupational Status (ISEI). The ISEI scores are "weighted averages of standardized measures of the income and education of incumbents of each occupation" (Ganzeboom and Treiman, 1996, p. 204)—based on relative weights for (standardized) education and earnings, "such that the direct effect of education on earnings is minimized. […] The resulting index was then projected onto a 10 … 90 range using linear transformation" (Ganzeboom and Treiman, 2010, p. 13). The ISEI score thus indicates the *relative* position of occupations in the hierarchical occupational stratification system. We assign

[7] These case numbers refer to the sample of 27 countries used in the main analysis.

scores based on one-digit 2008 International Standard Classification of Occupation (ISCO-08) codes. For respondents who worked at the time of interview, occupation codes refer to the current job. For those who did not work (but stopped working no more than five years ago) codes refer to the respondent's last job.

The one-digit ISCO-08 groups workers into ten broad occupational categories. It would be preferable to assign occupational status using occupational categories at the two- or higher-digit level, but four countries in our sample (Austria, Canada, Estonia, and Finland) only provide one-digit codes in their PIAAC public use file. To ensure consistency we use the one-digit version of ISCO-08 for all countries. Reassuringly, ISEI gaps based on more detailed occupational categories are almost identical to those based on one-digit groups for the countries where the former are available. For the 23 countries that provide two-digit ISCO-08 codes in their public use files, the Pearson correlation between ISEI gaps based on one-digit and two-digit codes is .98, after adjusting for literacy and numeracy skills and additional controls (see the discussion of "fully adjusted ISEI gaps" in Section 3.4). Even ISEI gaps based on four-digit occupation codes (which, in addition to the previously mentioned countries, are unavailable for Ireland, Sweden, and the United States) still show a Pearson correlation of .96 with the gaps based on one-digit occupation codes.

PIAAC also provides information on other labor market outcomes, most importantly on respondents' employment status and earnings. The primary reason why we do not analyze (un)employment is that, as noted above, the countries in our sample were facing very different macroeconomic conditions in the early 2010s. The employment rates of less-educated workers in particular have been found to be highly sensitive to overall labor market conditions (Farber, 1997). Adequately controlling for country differences in macroeconomic conditions would thus be crucial, but doing so is difficult given limited degrees of freedom at the country level and uncertainty about the precise functional form of the relationship. Education-related differentials in occupational status should be less sensitive to macroeconomic context, especially since we also observe the occupation in the last job for respondents who were not employed at the time of interview. Nevertheless, some of our specifications additionally control for the unemployment rate (see Section 4.4).

We have two main reasons for not analyzing wages or earnings in the main article. First, the estimated country-specific wage/earnings gaps between less- and intermediate-educated workers are noisier than the gaps in occupational status. We investigated this issue by computing I^2 statistics for the occupational status and various earnings/wage gaps after adjusting for literacy and numeracy skills and the additional controls. I^2 is commonly used in meta-analysis to distinguish "true" between-study variability in effect sizes from variability that is due to sampling error, that is, to the fact that the effect size for each individual study is subject to statistical uncertainty. In the present context, the statistic can be interpreted as the proportion of overall between-country variation in the estimated labor market outcome gap that is attributable to true between-country differences rather than to sampling error; in other words: to signal rather than noise. Formally, I^2 is calculated as $\hat{\tau}^2 / (\hat{\tau}^2 + \hat{\sigma}^2)$, where $\hat{\tau}^2$ denotes the estimated between-country variance and $\hat{\sigma}^2$ the estimated (average) statistical error of the country-specific estimates (for details on the underlying random effects model and its estimation, see Viechtbauer, 2010). For the ISEI gap between less- and intermediate-educated adults, a reasonable 73.9 percent of the between-country variance reflects true variation according to the I^2 statistic.[8] For log hourly earnings[9], this proportion is only 64.1 percent.[10] The second reason why we prefer to focus on occupational status is that an analysis of wage gaps would also need to account for several country-level factors that influence overall wage inequality (e.g., collective bargaining arrangements and minimum wage legislation; see Koeniger et al., 2007). Such factors are difficult to control due to imperfect measurement and limited degrees of freedom at the country level. In supplementary analyses, we reran the main sequence of regression models with the gap in hourly earnings as the dependent variable. The results provide less support for our hypotheses than those for occupational status, but we are inclined to attribute this to the abovementioned complications (see Section 4.4 for further details).

The unique feature of PIAAC is the availability of high-quality measures of respondents' *actual skills*. All PIAAC-participating countries administered test items to assess the reading and

[8] All estimates of I^2 reported here are based on the restricted maximum likelihood estimator as implemented in the R package *metafor* (Viechtbauer, 2010). Other estimation approaches such as empirical Bayes or standard maximum likelihood yield very similar values.

[9] For confidentiality reasons, some countries do not provide the exact hourly earnings of respondents in the PIAAC public use files. For these countries, only the respondent's decile rank in the distribution of hourly earnings is available. For consistency, we therefore used the median wage within a respondent's wage decile for all respondents, just like we generally used the average scores for the one-digit ISCO groups to assign ISEI scores. The decile medians were kindly provided by Simon Wiederhold. In a previous analysis of the PIAAC data, Hanushek et al. (2015) found that using decile medians instead of exact wages had only a very limited impact on the results.

[10] For two alternative earnings measures we considered, the individual's decile rank in the distribution of hourly wages and in the distribution of monthly earnings, I^2 estimates are only 44.6 and 40.9 percent, respectively.

text comprehension skills (*literacy*) and practical mathematical skills (*numeracy*) of participants (OECD, 2013, 2016). To limit respondent burden, each participant received only a relatively small number of test items, rendering individual competence estimates quite uncertain. PIAAC therefore provides ten plausible values rather than a single competence score for each case. To appropriately handle the plausible values (as well as the multiply imputed values for parental education and occupational status), we run all analyses ten times and apply the appropriate rules for multiply imputed data to obtain final point estimates, standard errors, and *p*-values (Little and Rubin, 2002).

We include several individual-level control variables: *sex*; *potential work experience* (linear and squared term); *foreign-birth/foreign-language status* (four categories; see Table 1); *parental educational attainment* (low = no parent has completed upper secondary education; intermediate = at least one parent has completed upper secondary education; high = at least one parent has completed tertiary education); *self-employment* in last/current job (dummy variable). Table 1 provides descriptive statistics for the individual-level variables.

Our sample includes both currently and formerly employed respondents, but we do not control for current employment status because it is endogenous to the outcome variable (people with lower occupational status have higher risks of unemployment). As a robustness check, we reran the analysis using only respondents who worked at the time of interview and results were similar (see Section 4.4).

