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Attained vs effective schooling: Assessing educational mismatch using PIAAC data

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Abstract. *This article proposes a measure of educational mismatch based on a novel definition of schooling that takes into account the different levels of skills acquired by individuals with the same education. It is assumed that less (more) able individuals could compensate for their skill deficit (surplus) with more (less) education, and PIAAC data are used to analyse the substitution between skill and educational mismatches in terms of wages. We use the proposed measure to assess the level of effective educational mismatch in a set of countries. When accounting for workers’ real skills, we find that overeducation tends to drop, the difference between observed and effective educational mismatch varying by country.*

Keywords: *schooling, skills, education mismatch, skill mismatch, substitution effects, effective schooling, effective educational mismatch, PIAAC.*

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1. Introduction

A substantial corpus of literature has emerged on the wage effects of educational mismatch, the bulk of it suggesting that overeducated (undereducated) workers tend to receive a pay penalty (premium) with respect to other individuals who, with the same level of schooling, are adequately educated for the jobs that they do.[1] The traditional explanation for the wage penalty associated with overeducation is based on the idea that overeducation implies an underutilization of workers' competencies. Accordingly, skill mismatch is seen as the counterpart of educational mismatch. The assumption behind this interpretation is that achieving a certain level of education implies attaining the corresponding skill level. However, several studies published over the last two decades have questioned this hypothesis, pointing out that individuals with similar schooling may have very different skill levels (Green, McIntosh and Vignoles 1999 and 2002; Quintini 2011).

Different lines of research, responding to the heterogeneity in knowledge among workers with the same level of education, have converged to suggest that overeducation does not necessarily imply an underutilization of skills. Some overeducated workers could actually have lower skill levels than expected given their schooling. Accordingly, traditional measures of overeducation would overstate the actual level of educational mismatch in the labour market (Chevalier 2003).

The idea behind this reasoning is that individuals could compensate for a lower skill level with surplus education. The level of knowledge acquired over a specified number of years of attained schooling, or for a specific academic degree, will be higher if the innate abilities or the motivation of the individuals are higher. Conversely, individuals with less ability might need more years of schooling to achieve a specific skill level. In such cases, the individuals would be considered to be overeducated in terms of schooling, but since the surplus schooling is counterbalanced by a deficit in ability, the years of effective overeducation could be overestimated.

In this context, the aim of this article is to improve the accuracy of the traditional measure of educational mismatch – which focuses only on the quantity of schooling attained by workers, thus ignoring its quality in terms of skills – and hence contribute to a better understanding of the phenomenon. To do this, we propose a novel definition of schooling that takes into account the different levels of skills acquired by individuals with the same level of educational attainment, and compensation between schooling and skills. Although other contributions have mentioned the correlation between overeducation and underskilling, the literature has not, to the best of our knowledge, analysed the substitution between educational and skill mismatches. Moreover, skill mismatch measurement is challenging since data on workers' real skill levels are rather sparse. We draw on data gathered by the Programme for the International Assessment of Adult Competencies (PIAAC) to assess whether individuals' observed skills differ from expected skills, given their human capital. Assuming that skill mismatch can be explained by the differences between observed and expected skills, we estimate the rate of compensation between educational and skill mismatches in terms of wages. According to this estimation, we propose the concept of "effective schooling", taking into account both the years of attained schooling and the skill mismatch. Therefore, effective schooling indicates the number of years of education adjusted in terms of skills. Lastly, we define the "effective educational mismatch" as effective schooling minus the years of schooling required by the job and assess the level of effective educational mismatch in a set of member countries of the Organisation for Economic Co-operation and Development (OECD). We conclude that overeducation figures tend to drop after accounting for workers' skills, with the difference between observed and effective educational mismatch varying by country.

Since the publication of the PIAAC data, various papers have proposed improvements to the skill mismatch measures existing in the literature – see Allen, Levels and van der

[1] For comprehensive reviews of the literature, see Hartog (2000), McGuinness (2006) or Leuven and Oosterbeek (2011).

Velden (2013) and Pellizzari and Fichen (2017). These papers classify individuals as well-matched, overskilled or underskilled, depending on their proficiency compared to the skill level required to perform a job successfully. By contrast, our strategy relies on defining a sharper indicator of individuals' human capital than the conventional measure (attained schooling), which can be accurately compared with the educational requirements of jobs, hence providing more reliable figures of educational mismatch than observed mismatch.

The structure of this article is as follows. In the second section, after a brief review of the literature, we examine the two pillars supporting our methodological proposal: (i) educational and skill mismatches have significant and distinct effects on wages and (ii) educational and skill mismatches might compensate for each other in terms of wages. To do this, the third section presents the data used in this study and offers an exploratory analysis. The fourth section then analyses the substitution between skill and educational mismatches in terms of wages, giving rise to the definition of effective schooling and effective educational mismatch. In the fifth section, we use these concepts to assess the level of effective over- and undereducation in a set of countries. The article closes, in the sixth section, with some conclusions.

2. Literature review

The idea that individuals who have received the same education are heterogeneous in terms of skills has led to three lines of research. The first uses panel data techniques to control for unobserved heterogeneity (Bauer 2002; Frenette 2004; Lindley and McIntosh 2009; Mavromaras et al. 2013), finding that the omission of unobserved abilities overstates the pay penalty associated with overeducation. The second line of research differentiates between educational and skill mismatches, showing that overeducation weakly correlates with skill underutilization and that the wage effects of schooling mismatch are unchanged when controlling for skill mismatch (Allen and Van der Velden 2001; Di Pietro and Urwin 2006; Green and McIntosh 2007). The third strand of this literature takes account of skill heterogeneity to distinguish between genuine and formal overeducation and estimate the monetary returns to overeducation depending on workers' skill levels. This suggests that, when skills are taken into consideration, overeducated workers do not constitute a homogeneous group (Chevalier 2003; Green and Zhu 2010; Pecoraro 2014; Mateos-Romeros and Salinas-Jiménez 2017). All in all, the results reported by these contributions clearly reject the hypothesis of skill homogeneity within educational levels.

There is broad consensus surrounding the idea that any level (or area) of education other than that required to get or do a job creates educational mismatch. This educational mismatch can be measured through job analysis, workers' self-assessment or the "realized matches" method, using objective, subjective or statistical methods, respectively (Leuven and Oosterbeek 2011). By contrast, both the concept and the measurement of skill mismatch appear to be less specific. As stated by McGuinness, Pouliakas and Redmon (2018), the term "skill mismatch" is used in the literature to refer not only to over- and underskilling related to an individual's attributes, but also to skill gaps and skill shortages at the firm level. Objective measures of workers' skills are rarely available in data sets and authors approach over-/underskilling using workers' subjective responses to questions about the extent to which their knowledge is above, below or unrelated to their job requirements. On the other hand, skill gaps and skill shortages are usually measured using employers' information about the difficulties that they have finding workers or applicants with the right competencies to carry out jobs or fill vacancies adequately.

Some papers have used PIAAC data to define new measures of skill mismatches. Allen, Levels and van der Velden (2013) compare individual standardized scores for academic skills with the standardized average use of skills at work. They define a scale according to which workers are well-matched if the difference between skill levels and skill use is no more than 1.5 points above or below zero; otherwise, skills would be over- or underutilized. Pellizzari and Fichen (2017) focus on workers who describe themselves as being well-matched, in the sense that, according to their skills, they do not require any additional training to perform their tasks but cannot manage more demanding duties. They define minimum and maximum levels of assessed skills by occupation for well-matched workers, and individuals whose skills are below or above the interval are classified as underskilled and overskilled, respectively.[2] Flisi et al. (2017) analyse occupational mismatch based on both educational and skill variables. They compute a wide set of both objective and subjective measures indicating whether individual educational/skill levels differ from what is required to perform the job. The main conclusion of these studies, as explicitly stated by Flisi et al. (2017), is that, rather than counterparts, educational mismatch and skill mismatch are two distinct phenomena.

The above-mentioned papers contribute to a better understanding of skill mismatches. However, the extent to which skill use at work is representative of the knowledge required by the labour market is a matter of concern. As Pellizzari and Fichen (2013) acknowledge, skill use at work strongly depends on the effort made by the individual. By contrast, educational level appears to be a more general indicator, although the use of schooling to measure human capital has the disadvantage of ignoring the heterogeneity of skills within educational levels. To sum up, a focus on either skill use at work or attained schooling to measure labour market mismatches results in unclear indicators. This article addresses this limitation by looking not only at the years of attained schooling but also at workers' real skill levels. By defining "effective schooling", we propose an indicator that is sharper than attained education and broader than skill use at work. Since effective schooling measures the years of attained education adjusted by the skills actually acquired by the individual, we can draw a fair comparison with the education required by the job, thus providing more reliable educational mismatch figures than the data documented in previous papers.