Table 1. Individual-level descriptive statistics by country

							Foreign-birth/foreign-language status				Parental education				
	Mean ISEI score	% less-educated (ISCED 0-2)	% intermediate-educated (ISCED 3-4)	Mean literacy score	Mean numeracy score	Mean potential work experience (years)	% native-born, test language is first language	% native-born, test language is not first language	% foreign-born, test language is first language	% foreign-born, test language is not first language	% with low parental education	% with intermediate parental education	% with high parental education	% self-employed	N
Austria	41.0	16.8	83.2	270.5	277.0	24.0	93.8	1.9	1.6	2.7	28.7	57.9	13.4	11.2	1,892
Belgium	36.8	18.5	81.5	266.5	272.8	24.0	94.5	3.1	1.2	1.3	48.2	38.1	13.7	12.1	1,391
Canada	41.7	18.6	81.4	265.4	255.2	23.6	86.0	5.8	3.8	4.4	32.1	42.3	25.6	13.8	6,095
Chile*	28.6	38.7	61.3	205.2	191.3	22.3	98.8	0.4	0.5	0.3	60.4	31.4	8.2	25.9	1,777
Czech Rep.	36.6	8.5	91.5	268.9	271.0	21.7	98.0	0.0	1.7	0.2	10.8	81.0	8.2	16.9	2,055
Denmark	37.7	27.3	72.7	265.9	275.0	20.4	94.6	0.6	1.2	3.5	34.5	46.8	18.7	10.7	1,395
Estonia	35.0	19.5	80.5	265.7	263.9	20.6	90.5	2.0	6.7	0.7	31.5	43.2	25.3	9.9	2,123
Finland	33.5	15.4	84.6	284.1	277.4	19.8	95.7	1.8	1.3	1.2	44.2	44.9	10.9	13.0	1,174
France	35.3	24.4	75.6	256.4	248.2	21.9	91.0	2.8	2.9	3.3	52.6	39.1	8.3	9.8	2,117
Germany	35.8	10.5	89.5	263.6	267.2	21.7	90.1	2.2	2.1	5.5	11.5	63.9	24.6	7.8	1,938
Greece*	31.6	35.9	64.1	245.9	245.5	24.0	92.5	0.6	4.5	2.4	75.3	18.9	5.8	29.9	1,651
Ireland	35.6	34.3	65.7	261.3	249.2	21.4	92.8	0.9	5.4	0.9	66.1	25.0	8.9	17.6	1,584
Italy	35.3	52.7	47.3	252.3	252.4	24.9	95.4	2.1	1.6	0.8	81.4	16.6	2.0	19.4	1,803
Japan	36.0	14.9	85.1	292.7	282.7	23.6	99.6	0.1	0.3	0.0	28.4	53.3	18.3	9.9	1,135
Korea	32.5	19.6	80.4	260.0	250.4	25.4	99.6	0.3	0.0	0.0	69.3	24.5	6.2	25.9	1,804
Lithuania*	31.4	8.9	91.1	256.9	255.9	23.4	87.5	9.7	1.5	1.3	39.2	28.0	32.8	9.0	1,616
Netherlands	43.0	35.0	65.0	280.2	277.4	21.8	93.4	0.8	2.6	3.1	59.6	26.0	14.4	13.4	1,471
New Zealand*	40.3	40.0	60.0	272.9	262.9	22.0	88.7	2.7	5.6	3.1	46.2	27.3	26.5	14.5	1,306
Norway	38.6	30.7	69.3	276.4	276.4	19.6	93.4	1.6	0.7	4.3	31.4	46.2	22.4	9.2	1,197
Poland	31.8	9.7	90.3	254.2	250.2	21.5	99.0	0.9	0.0	0.0	31.6	63.7	4.7	17.8	1,881
Singapore*	39.4	35.2	64.8	228.0	222.5	28.3	17.2	78.7	0.7	3.4	73.9	23.4	2.7	16.1	976
Slovak Rep.	37.0	11.4	88.6	273.0	275.8	21.8	92.9	5.7	0.9	0.6	28.0	66.6	5.4	16.0	2,223
Spain	32.1	65.9	34.1	246.3	241.5	24.5	94.0	2.8	2.5	0.7	85.1	10.5	4.4	14.7	1,705
Sweden	39.4	18.7	81.3	280.7	280.3	20.5	88.2	2.8	1.5	7.6	45.0	26.8	28.2	10.4	1,153
Turkey*	32.0	71.7	28.3	225.4	221.6	24.3	96.1	3.9	0.0	0.0	94.1	4.6	1.3	24.3	1,601
United Kingdom	36.7	34.1	65.9	266.5	255.4	20.4	92.8	1.5	3.4	2.2	38.8	48.9	12.3	16.8	2,359
United States	38.1	10.9	89.1	262.6	245.8	23.0	91.5	3.1	2.4	3.0	18.2	52.8	29.0	14.2	1,944

Notes: * Second PIAAC round. Values for ISEI score, literacy, numeracy, and parental education are averages across 10 imputations. ISEI=International Socio-Economic Index of Occupational Status; ISCED=International Standard Classification of Education. Low parental education: no parent has completed upper secondary education; intermediate parental education: at least one parent has completed upper secondary education, but no parent has completed teriary education; high parental education: at least one parent has completed tertiary education.

Sources: PIAAC (rounds 1 and 2), authors' calculations.

3.3 Country-level predictors

A key innovation of our study is to measure *skills transparency* directly using the *skills gap* between less- and intermediate educated adults and the *internal homogeneity* of these groups. In constructing the respective measures, we closely follow the work of Heisig and Solga (2015) and Heisig (2018).

The *skills gap* is the adjusted mean skills difference between less- and intermediate-educated adults. We construct this measure by running country-specific regressions of literacy and numeracy skills on a dummy variable for highest educational attainment, with sex, potential experience, foreign-birth/foreign-language status, and parental education as controls. We adjust the skills gap for these characteristics because they are readily observable and because we want to isolate the additional information conveyed by an individual's educational degree.[11] The skills gap for a given country is the coefficient estimate on having intermediate rather than low formal qualifications in the country-specific regression. Note that this coding is the opposite of that used in the regression models for occupational status, so larger (i.e., more positive) values correspond to a larger skills gap. Our final measure is the unweighted average of the estimated literacy and numeracy gaps for each country.

The index of internal homogeneity measures how homogenous the skills distribution within educational groups is, independent of their levels of skills. To compute the index, we first obtain the residuals from the country-specific regressions used in constructing the skills gap measure. For each educational group and for both literacy and numeracy, we then calculate the standard deviation of the residuals as a straightforward measure of within-group heterogeneity. The resulting four standard deviations (i.e., of the residual literacy and numeracy scores for less- and intermediate-educated adults, respectively) turn out to be strongly positively correlated (Heisig, 2018). To reduce the dimensionality, we run a principal factor analysis of the four standard deviations. The first factor loads positively on all four standard deviations and has an eigenvalue of 2.17 (averaged across the ten plausible values). The internal consistency of the four standard deviations is high, with the value of Cronbach's alpha (standardized) being equal to .79 (again, averaging across the ten plausible values). We reverse-code the factor scores so that higher values on the index indicate greater homogeneity.

[11] Parental education might be more difficult to observe than the other characteristics, but there is evidence that employers infer class background from other worker characteristics such as name, school attended, and leisure activities (Jackson, 2009). We also reran the analyses without adjusting the skills gap (and the index of internal homogeneity, see next paragraph) for parental education and results were similar (see Section 4.4).

We measure tracking in secondary education using the *external differentiation index* by Bol and van de Werfhorst (2013). The index is based on a principal factor analysis of three measures: age of first selection into different tracks (reverse coded), number of tracks available at age 15, and length of tracked education as a proportion of the total duration of primary and secondary education. Values for these variables refer to 2003 (age of first selection and number of tracks at age 15) and 2002 (length of tracked curriculum) or the closest year available (for details, see Bol and van de Werfhorst, 2013). The index is not available for three of the countries in our main analysis sample: Estonia, Lithuania, and Singapore.

As discussed in Section 2.2, our country-level regressions generally control for the *prevalence of vocational enrollment*, measured by the percentage of students in upper secondary education who are enrolled in a vocational program. To reduce measurement error, we average the values provided in two sources: OECD (2006: Table C2.5) and UNESCO's online database (http://data.uis.unesco.org/). Values refer to 2004 (OECD) and 2006 (UNESCO) or the closest year available.[12] Our indicator is highly correlated (r = .99) with Bol and van de Werfhorst's (2013) vocational orientation index, which is based the same sources but not available for all countries in our sample.

Table 2 reports the values of the focal country-level predictors and of the unadjusted and fully adjusted ISEI gaps (see Section 3.4). Table 3 shows the pairwise correlations among them. In supplementary analyses (see Section 4.4), we include the unemployment rate and the employment shares of different economic sectors and labor market segments in the country-level regressions. We provide further details on these measures in Section 4.4 and in Section A of the Online Supplement.

[12] For a few countries, the OECD measure is unavailable. We simply use the UNESCO measure in these cases. Neither the OECD nor UNESCO provide data for Singapore, so we had to use the enrollment data from the World Bank available at http://datatopics.worldbank.org/education/.

Table 2. Values of main country-level variables

	Country code	Unadjusted ISEI gap (1)	Fully adjusted ISEI gap (2)	Skills gap (3)	Index of internal homogeneity (4)	Index of external differentiation (5)	Prevalence of vocational enrollment (6)
Austria	AT	-11.2	-7.9	22.7	0.85	1.82	78.3
Belgium	BE	-7.8	-5.3	20.9	0.49	1.02	61.8
Canada	CA	-9.0	-4.8	38.4	-1.44	-1.32	2.8
Chile*	CL	-6.9	-5.1	35.1	-0.16	0.32	37.0
Czech Rep.	CZ	-10.6	-8.0	24.1	1.32	1.62	79.2
Denmark	DK	-6.4	-5.1	22.2	-0.55	-0.87	50.6
Estonia	EE	-7.9	-5.3	26.7	-0.09	Not available	31.0
Finland	FI	-2.9	-2.6	13.7	-0.49	-0.87	57.1
France	FR	-4.9	-4.0	25.4	-0.71	-0.47	49.6
Germany	DE	-10.4	-5.7	40.7	-0.45	1.86	60.3
Greece*	GR	-7.9	-5.8	21.8	-0.25	-0.47	33.9
Ireland	IE	-8.2	-6.3	30.2	0.30	-0.30	32.9
Italy	IT	-13.1	-11.6	30.0	0.49	0.17	61.7
Japan	JP	-6.7	-5.7	21.8	1.39	-0.47	24.6
Korea	KR	-7.4	-4.8	25.2	1.54	0.07	28.6
Lithuania*	LT	-7.2	-5.8	15.2	-0.09	Not available	28.2
Netherlands	NL	-9.5	-6.7	26.1	0.37	0.94	68.5
New Zealand*	NZ	-7.0	-3.7	29.4	-0.52	-0.42	24.3
Norway	NO	-2.7	-1.9	13.3	0.71	-1.04	60.2
Poland	PL	-7.6	-4.9	18.9	-1.32	-0.08	47.3
Singapore*	SG	-12.6	-7.1	50.6	-2.06	Not available	11.3
Slovak Rep.	SK	-13.3	-8.6	30.0	0.85	1.62	73.6
Spain	ES	-9.6	-7.3	26.0	1.07	-1.02	40.6
Sweden	SE	-7.7	-5.0	21.8	0.60	-0.87	55.8
Turkey*	TR	-8.3	-7.3	29.7	-0.04	1.20	37.6
United Kingdom	UK	-7.8	-5.2	23.5	-1.05	-1.04	51.6
United States	US	-8.0	-4.3	31.1	-0.77	-1.32	0.0
Mean		-8.2	-5.8	26.5	-0.00	0.00	44.0
Standard deviation		2.6	1.9	8.2	0.91	1.05	21.4

Notes: * Second round of PIAAC. For the country-level regressions, all predictors were (re-)standardized to have a mean of 0 and a standard deviation of 1 within the sample of 27 countries included in the analysis.

Sources: (1)-(4): PIAAC, rounds 1 and 2, authors' calculations; (5): Educational Systems Database, Version 4 (Bol and Van de Werfhorst, 2013); (6): OECD (2006, Table C2.5), UNESCO online database (http://data.uis.unesco.org/) and World Bank online database (http://datatopics.worldbank.org/education).

Table 3. Pairwise Pearson correlations between focal country-level predictors

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Unadjusted ISEI gap	1					
(2) Fully adjusted ISEI gap	0.872^{***}	1				
(3) Skills gap	-0.603^{***}	-0.331	1			
(4) Index of internal homogeneity	-0.062	-0.278	-0.409^{*}	1		
(5) Index of external differentiation	-0.586^{**}	-0.545^{**}	0.248	0.373	1	
(6) Prevalence of vocational enrollment	-0.146	-0.298	-0.387^{*}	0.457^{*}	0.619^{**}	1

Notes: N=27. For pairwise correlations involving index of external differentiation N=24 because the index is not available for Estonia, Lithuania, and Singapore. + p < 0.1, * p < 0.05, ** p < 0.01 (two-tailed tests).

Sources: See Table 2.

3.4 Analytical strategy and estimation

In the first step of the analysis, we seek to test hypothesis 1, which states that individual-level differences in literacy and numeracy skills can partly account for the labor market disadvantage of less-educated adults and thereby for cross-national variation in its magnitude.[13] We use the decomposition technique pioneered by Kitagawa (1955), and commonly referred to as the Oaxaca-Blinder decomposition, to assess these hypotheses. Following the notation of Fortin, Firpo, and Lemieux (2011), the variant of the decomposition that we use takes the following form:

$$\hat{\Delta}_O^{\mu} = \underbrace{(\bar{X}_B - \bar{X}_A)\hat{\beta}^*}_{\hat{\Delta}_X^{\mu}} + \underbrace{[\bar{X}_B(\hat{\beta}_B - \hat{\beta}^*) + \bar{X}_A(\hat{\beta}^* - \hat{\beta}_A)]}_{\hat{\Delta}_S^{\mu}} \tag{1}$$

where the subscripts A and B index the two groups being compared and $\hat{\Delta}_O^{\mu} = \mu_B - \mu_A$ is the observed difference in the group means of the outcome variable (i.e., the unadjusted ISEI gap). In our case, the less educated are group B and the intermediate educated group A. $\hat{\Delta}_O^{\mu}$ is decomposed into an explained part $\hat{\Delta}_X^{\mu}$ and an unexplained part $\hat{\Delta}_S^{\mu}$. The explained part is the sum of the differences in the group means for a set of k explanatory variables (i.e., $\bar{X}_B - \bar{X}_A$), with the mean difference for each variable weighted (or "priced") according to the corresponding coefficient estimate from the vector $\hat{\beta}^*$. This vector is estimated by running a regression of the ISEI score on the explanatory variables (the skill measures and the individual-level controls) using the data of both educational groups.[14] The terms $\hat{\beta}_A$ and $\hat{\beta}_B$ in the unexplained part represent the coefficient vectors estimated using only the data from group A or B (for further details, see Fortin et al., 2011).

Due to the linear additive nature of the decomposition, it is possible to calculate the contributions of individual variables or subsets of variables, often referred to as a "detailed decomposition" (Jann, 2008; Fortin et al., 2011). Given our research questions, we are particularly interested in the combined contribution of group differences in literacy and numeracy skills to the ISEI gap. To assess hypothesis 1, we investigate whether adjusting for

[13] For simplicity, the following presentation of our empirical approach abstracts from the fact that we have to run each analysis step multiple times to account for the multiply imputed/plausible values.

[14] As recommended in the literature, this regression also includes a group indicator (i.e., a dummy for having intermediate education; see Fortin et al., 2011).

differences in literacy and numeracy skills reduces the cross-country variation of the ISEI gaps. That is, we investigate whether the cross-country variance of the unexplained portion of the gap remaining after adjusting for group differences in literacy and numeracy skills, the "skills-adjusted" ISEI gap, is smaller than the cross-country variance of the observed (unadjusted) ISEI gap.[15]

In the second step of the analysis, we test hypotheses 2 to 4 using country-level regressions. The dependent variable in these regressions is the "fully adjusted" ISEI gap, that is, the ISEI gap after adjusting not only for differences in literacy and numeracy skills but also for compositional differences with respect to the socio-demographic controls. To estimate it, we run country-specific regressions of the ISEI score on the skill measures, the individual-level controls, and an indicator for belonging to the less-educated group, with the coefficient on the latter variable providing the estimate of the fully adjusted ISEI gap. The full results of these country-specific regressions are reported in Table C1 in the Online Supplement. While we use pooled regressions with a group dummy to estimate the fully adjusted gap, it is worth noting that it is conceptually equivalent to the unexplained component of the ISEI gap (i.e., $\hat{\Delta}_S^{\mu}$) in Equation 1 above (Elder et al., 2010).[16]

The independent variables in the country-level regressions are the focal explanatory variables (i.e., the skills transparency measures, the prevalence of vocational enrollment, and the index of external differentiation) and the additional country-level controls (i.e., the unemployment rate and sectoral composition). The regressions are estimated using a Feasible Generalized Least Squares (FGLS) approach that accounts for the fact that the dependent variable is estimated rather than observed and therefore subject to sampling error (i.e., the regressand is a set of coefficient *estimates* from the first-step regressions rather than the unobservable true coefficients). By accounting for country differences in the precision of the first-step estimates, FGLS addresses the resulting heteroskedasticity and achieves greater efficiency than OLS estimation of the country-level relationships (Heisig et al., 2017; Lewis

[15] Note that while the skills-adjusted ISEI gap is adjusted only for group differences in average literacy and numeracy skills (and not for differences in the socio-demographic controls), the "skill prices" (i.e., the coefficient estimates) used in calculating the adjustment are "net" skill prices from a (pooled) regression that does include the controls (and a group dummy) in addition to the skill measures.