3. Wage effects of educational and skill mismatches

3.1. Data

This article draws on PIAAC data for 2012. The PIAAC Survey of Adult Skills aims to assess the competencies of the population aged 16–65 and is carried out at the international level by the OECD. Even though other surveys (such as the International Adult Literacy Survey (IALS) and the Adult Literacy and Life Skills Survey (ALLSS)) have previously measured the skills of the adult population, PIAAC's survey includes a greater number of participating countries and evaluates a wider range of competencies (not only language skills, like IALS and ALLSS, but also mathematical skills and the use of new technologies). The competencies included by PIAAC are measured using specific tests and the results are provided in terms of plausible values. In particular, the database provides ten plausible values for each skill tested. These plausible values indicate the performance of each individual on a scale of 0 to 500 points (in this article they have been rescaled from 0 to 1,000 to facilitate their interpretation). The survey also provides harmonized information on the socio-demographic characteristics of the respondents (e.g. gender, age, education) and on their job-related characteristics (e.g. work experience, wage, working hours).

The PIAAC survey has been conducted by the OECD in a number of countries and at the time of the writing one single cycle of data had been published. The first cycle of data consists of three rounds of data collection between 2011 and 2018. We use the data from the first round (2011–12), selecting those countries whose data raise no concerns with respect to their reliability and which also provide full information on each variable used in our study.[3] Self-employed individuals are excluded from the sample, as the research focuses on wage earners. Our variables provide information regarding the *log of hourly wage*, *age*,

[2] McGowan and Andrews (2017) follow a very similar approach to Pellizzari and Fichen (2017), and Perry, Wiederhold and Ackerman-Piek (2014) propose a measure that combines the proposals of both Allen, Levels and van der Velden (2013) and Pellizzari and Fichen (2013) – a previous version of their 2017 paper.

[3] The countries included in the sample are Belgium, Czechia, Denmark, Estonia, Finland, Ireland, Italy, Japan, Netherlands, Norway, Republic of Korea, Slovakia, Spain and the United Kingdom.

Table 1. Descriptive statistics

	Mean	SD	Min.	Max.
Log of hourly wage	2.576	0.61	0.10	6.89
Age	40.20	11.91	16	65
Women	0.4810	0.4978	0	1
Experience	17.56	11.70	0	55
Schooling	13.06	2.88	3	22
Overeducated	0.3126	0.4635	0	1
Undereducated	0.1437	0.3508	0	1
Adequately educated	0.5436	0.4980	0	1
Mathematical skills	554.28	90.93	49.69	885.67
Standardized maths skills	0.1414	0.9372	−5.0603	3.5576
Literacy skills	564.62	85.06	157.52	821.29
Standardized literacy skills	0.1852	0.9566	−4.3930	3.0718
Agriculture	0.0177	0.1320	0	1
Industry	0.2104	0.4076	0	1
Construction	0.0652	0.2469	0	1
50–249 employee firm	0.2247	0.4174	0	1
>250 employee firm	0.1938	0.3953	0	1
Public firm	0.2129	0.4094	0	1
Indefinite contract	0.7393	0.4390	0	1
Number of observations	48 782			

Notes: SD = standard deviation. Medium firms = 50–249 employees; large firms = >250 employees.
Source: Own calculations based on PIAAC data.

experience, *educational level*, *gender* and *mathematical* and *literacy competencies*.[4] PIAAC defines numeracy and literacy in the following terms: "Numeracy is the ability to access, use, interpret and communicate mathematical information and ideas [...]. Literacy is the ability to understand, evaluate, use and engage with *written texts* to participate in society, to achieve one's goals, and to develop one's knowledge and potential." (OECD 2021, 32–34). *Hourly wage* is expressed in terms of purchasing power parities (PPP) to ensure comparability between countries (in particular, this variable is provided by PIAAC as "hourly earnings including bonuses for wage and salary earners, PPP"[5]). *Experience* measures individuals' years of paid work over their lifetime. The variables *mathematical* and *literacy skills* are the average of their respective ten plausible values and they have been standardized to facilitate the interpretation of the estimated coefficients. Observed educational mismatch is obtained by comparing years of attained schooling by workers with the years of schooling they consider are needed to get their job: workers would be adequately educated if attained and required schooling are equal, but they will be overeducated (undereducated) if their years of attained schooling are higher (lower) than what is required to get the job.[6]