[16] In the present case, the two methods of obtaining the "fully adjusted" or "unexplained" gap (i.e., pooled regression and decomposition) are even mathematically equivalent, at least with respect to the point estimate, because we use a pooled regression with a group membership dummy to estimate the coefficient vector for the decomposition (this mathematical equivalence would not hold if the model for the reference coefficient were estimated using only one of the groups or if we did not include a dummy in the pooled model; see Elder et al., 2010). The two methods produce somewhat different standard error estimates, however, and we prefer the ones from the pooled regression, which tend to be more conservative.

and Linzer, 2005). We further obtain so-called HC3 robust standard errors to adjust the standard errors for any remaining heteroscedasticity.

4 RESULTS

We start this section with the results for the role of individual-level differences in skills based on country-specific decompositions. We then turn to a country-level analysis to examine the roles of skills transparency (measured using the skills gap and internal homogeneity of the educational groups), while taking country differences in vocational enrollment into account. The next step of the analysis investigates whether the well-documented effect of external differentiation (tracking) in secondary education on labor market inequalities is mediated by skills transparency. The section concludes with several robustness checks (e.g., for the role of macroeconomic context and sectoral composition).

4.1 The role of individual-level differences in skills

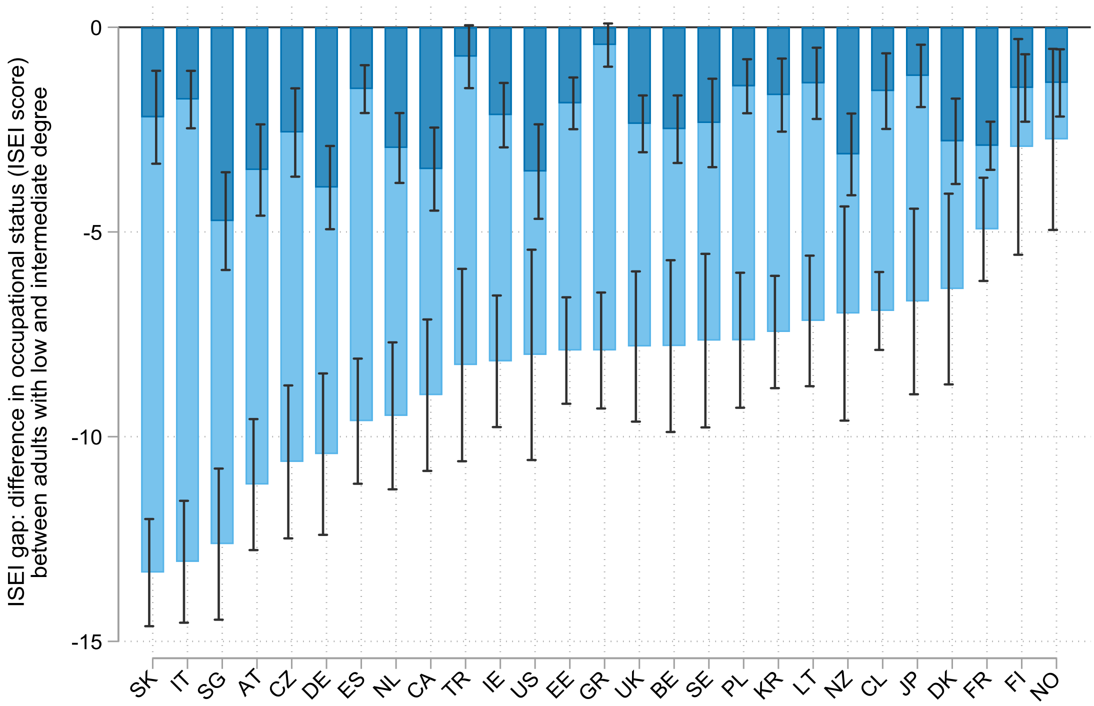
Figure 1 summarizes the country-specific Kitagawa-Oaxaca-Blinder decompositions of the occupational status (ISEI) gap between adults with low (ISCED 0-2) and intermediate (ISCED 3-4) formal qualifications. As throughout this paper, the gap is calculated as the average ISEI score for less-educated adults minus the average score of intermediate-educated adults. "More negative" values thus correspond to a greater labor market disadvantage for the less educated.

For each of the 27 countries in our main analysis sample, Figure 1 shows the unadjusted ISEI gap between less-and intermediate-educated adults as well as the part of the gap that is attributable to group differences in literacy and numeracy skills. The unadjusted gap is represented by the overall length of the bars. It is negative and statistically significant ($p < .05$, two-tailed test) in all countries. Cross-national variation is considerable, with the gap ranging from -13.3 points in Slovakia and -13.1 points in Italy to only -2.9 and -2.7 points in Finland and Norway, respectively (see also Table 2 above). The average unadjusted gap equals -8.2 points, with a cross-country standard deviation of 2.6 points.

To what extent can the labor market disadvantage of less-educated adults be attributed to individual-level differences in literacy and numeracy skills? This question is answered by the darker segments of the bars in Figure 1, which represent the part of the gap that is explained by differences in literacy and numeracy skills according to the decomposition results. In most countries, differences in literacy and numeracy skills account for a substantial portion of the

ISEI gap (and this portion is statistically significant at the five percent level for all countries except Greece and Turkey). The explained part of the occupational status gap averages -2.3 ISEI points across the 27 countries, somewhat less than 30 per cent of the total gap of -8.2 points. These results corroborate the findings from previous studies: In all countries, less-educated workers attain lower occupational status than intermediate-educated workers, and this disadvantage of less-educated adults is partly explained by differences in individual literacy and numeracy skills. The average unexplained part, represented by the lighter segments of the bars in Figure 1, is -6.0 (≈ -8.2 – [-2.3]) ISEI points and thus remains substantial, however.

Figure 1. The ISEI gap between less- and intermediate-educated adults in 27 countries



Notes: See Table 2 for country codes. The bars represent the occupational status gap, measured in ISEI points, between less- and intermediate-educated adults. The darker segment indicates the part of the gap that is attributable to differences in literacy and numeracy skills according to the decomposition results (see text for details). The capped lines indicate 95% confidence intervals for the overall gap and for thr portion attributable to skills.

Sources: PIAAC (rounds 1 and 2), authors' calculations.

Hypothesis 1 states that accounting for individual-level differences in skills will reduce cross-national variation in the ISEI gap. Consistent with this prediction, we find that the unexplained portion of the ISEI gap that remains after accounting for skills exhibits less cross-country variation than the unadjusted gap (i.e., the length of the lighter segments of the bars in Figure 1 is less variable than the overall length). Whereas the cross-country variance is 6.7 in the unadjusted case, it is only 5.6 after accounting for literacy and numeracy skills—a reduction of approximately 15 percent.

The overall cross-country variation of the estimates for both the unadjusted gap and the unexplained portion that remains after adjusting for skills comprises both "true" variation in the ISEI gap and variation due to sampling error. When we estimate a random effects model to separate the two components (see the discussion in Section 3.2 above), we find that the true variation (τ^2) declines from 5.7 (95% confidence limits: 3.2; 11.5) to 4.6 (95% confidence limits: 2.5; 9.5)—a reduction of approximately 20 percent.[17] As expected by hypothesis 1, accounting for individual-level differences in skills thus appears to reduce cross-country variation in the estimated ISEI gap, but the considerable overlap between the confidence intervals indicates that this result must be viewed as suggestive.

We also investigated to what extent the ISEI gap can be explained by the control variables (sex, foreign-birth/foreign-language status, parental education, and potential experience). As discussed above (see Section 3.4), the "fully adjusted gap" (i.e., the dependent variable in the country-level regressions presented below) is effectively the unadjusted gap minus the contributions of literacy/numeracy skills and of the lower-level controls. Figure B1 in the Online Supplement shows that the combined contribution of the control variables is ambiguous. In most countries, compositional differences with respect to the controls contribute to the ISEI gap, but the contribution tends to be smaller than for the skills measures and is statistically insignificant for many countries.

4.2 The role of skills transparency

How can the remaining cross-country variation in the ISEI gap be explained and what, in particular, is the role of skills transparency? We make a first attempt to answer these questions in Figure 2 where we visually explore the relationships between the skills transparency measures and the fully adjusted ISEI gap (i.e., the unexplained gap that remains after adjusting the ISEI gap for literacy and numeracy skills as well as the additional control variables). We also include vocational enrollment as a potentially important confounder that has received

[17] For technical reasons, the standard errors for the unexplained part of the ISEI gap cannot be corrected for the complex sampling design using the jackknife replication weights. To address this issue, we multiplied the uncorrected standard errors for the unexplained part by the ratio of the corrected and the uncorrected errors for the unadjusted gap.

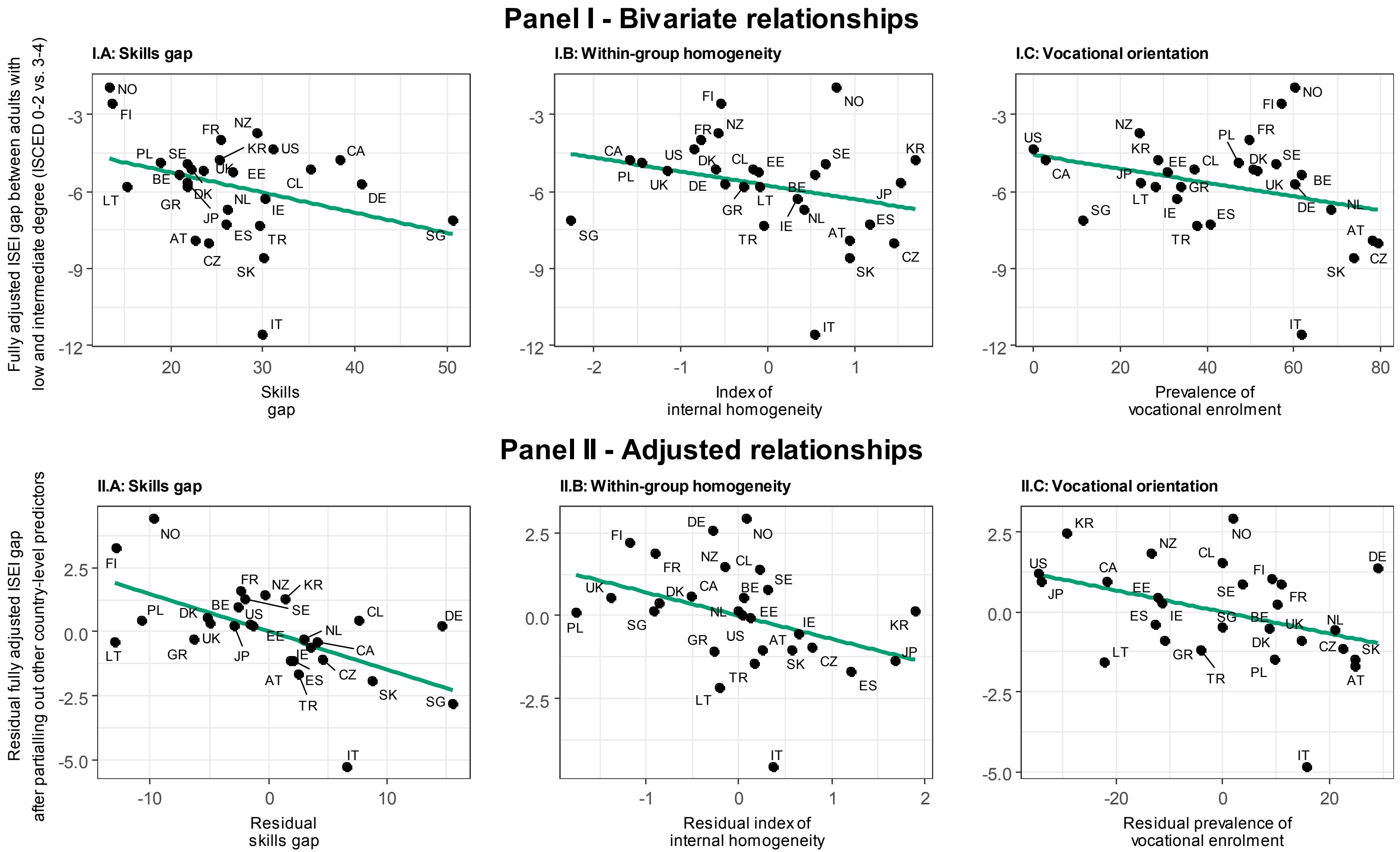
considerable attention in previous research. The graphs in Panel I (top row) depict simple bivariate relationships, with the lines representing linear fits estimated by OLS.[18]

Consistent with hypotheses 2 and 3, we find that the ISEI gap between less- and intermediate-educated adults tends to increase with the skills gap (Panel I.A) between less- and intermediate-educated adults and with the internal homogeneity of these groups (Panel I.B): The ISEI gap becomes "more negative" as these two country-level characteristics increase. None of the relationships seems to be driven by single countries, although there are clearly some potentially influential cases. Finland and Norway, the two countries where the ISEI gap is smallest, also have very small skills gaps. Singapore stands out as a country with a very large skills gap and very low levels of internal homogeneity. We further check for potential outlier issues below (see Section 4.4 and Section D in Online Supplement). Consistent with previous research (e.g., Bol and van de Werfhorst, 2011; Shavit and Müller, 1998), Panel I.C indicates that the ISEI gap also tends to be larger in countries with a stronger vocational orientation of upper secondary education.

Panel II of Figure 2 displays the partial relationships between the ISEI gap and the three country-level characteristics. The graphs relate residual variation in the ISEI gap to residual variation in these characteristics, after accounting for the effects of the respective other two characteristics. For example, we regressed the ISEI gap and the skills gap on the indices of internal homogeneity and prevalence of vocational enrollment to compute the residuals depicted in Panel II.A. According to the Frisch-Waugh-Lovell theorem, this has the same effect as controlling for the other two characteristics in conventional multiple regression (Davidson and MacKinnon, 2004, Chapter 2). We see that the partial relationships continue to go in the expected negative direction. Especially for the skills gap and the index of internal homogeneity, the adjusted relationships appear clearer than the simple bivariate associations. Several countries that look like potential outliers in the bivariate case no longer appear problematic when the respective other two characteristics are taken into account. The Singaporean case in particular gives less reason for concern in Panels II.A and II.B than in Panels I.A and I.B. Again, we investigate potential outlier issues more systematically in Section 4.4 below.

[18] The slopes of these lines differ somewhat from those estimated in the formal country-level regression analysis (see Table 4 below) because they are based on the final point estimates (rather than running the country-level regressions on each of the ten imputed data sets). Moreover, they are based on unweighted regressions, whereas the formal country-level regression analysis uses an FGLS approach that gives greater weight to more precise estimates of the ISEI gap (see Section 3.4).

Figure 2. Country-level relationships between fully adjusted ISEI gap and measures of skills transparency



Notes: See Table 2 for country codes. Lines are linear fits estimated using ordinary least squares. Panel II shows relationships after partialing out the effects of the respective other two characteristics.