[4] We do not consider proficiency in the use of new technologies because this information is not available for all of the countries included in our sample.
[5] See PIAAC data public use files, available at: https://www.oecd.org/en/data/datasets/piaac-1st-cycle-database.html.
[6] Note that, although commonly used to measure the educational mismatch, subjective methods such as those described above have some limitations (McGuinness, Pouliakas and Redmon 2018); for example, the self-reported level of education required to get a particular job may vary between recently hired workers and those who have been in their job for longer.

Table 1 presents the descriptive statistics for these variables for the full sample (descriptive statistics by country are presented in table A1 in Appendix 1). We find that 31.26 per cent of the individuals in the sample are overeducated, whereas undereducated workers account for 14.37 per cent of the sample. The average value for mathematical skills is 554.28 out of 1,000 (or 0.1414 standardized points) and the values for literacy skills are quite similar. At the same time, average schooling is slightly over 13 years. The average age is around 40, average work experience is 17.56 years and 48.1 per cent of the sample are women. The total number of observations is 48,782.

3.2. Exploratory analysis: Wage effects of educational and skill mismatches

We offer an exploratory analysis that aims to assess the extent to which the data support the two pillars underlying our methodological proposal, namely: (i) educational and skill mismatches have significant and distinct effects on wages; and (ii) these two types of mismatches might compensate for each other: underskilled individuals might seek to counterbalance skill gaps by attaining more schooling and overskilled individuals might take advantage of their talent to get jobs that require less gifted individuals to undergo more years of formal education.

Our starting point is a standard wage equation based on human capital theory, which explains the logarithm of wages per hour, ln*W*, based on two components:

(i) Expected productivity of the worker, $E(\pi)$, conditional upon the human capital (*HK*) that the individual has acquired through years of schooling and years of labour market experience, also considering their gender:

$$E\left(\frac{\pi / Years\ of\ schooling, Years\ of\ experience, Dummy\ of\ gender}{HK}\right) = E(\pi / HK) \tag{1}$$

(ii) Difference between observed productivity and expected productivity:

$$\pi - E(\pi / HK) \tag{2}$$

These two components can be used to define the following wage equation:

$$\ln W = \underbrace{\beta E(\pi / HK)}_{Expected\ productivity} + \theta \underbrace{[\pi - E(\pi / HK)]}_{Surprises} \tag{3}$$

Worker productivity is not observable for the calculation of surprises. However, it can be assumed that surprises are proportional to the difference between the observed skills and the expected skills, taking into account the individual's education and experience:

$$[\pi - E(\pi / HK)] = \lambda [Sk - E(Sk / HK)] \tag{4}$$

Note that a difference between the observed and the expected skills represents a skill mismatch: if an individual has skills over (under) what is expected given their education and experience, then they could be considered to be overskilled (underskilled).

In addition to the above, it is well known from the educational mismatch literature that years of overeducation (undereducation) lead to a pay penalty (premium) relative to the wages earned by individuals who, with the same level of schooling, are adequately educated for their jobs. Taking this point into account and substituting in equation (3), the wage equation can be formulated as:

$$\begin{aligned}\ln W &= \beta_0 + \beta_1 S + \beta_2 Years\ Exper + \beta_3 (Years\ Exper)^2 + \beta_4 Gender + \beta_5 \underbrace{[Sk - E(Sk/HK)]}_{Skill\ mismatch:Skmm} \\ &+ \beta_6 \underbrace{(S - S^*)}_{\substack{Educational \\ mismatch:edmm}} + u = \beta_0 + \beta_1 S + \beta_2 Years\ Exper + \beta_3 (Years\ Exper)^2 \\ &+ \beta_4 Gender + \beta_5 Skmm + \beta_6 edmm + u\end{aligned} \tag{5}$$

where S is the observed number of years of attained schooling and S^* is the required number of years of schooling to get the job.[7]