Table 4 displays the results of the more formal country-level analysis based on FGLS regressions. We present six models. Models 1 and 2 include the skills transparency measures one at a time and Model 3 includes them both together. Models 3 to 6 repeat this sequence with the prevalence of vocational enrollment added as an additional (control) variable. All three country-level predictors are z-standardized, so the coefficient estimates can be interpreted as the predicted change in the fully adjusted ISEI gap associated with a standard deviation increase in the respective characteristic.

The signs of the coefficient estimates in Table 4 are generally consistent with hypotheses 2 and 3: The coefficient estimates for the skills gap and homogeneity index are negative throughout, indicating that an increase in the respective predictor is associated with a greater labor market disadvantage of less-educated adults. The bivariate associations in Models 1 to 2 do not reach statistical significance, but the relationship with the ISEI gap becomes stronger and statistically significant for both skill transparency measures when they are included simultaneously in Model 3.

Table 4. Country-level regressions of ISEI gap on measures of skills transparency and vocational orientation

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Skills gap	-0.623		-0.955*	-0.966*		-1.124*
	(0.373)		(0.431)	(0.525)		(0.540)
Index of internal homogeneity		-0.548	-0.885*		-0.347	-0.634*
		(0.396)	(0.409)		(0.382)	(0.342)
Prevalence of vocational enrollment				-0.996*	-0.495	-0.774*
				(0.418)	(0.353)	(0.418)
Intercept	-5.862***	-5.837***	-5.847***	-5.844***	-5.829***	-5.833***
	(0.391)	(0.387)	(0.367)	(0.361)	(0.383)	(0.354)
N	27	27	27	27	27	27
R^2	0.09	0.08	0.27	0.31	0.13	0.39
Adjusted R^2	0.06	0.04	0.21	0.25	0.06	0.31

Notes: Feasible Generalized Least Squares (FGLS) estimates, based on 10 imputations/plausible values. Dependent variable: the fully adjusted ISEI gap between less-educated and intermediate-educated adults aged 25-54 (see Figure 1 above and Section A in Online Supplement). All country-level variables are z-standardized (mean of 0, standard deviation of 1). Robust HC3 standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 (one-tailed tests).

Sources: PIAAC (rounds 1 and 2), authors' calculations.

Our preferred specification is Model 6, which includes the two skills transparency measures while also controlling for the prevalence of vocational enrollment. According to this specification, a standard deviation increase in the skills gap is associated with a -1.124 point change in the ISEI gap between less- and intermediate-educated adults ($p < .05$; one-sided).

This effect size is substantial, given that the average fully adjusted ISEI gap across the 27 countries in our sample is -5.8 points, with a cross-country standard deviation of 1.9 points (see Table 2 above). It corresponds to about 58 percent of the standard deviation. This result supports hypothesis 2, which expects the aggregate skills differential between less- and intermediate-educated adults to have an independent effect on the labor market disadvantage of less-educated adults above and beyond the direct individual-level effect of skills (which is accounted for in the first-step regressions).

Hypothesis 3, which posits that higher internal homogeneity of the educational groups increases the ISEI gap between less- and intermediate-educated adults, is supported as well. The ISEI gap is larger in countries where the less- and intermediate-educated groups are internally more homogeneous in terms of literacy und numeracy skills. According to Model 6, the ISEI gap grows by -.634 points ($p < .05$; one-sided) with each standard deviation increase in the index of internal homogeneity. This equates to approximately 33 percent of the cross-country standard deviation of the fully adjusted ISEI gap.

These results support the notion that skills do not only matter at the individual level. The skills transparency of educational certificates (as captured by the skills gap and internal homogeneity of educational groups) appears to be an additional source of cross-national variation in the labor market disadvantage of less-educated workers.

A short note on the role of vocational education and training systems: the ISEI gap between less- and intermediate-educated adults is larger in countries where upper secondary education puts greater emphasis on occupation-specific skills. This is consistent with previous findings (e.g., Bol and van de Werfhorst, 2011; Shavit and Müller, 1998; van de Werfhorst, 2011). In Model 6, the coefficient of vocational enrollment is statsitically significant and of broadly similar magnitude as the one for internal homogeneity (Model 7, b = -.774, $p < .05$, one-sided).

4.3 Does skills transparency mediate the effect of external differentiation?

Can our novel measures of skills transparency help us make better sense of findings in the existing literature? In particular, can we provide more direct evidence that the effect of external differentiation (tracking) in secondary education on the relationship between educational attainment and occupational status is mediated by skills transparency (Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011)? We address these questions with an additional sequence of regression models in Table 5. As noted above (see Section 3.3), the external differentiation index is unavailable for Estonia, Lithuania, and Singapore. We therefore have to exclude these countries from this step of the analysis, which reduces the country sample to 24 cases.

Model 1 in Table 5 regresses the fully adjusted ISEI gap on the external differentiation index. Consistent with previous research (e.g., Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011; van de Werfhorst, 2011), the coefficient estimate is negative and statistically significant, indicating that the labor market disadvantage of less-educated adults increases with the extent of tracking in secondary education. At -1.096 ($p < .01$, one-sided) the size of the coefficient is quite substantial and broadly comparable to that of the skills gap in Table 4 above. Model 2 adds the prevalence of vocational enrollment as a potential confounder because tracked systems are also often found in countries with developed vocational education systems. The coefficient of vocational enrollment is negative, but rather small and statistically insignificant in this specification. The coefficient on the external differentiation index is only slightly weaker than in Model 1 and remains significant at the five percent level. Thus we are able to reproduce the finding that stronger external differentiation is associated with greater labor market disadvantages for less-educated adults.

Adding the direct measures of skills transparency (Model 3) leads to a dramatic attenuation of the effect of external differentiation; the absolute size of the coefficient estimate declines enormously relative to Model 2: from -0.979 to -0.027. By contrast, the coefficients on the direct measures of skills transparency—the skills gap and the index of internal homogeneity—are similar in size to those from the previous step of the analysis (see Model 6, Table 4 above). They do not attain statistical significance, however, because the standard errors are considerably larger than in Table 4.

Thus, the coefficient of the external differentiation index essentially drops to zero when the direct measures of skills transparency are included, whereas the coefficients of the latter are very robust to the inclusion of the tracking measure. This latter result is underlined by Model 4 in Table 5, which shows that the coefficients of both the skills gap and the index of internal homogeneity do not change when the external differentiation index is dropped (while maintaining the reduced sample of 24 countries). The estimates are also very similar (and in fact even somewhat larger in absolute size) than in the corresponding model for the full country sample (Model 6 in Table 4). Unlike in Table 4, the coefficient of the skills gap does not attain statistical significance in this specification (p = .053, one-sided), however, because the standard error is considerably larger than in the full country sample.

Table 5. Country-level regressions of ISEI gap on measures of external differentiation, skills transparency, and vocational orientation

	Model 1	Model 2	Model 3	Model 4
Index of external differentiation	-1.096**	-0.979*	-0.027	
	(0.322)	(0.565)	(0.886)	
Skills gap			-1.312	-1.323
			(1.018)	(0.778)
Index of internal homogeneity			-0.694	-0.695*
			(0.494)	(0.377)
Prevalence of vocational enrollment		-0.192	-0.924	-0.944*
		(0.547)	(0.927)	(0.455)
Intercept	-5.828***	-5.797***	-5.687***	-5.690***
	(0.401)	(0.367)	(0.393)	(0.382)
N	24	24	24	24
R^2	0.27	0.28	0.45	0.45
Adjusted R^2	0.24	0.21	0.34	0.36

Note: Estonia, Lithuania, and Singapore are excluded because of missing information for the index of external differentiation. All variables are z-standardized (mean of 0, standard deviation of 1). Robust HC3 standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (one-tailed tests). See text and note to Table 4 for further information.

Sources: PIAAC (rounds 1 and 2), authors' calculations.