As mentioned earlier, the values for educational mismatch are obtained by comparing attained schooling with the schooling required to get the job, while the skill mismatch is calculated as follows:

(i) An equation explaining skills using schooling, experience, as well as age and gender as regressors, is estimated as follows:

$$Sk = \alpha_0 + \alpha_1 S + \alpha_2 Age + \alpha_3 Years\,Exper + \alpha_4\,Years\,Exper^2 + \alpha_5 Gender + \varepsilon \tag{6}$$

(ii) The difference between the observed value and the expected value for skills conditional upon attained schooling, experience, and age and gender is identified with the skill mismatch:

$$\begin{aligned}&Skill\ mismatch = Sk - \widetilde{Sk} \\ &\widetilde{Sk} : Expected\ value\ of\ skills\end{aligned} \tag{7}$$

Note that the difference between observed and expected skills is captured by the random disturbance term, ε. For symmetric distributions of the error term, the expected value of ε is zero and then the skill mismatch can be calculated directly as the difference between the observed value of skills and the fitted value of the explanatory variables in equation (6). But if the distribution of ε is not symmetric, then the most probable value of the dependent variable, conditional upon the observed values of the regressors, would be given by their fitted value plus the mode of the error term:

$$Most\ probable\ value\ of\ Sk\ conditional\ upon\ x = x'\alpha + Mode(\varepsilon) \tag{8}$$

where x represents the set of regressors and α is the corresponding vector of parameters. Thus, the skill mismatch can be defined as:

$$Skmm = \varepsilon - Mode(\varepsilon) \tag{9}$$

which is the definition that we follow in our study, given the observed asymmetry in the distribution of ε.

[7] It should be acknowledged that wages do not only represent compensation for workers' productivity but may also compensate for adverse working conditions. Thus, although equation (5) is based on human capital theory, wage differentials associated with being over-/undereducated may also be explained by other theories, such as the efficiency wages (Akerlof and Yellen 1986; Katz 1986) or the signalling theory (Weiss 1995). Table A2 in Appendix 1 reports the results of estimating wages by incorporating some exogenous demand-side variables often used to show evidence of various types of efficiency wages. In particular, we add the following information: activity sector (agriculture, industry or construction), firm size (medium for firms with 50–249 employees, or large for firms with 250 employees or more) and ownership (public/private), as well as type of contract.

Table 2 shows the wage effects associated with educational and skill mismatches. They are derived from the estimation of equation (6), including as regressors (besides schooling, experience and gender) either educational or skill mismatch only (columns I and II, respectively) and both types of mismatch together (column III). For the sake of simplicity, we report the results associated with mathematical skills in the main body of the article. The results for literacy skills are reported in Appendix 2 to demonstrate the robustness of our estimations, as the two sets of results are almost identical, both quantitatively and qualitatively.

Table 2. Educational and skill mismatch wage effects

	I Only educational mismatch	II Only skill mismatch	III Educational and skill mismatches
Schooling	0.0859***	0.0737***	0.0845***
	(22.04)	(27.49)	(22.54)
Experience	0.0264***	0.0284***	0.0261***
	(11.40)	(11.49)	(11.51)
Experience^2	−0.0004***	−0.0004***	−0.0004***
	(−9.75)	(−9.77)	(−9.60)
Overeducation	−0.0478***		−0.0447***
	(−10.43)		(−10.11)
Undereducation	0.0543***		0.0491***
	(11.68)		(12.00)
Higher than expected skills		0.1044***	0.0845***
		(8.07)	(7.12)
Lower than expected skills		−0.0865***	−0.0637***
		(−8.74)	(−7.47)
Women	−0.1842***	−0.1832***	−0.1817***
	(−6.21)	(−5.96)	(−5.99)
Country dummies	Yes	Yes	Yes
R^2	0.5448	0.5267	0.5517
N	48 781	48 781	48 781

*** indicates significance at the 1 per cent level.
Note: *t*-statistics appear in parentheses.
Source: Own calculations based on PIAAC data.

The results suggest that educational mismatch has statistically significant effects on wages. An overeducated (undereducated) worker would thus earn 5 per cent less (more) than an individual with the same educational level doing a more (less) demanding job that is commensurate with their education. Skill mismatch also has statistically significant effects on wages, with overskilled (underskilled) individuals receiving a wage premium (penalty) of around 10.4 (8.6) per cent with respect to other individuals who have the expected skills, given their educational level and experience. The results remain unchanged for individuals who might have both educational and skill mismatches, and the magnitudes of the wage effects are quite similar to the above, suggesting that wage premiums and penalties associated with educational (skill) mismatch are robust to the possibility that the individual also has mismatched skills (education).

We also hypothesize that educational and skill mismatches might compensate for each other. This possibility is tested by estimating discrete choice models, where overeducation and undereducation appear as dependent variables. In particular, column I (II) in table 3 reports the results of estimating a probit model where the categorical dependent variable is a dummy indicating whether the individual holds an educational level higher (lower) than that required to get their job, and the regressors control for skill mismatch, as well as schooling, experience and gender. We also estimate an ordinary least squares (OLS) regression with the years of educational mismatch as the dependent variable (column III), where variables referring to skill mismatch act as regressors (in addition to schooling, experience and gender).

The results reported in table 3 support the hypothesis that individuals who have higher (lower) competencies than expected, given their educational level and experience, show a

Table 3. Relationship between educational mismatch and skill mismatch

	I Overeducated	II Undereducated	III Educational mismatch
Schooling	0.0715***	−0.1715***	0.2329***
	(33.29)	(−62.32)	(11.23)
Experience	−0.0123***	0.0169***	−0.0290***
	(−25.32)	(30.33)	(−5.33)
Overskilled	−0.1197***	0.2768***	−0.3938***
	(−7.68)	(16.05)	(−6.98)
Underskilled	0.1782***	−0.1538***	0.5015***
	(15.13)	(−9.87)	(8.69)
Women	0.0002	−0.0056	0.0254
	(0.02)	(−0.41)	(0.75)
Country dummies	Yes	Yes	Yes
(Pseudo-)R^2	0.0524	0.1618	0.1271
N	55 541	55 541	55 541

*** indicates statistical significance at the 1 per cent level.
Note: *t*- and *z*-statistics appear in parentheses.
Source: Own calculations based on PIAAC data.

lower (higher) probability of being overeducated and a higher (lower) probability of being undereducated. Also, overskilled (underskilled) individuals who are mismatched in terms of education have fewer (more) years of educational mismatch. These results suggest that educational and skill mismatches could compensate for each other in terms of wages.

4. An analysis of the substitution between skill and educational mismatches: Effective schooling and effective educational mismatch

The wage equation (5) can be used to compare how the market evaluates the mismatch in schooling and the mismatch in skills in monetary terms. Once the equation has been estimated, it is possible to calculate the rate of substitution between educational mismatch and skill mismatch to keep the individual's wage unchanged. In other words, we can calculate how many additional years of schooling are needed to counterbalance a one-unit skill mismatch and vice versa – how many units of skill surplus (deficit) are needed to compensate for one year of undereducation (overeducation).

Accepting the hypothesis that there is a direct correspondence between productivity and wages, a unit of skill mismatch can, based on the estimation of equation (5), be compensated for in terms of wages by *r* years of schooling, where *r* is the rate of substitution:

$$r = \frac{\beta_5}{\beta_6} \tag{10}$$

This ratio can be used to derive the mismatch of skills necessary to compensate for the mismatch in schooling and ensure that the worker is adequately qualified (that is, has no educational or skill mismatch) in terms of wages. Specifically, *r* units of skills over (under) the expected level can be compensated for by one year of undereducation (overeducation).

Following this reasoning, it is also possible to distinguish between attained schooling declared in the PIAAC survey (S) and effective schooling as the years of schooling that account for potential skill mismatches expressed in equivalent terms (S_e):

$$S_e = S + r.skmm \tag{11}$$

Hence, effective educational mismatch – as opposed to observed educational mismatch – can be defined as:

$$\begin{aligned} &Observed\,educational\,mismatch = S - S^* \\ &Effective\,educational\,mismatch = S_e - S^* \end{aligned} \tag{12}$$

where S^* indicates the years of attained schooling required by the job. To sum up, an individual who claims to be overeducated is only effectively overeducated if:

(i) their observed competencies are at least equal to the expected skills corresponding to their education and experience; or

(ii) the years of declared overeducation more than compensate for their skill deficit.