In sum, these findings provide substantial support for hypothesis 4 which expects the well-document effect of external differentiation on the labor market disadvantage of less-educated adults to be attenuated substantially once direct measures of skills transparency are included in the regression. In more substantive terms, these findings indicate that skills transparency is an important channel through which external differentiation is related to labor market inequalities among educational groups.

4.4 Alternative explanations and robustness checks

In Table 6, we present a series of further analyses to assess potential alternative explanations (see Section 2.2 above) and explore the robustness of our findings. The first two models control for the unemployment rate to address the concern that our results might be driven by country differences in macroeconomic conditions. Data come from the World Bank.[19] We use the mean of the 2011 and 2012 values for the first-round and the mean of the 2014 and 2015 unemployment rates for the second-round countries.

[19] https://data.worldbank.org/, downloaded on September 3, 2018.

Model 1 includes the unemployment rate linearly and Model 2 adds a squared term. The linear term is z-standardized, while the squared term is the square of the standardized variable. The untransformed values of the unemployment rate can be found in Table A3 in the Online Supplement. Model 1 indicates that less-educated workers tend to face greater disadvantages when unemployment is high. More importantly, the effects of our two focal country-level predictors—the skills gap and the index of internal homogeneity—are very similar to Model 6 in Table 4 and remain statistically significant. This does not change when we add the square of the unemployment rate to allow for a non-linear effect in Model 2.

Models 3 to 6 account for some of the country differences in the industrial and job structure by including the prevalence of employment in different sectors and in more detailed labor market segments, expressed as the share of overall employment. The employment shares are based on International Labour Office (ILO) data on employment by industry, defined according to the fourth revision of the International Standard Industrial Classification (ISIC).[20] As with the unemployment rate, we use the mean of the 2011 and 2012 shares for first-round and of the 2014 and 2015 shares for second-round countries.[21]

Models 3 and 4 include the share of employment in the primary and secondary (manufacturing) sector. The employment share of the tertiary (service) sector is omitted because it is perfectly collinear with the employment shares of the other two sectors. Models 5 and 6 use a more fine-grained typology that groups industries into six labor market segments. It builds on the work of Stinchcombe (1979), as implemented in Carroll and Mayer (1986), and distinguishes among the following segments: traditional primary; small competitive; competitive; large-scale engineering; professional; bureaucratic. [22] We omit the share of the traditional primary segment from the regressions to avoid perfect multicollinearity. We provide further information on the different segment measures in Section A in the Online Supplement, including the values of the employment shares for each country (see Table A3). For the regression models, the measures were again z-standardized.

[20] Data were obtained from https://www.ilo.org/global/statistics-and-databases/lang--en/index.htm on October 8, 2018. For two countries, Canada and Chile, industries are classified according to the third revision of the ISIC.

[21] The one exception is Canada where we have to use the values for 2016, the only year covered by the ILO data.

[22] Carroll and Mayer (1986) identify a seventh segment, "classical capitalist", but the industry classification provided by the World Bank is not fine-grained enough to differentiate it from the "small competitive" segment.

Table 6. Additional country-level regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Skills gap	-1.202*	-1.209*	-1.123*		-0.742	
	(0.534)	(0.542)	(0.546)		(0.755)	
Index of internal homogeneity	-0.590*	-0.717*	-0.598		-0.164	
	(0.313)	(0.377)	(0.345)		(0.709)	
Prevalence of vocational enrollment	-0.883*	-0.798*	-0.745*		-0.868	
	(0.407)	(0.401)	(0.428)		(0.772)	
Unemployment rate	-0.582*	-1.139*				
	(0.271)	(0.653)				
Unemployment rate (squared)		0.305				
		(0.312)				
Employment shares of broader sectors (Ref.: tertiary sector)						
Primary sector			-0.411	-0.072		
			(0.286)	(0.313)		
Manufacturing			-0.336	-0.833**		
			(0.239)	(0.322)		
Employment shares of detailed segments (Ref.: traditional primary segment)						
Small competitive					-0.724	-1.091
					(1.236)	(0.933)
Competitive					0.341	0.260
					(0.579)	(0.468)
Large-scale engineering					-0.667	-1.394
					(1.034)	(0.919)
Professional					0.359	0.036
					(0.903)	(1.008)
Bureaucratic					-0.135	-0.543
					(0.582)	(0.435)
Intercept	-5.793***	-6.072***	-5.826***	-5.849***	-5.782***	-5.785***
	(0.344)	(0.456)	(0.348)	(0.380)	(0.398)	(0.380)
N	27	27	27	27	27	27
R2	0.48	0.52	0.46	0.19	0.54	0.39
Adjusted R2	0.39	0.41	0.33	0.12	0.33	0.25

Note: All variables, except square of unemployment rate, are z-standardized (mean of 0, standard deviation of 1). Square of unemployment rate is the square of the z-standardized unemployment rate. Robust HC3 standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (one-tailed tests). See text and note to Table 4 for further information.

Sources: PIAAC (rounds 1 and 2), authors' calculations.

The coefficients of the skills gap and internal homogeneity are quite robust to the inclusion of the broader sector share measures in Model 3 in Table 6. The coefficient estimates are very similar to Model 6 in Table 4. The coefficient estimate for the skills gap remains statistically significant at the five percent level, whereas the *p*-value for the homogeneity measure now barely misses the five percent threshold ($p = .050$).The coefficients of the sectoral share measures are relatively small and statistically insignificant in Model 3. When we include only the sectoral share measures and drop the skill transparency and vocational orientation measures (Model 4) the manufacturing share begins to show a negative and statistically significant coefficient (b = -.833; $p < .01$, one-sided). While this provides some evidence for the relevance of economic structural explanations, it does not indicate that sectoral composition—at least at this level of aggregation—is a major driver of cross-national differences in the labor market disadvantage of less-educated adults. In particular, the effects of both skills transparency measures appear more robust to the inclusion of the sectoral composition measures than *vice versa*.

Model 5 in Table 6 includes the segment shares in addition to the skills transparency measures and vocational enrollment. It fails to show any statistically significant effects. The effect of the skills gap is more robust to the inclusion of the segment shares than the effect of internal homogeneity, but even the former is far from reaching statistical significance. However, the segment measures themselves are not strongly predictive of the ISEI gap either. This is confirmed by Model 6, which drops the skill transparency and vocational orientation measures. While the coefficients of the small competitive and the large-scale engineering segment are quite sizable in this specification, they still fail to attain statistical significance. In addition, comparisons with Model 5 in Table 6 (and with Model 6 in Table 4) make clear that the coefficients of the segment share measures are at least as sensitive to the inclusion of the skills transparency and vocational orientation measures than *vice versa*.

In summary, the supplementary analyses presented in Table 6 yield two main conclusions. First, country differences in labor market conditions, while potentially of some relevance, do not seem to drive the relationships between our focal predictors and the labor market disadvantage of less-educated adults. Second, country differences in the industrial and job structure may likewise play some role for cross-national variation in the labor market disadvantage of less-educated adults. However, we find no clear evidence that the relationships between our focal predictors and the ISEI gap are spurious and ultimately attributable to cross-national differences in economic structural factors.

We conducted several further robustness checks, which we report in the Online Supplement. In a first set of analyses, reported in Section D of the Online Supplement, we examined the influence individual country cases and pairs of countries on the country-level regression results, focusing on our preferred specification from the main sequence of regression models, Model 6 in Table 4 above. Initial analyses showed that Israel and Slovenia jointly have a dramatic impact on the regression results, as measured by the DFBETA and Cook's D influence statistics. This led us to exclude these to countries from the main analysis. The main difference between the results presented above and those based on the full country sample including Israel and Slovenia is that there is essentially no support for H3 (internal homogeneity) in the latter case. Additional influence diagnostics for the main analysis sample of 27 countries revealed no further cases with extreme influence.