In turn, an individual who claims to be undereducated might be effectively overeducated if they have a skill surplus that more than compensates for their lack of schooling.

Table 4 provides the results of the estimation of equation (5) using PIAAC data and table 5 shows the rate of substitution between educational and skill mismatch, calculated from the values provided by this estimation.[8, 9]

As has been widely documented in the literature, the returns to attained schooling are positive but their magnitude depends on the extent to which the years of attained schooling meet the requirements of the job, and the penalty associated with the years of educational mismatch is lower than the above returns. Moreover, it is the competencies actually acquired by workers throughout their formal education, rather than just the quantity of schooling, that play a significant role in wage determination: individuals with higher-than-expected

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8 We also provide stepped estimations of equation (5) including (i) only schooling, experience and gender, following the basic Mincerian wage equation; (ii) adding country dummies to control for country fixed effects; (iii) adding either educational or (iv) skill mismatches and also (v) both types of labour market mismatches together, in accordance with table 2. These estimations are reported in table A3 of Appendix 1. The estimated coefficients for the variables of interest barely change with the inclusion of new variables once country fixed effects are considered.

9 Note that the wage effects of skill (educational) mismatch are measured by a unique variable for either over- or underskilling (over- or undereducation). We have previously tried to include two separate variables and the data do not reject the null hypothesis of equity for the associated coefficients. Thus, for the sake of simplicity, we consider a unique variable to measure the wage effects of the skill (educational) mismatch.

Table 4. Wage equation estimations

Dependent variable: log of hourly wage	Coefficient	*t*
Attained schooling	0.0841***	22.17
Educational mismatch	−0.0459***	−11.59
Skill mismatch	0.0725***	11.05
Experience	0.0261***	11.43
Experience^2	−0.0004***	−9.56
Women	−0.1822***	−5.98
Constant	1.6234***	23.11
Country dummies: Yes		
R^2	0.5516	
N	48 781	

*** indicates significance at the 1 per cent level.
Source: Own calculations based on PIAAC data.

Table 5. Rate of substitution between educational mismatch and skill mismatch

Rate of substitution	Values
Mean	−1.5777***
Standard deviation	0.1155
t-statistic	13.65

*** indicates significance at the 1 per cent level.
Source: Own calculations based on PIAAC data.

skills receive a wage premium with respect to their less capable classmates.[10] Lastly, as table 5 indicates, an individual might compensate for a one-unit mismatch of standardized skills with around 1.6 years of additional schooling. In other words, on average, if a student does not acquire the expected skills within the course year, it takes 1.6 years of additional education to reach the skills of another student who has acquired them within the year. In this case, the extra schooling of the less able student should not be seen as overeducation, but as compensation for their lower ability.

5. Observed educational mismatch and effective educational mismatch: Results by country

In this section, we present the results of estimating effective educational mismatch by country, using our data set. The figures reported in table 6 illustrate the idea that an individual who has the educational level required by a job will not necessarily have acquired the expected skill level from that education.[11] Hence, it is important, for some countries especially, to make a distinction between observed and effective educational mismatch.

[10] Note that the coefficient associated with educational mismatch is not directly comparable with the coefficient associated with the skill mismatch, as skills are expressed in standardized terms.

[11] Following the suggestion of a referee, we have converted the continuous mismatch variable into a discrete one to provide a clear-cut classification of adequately skilled, and over- and underskilled workers. To do this, we assume that workers are adequately skilled if their skills are within 0.5 standard deviation of the average skills. The results are reported in table A4 in Appendix 1 (see table A10 in Appendix 2 for literacy competencies).

Thus, the percentage of adequately educated workers whose skills are lower than expected ranges from less than one third in Japan to more than three quarters in Ireland.

Table 6. Skill mismatch for adequately educated workers

Country	Difference between observed and expected skills	Observed<Expected (%)	Observed>Expected (%)
Belgium	0.2090	35.98	64.02
Czechia	0.0068	46.56	53.44
Denmark	0.1251	41.01	58.99
Estonia	0.0874	42.24	57.76
Finland	0.2612	34.39	65.61
Ireland	−0.6158	78.36	21.64
Italy	−0.2709	59.72	40.28
Japan	0.2765	31.57	68.43
Netherlands	0.0664	43.58	56.42
Norway	−0.0120	45.58	54.42
Republic of Korea	−0.1704	59.03	40.97
Slovakia	−0.0050	48.20	51.80
Spain	−0.3155	64.40	35.60
United Kingdom	−0.1475	55.82	44.18
Full sample	−0.0214	47.98	52.02

Source: Own calculations based on PIAAC data.