In a second set of robustness checks, we explored the impact of changing the individual-level sample restrictions. In particular, we reeaximined the main sequence of country-level regressions in Table 4 above after excluding respondents who were not employed at the time of interview (see Section E in the Online Supplement) and after exluding respondents who were self-employed (see Section F in the Online Supplement). Results were similar to the main analysis, with the most noteworthy difference being that the coefficient of the index of internal homogeneity is somewhat smaller in absolute size and no longer statistically significant in Model 6 when the self-employed are excluded (b = -.492; se = .335; p = .078, one-sided).

In a third robustness check (see Section G in the Online Supplement), we omitted parental education from the control variables used in constructing the skills transparency indicators (the skills gap and index of internal homogeneity) because parental education may be less readily visible to employers than the other characteristics that we adjusted for in constructing these measures (sex, age, and foreign-birth/foreign-language status). Results were very similar to the main analysis.

In a fourth check (see Section H in the Online Supplement), we reran the regressions in Table 4 with the gap in log hourly wages (rather than occupational status) as the dependent variable. This analysis provides no clear evidence for either Hypothesis 2 or 3. As noted above (see Section 3.2), we suspect that these inconclusive results are due to a combination of more noise in the measured wage gaps and unmodeled confounding by contextual factors such as collective-bargaining institutions and minimum wage regulations.

5 CONCLUSIONS

The main goal of our paper was to further our understanding of the role of skills and, in particular, the role of skills transparency of educational certificates for cross-national differences in the labor market disadvantage of less-educated adults. We used the recent PIAAC data, which provide higher quality measures of the actual (literacy and numeracy) skills of adults than previous cross-national data sets. A crucial improvement of our study is to account for individual-level differences in skills while also allowing for effects of the aggregate relationship between formal qualifications and skills (i.e., of the skills transparency of educational degrees).

Our results concerning the role of individual-level differences show that the actual skills of less-educated workers are an important predictor of their occupational status attainment, as suggested by human capital theory. Hence, country differences in the (relative) level of skills achieved by less-educated adults appear to be an important source of country variation in their labor market disadvantage. An obvious policy implication of this finding is to improve the education system and adult training in order to raise the skills of less-educated adults (Heisig and Solga, 2015; Park and Kyei, 2011).

The most intriguing and novel result of our analysis is that the relationship between formal qualifications and skills appears to shape labor market inequalities above and beyond these direct individual-level effects. We find that the occupational status gap between less- and intermediate-educated adults is larger in countries where educational degrees are more skills transparent, even after accounting for skills at the individual level. More specifically, we show the labor market disdavantage of the less educated to increase with the skills gap (i.e., the mean skills difference) between less- and intermediate-educated adults and with the homogeneity of the skills distribution within these groups. These results are consistent with theories of labor market signaling and screening (Arrow, 1973; Spence, 1973). In countries where skills transparency is high—and a person's formal qualifications therefore send a stronger signal about his/her actual skills—employers seem to be more likely to use these qualifications as a basis for statistical discrimination, having a stronger preference to hire intermediate-educated adults for higher quality jobs over less-educated adults.

Our analysis also sheds new light on the finding that formal qualifications are more important for occupational attainment in countries with extensive ability-related external differentiation or "tracking" in secondary education (e.g., Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011; Shavit and Müller, 1998). Some authors (Andersen and van de Werfhorst, 2010; Bol and van de Werfhorst, 2011) have speculated that differences in the skills transparency of educational certificates are the major mediating channel behind this moderating effect of external differentiation, but this possibility has not been investigated empirically so far. In the present paper, we were not only able to confirm that stronger external differentiation of upper secondary education systems is associated with larger labor market disadvantages for less-educated adults. More importantly, we also found that this association can largely be accounted for by the two direct measures of skills transparency, the skills gap and the index of internal homogeneity. Our results thus support the skills transparency interpretation of the effects of external differentation documented in previous research.

Our findings concerning the role of skills transparency point to a possible trade-off that may need to be taken into account when designing policies to improve the labor market prospects of less-educated adults. On the one hand, skills transparency (in the sense of a stronger association between formal qualifications and skills) should facilitate labor market matching and may contribute to merit-based hiring and promotion decisions. Low skills transparency might undermine trust in educational degrees and, thus, employers might pay greater attention to social origin, ethnicity, or gender when assessing applicants, raising inequalities by these (ascriptive) characteristics.

On the other hand, a potential downside of high levels of skills transparency is that it may reinforce the disadvantages of less-educated adults who are perceived to have low skills, possibly even leading to a stronger (statistical) discrimination of the group (Solga, 2002). Even in "skills transparent" countries where the less educated are relatively homogeneous, we still find substantial within-group variation in literacy and numeracy skills (Heisig, 2018). Yet if less-educated workers are facing statistical discrimination based on their formal qualification, the more skilled members of the group might find it difficult to translate their higher skills into better labor market outcomes (e.g., because they are screened out during the early stages of the hiring process). This suggests that labor market returns to skills may be particularly low for the less educated. Moreover, skills transparency might moderate this individual-level interaction between formal qualification and skills, the reason being that when skills transparency is high, statistical discrimination based on formal qualifications should be stronger as well (i.e., there may be a three-way interaction between skills and educational degrees at the individual and skills transparency at the country level). Future research should investigate this possibility in greater depth, although much larger sample sizes than provided by PIAAC are probably needed to identify such complex relationships (for some suggestive evidence, see Heisig and Solga, 2017).

We conclude with some limitations of our study and with related questions for future research. A first limitation is that our direct measures of skills remain incomplete. While PIAAC is the richest and most advanced cross-national survey of adult skills to date, general literacy and numeracy skills are not the only skills that matter for labor market attainment.[23] One additional class of skills emphasized in the literature are occupation-specific skills (e.g., Muja et al. 2019; van de Werfhorst, 2011). Like previous studies (Bol and van de Werfhorst,

[23] However, it should be noted that our skill measures will partly pick up the effects of other types of skills if the latter are correlated with them.

2011; Shavit and Müller, 1998; van de Werfhorst, 2011), we lacked direct measures of occupation-specific skills and could only include a country-level indicator for vocational orientation of upper secondary education. In line with previous findings, we found that a stronger vocational orientation exacerbates the labor market disadvantage of less-educated adults, even after accounting for individual-level differences in general skills and for country differences in the (general) skills transparency of educational degrees. Non-cognitive skills are another class of skills that have received much attention in the literature (e.g., Heckman et al., 2006) The next round of PIAAC (planned for 2021/22), which is set to collect also some information on non-cognitive skills, will be a valuable resource for extending and refining our analysis in this regard.

A second limitation is that we cannot rule out that our results are confounded by unobserved third variables. This concern looms particularly large in cross-national comparisons where small country-level samples and a lack of data on relevant country characteristics limit our ability to control for potential confounders. That being said, we analyzed occupational status, a labor market outcome less prone to confounding by unmeasured third variables, and we did account for country differences in overall labor market conditions and in the industry/job structure—and found little evidence that it is these factors, rather than the extent of skills transparency, which drives cross-national variation in the labor market disadvantage of less-educated adults.

Third, while employer perceptions and employer behavior play a central role in theoretical explanations for the labor market disadvantage of less-educated workers, we cannot observe them directly with survey data like PIAAC. A few studies have recently begun to use innovative designs such as correspondence studies and factorial surveys to better understand employer decision making (e.g., Di Stasio, 2015; Di Stasio and van de Werfhorst, 2016; Protsch and Solga, 2015), and at least one of these studies has included a country-comparative element (Di Stasio and van de Werfhorst, 2016). This line of research nicely complements studies such as ours that approach the process of labor market attainment from the employee side.

Finally, we focused on the less educated as a group that faces particularly high labor market risks. One obvious extension would be to study the labor market advantage of higher-education graduates, but our design might be useful for understanding other dimensions of social inequality as well. The literature on statistical discrimination argues that employers will also look to characteristics other than education when they want to infer an individual's actual level of skills. Hence, the approach taken in this paper—to explain labor market inequalities not only with the skills of an individual herself, but also with the "skill profile" of the groups that she belongs to—might also be useful for understanding inequalities by race, sex, or age.

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