In view of the above, we can expect one year of attained schooling to lead to different years of effective schooling depending on the competencies actually acquired by individuals. Table 7 provides information on the difference between these two variables as well as the average attained and effective schooling,[12] by country and for the workforce as a whole, while table 8 reports the same information, focusing on workers who claim to be over- or undereducated. Note that effective schooling is slightly lower than attained schooling for the sample as a whole and varies greatly by country. Thus, effective schooling falls far below attained schooling in Ireland – and, to a lesser extent, in Spain and the United Kingdom – while the opposite is the case for Japan and Finland. These results are in line with the findings reported by Calero, Murillo Huertas and Raymond (2021) who, using the same data set, conclude that the efficiency with which the education system transforms schooling into skills varies notably by country. In particular, they single out Japan and Finland as being among the most efficient, with Ireland, the United Kingdom and Spain at the opposite end of the scale.

Related to the above, we should note that the average years of educational mismatch observed in the countries in our sample differ substantially when considering compensation between skills and schooling (table 7 and figure 1). Especially striking is the case of Ireland, declaring on average 0.77 years of overeducation for their effectively undereducated

[12] The absolute value of the difference between attained and effective education has been calculated as follows: for each year of attained schooling, the different values of effective years of schooling have been calculated taking account of potential skill mismatches, as illustrated in figure A1 in Appendix 2. Then, we calculated the difference between attained education and these different figures of effective education by individual. These differences by individual are summed up as absolute values to avoid compensation between positive and negative deviations of effective education with respect to attained education. The figures reported in the tables are the average of the absolute value differences by country.

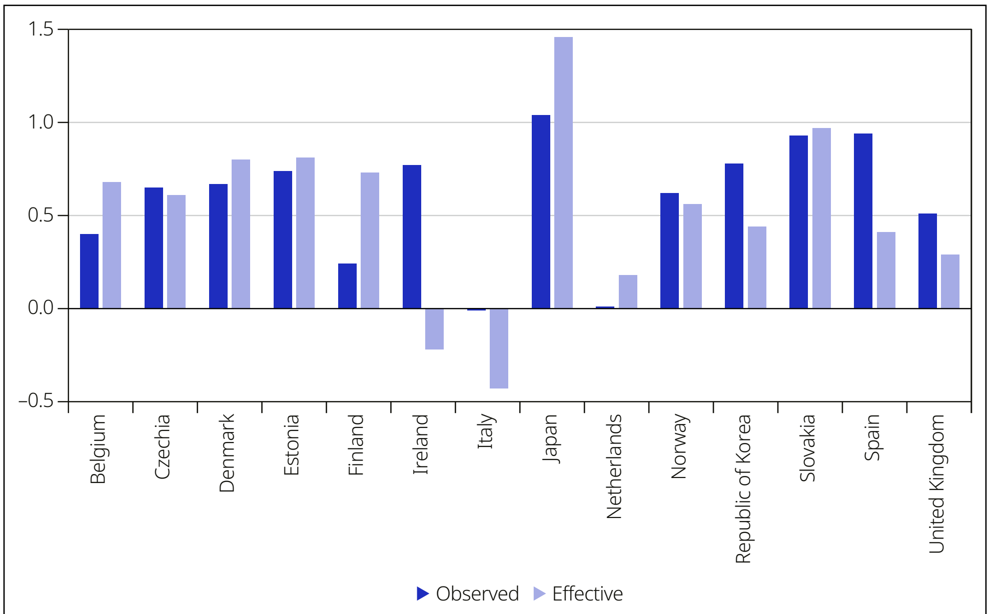
individuals, with Italy showing a similar pattern. Finland and Japan, by contrast, underestimate their corresponding average years of overeducation, as effective educational mismatch increases by about half a year, taking into account workers' competencies.

Table 7. Observed vs effective educational mismatch (all workers)

Country	Years of attained schooling	Years of effective schooling	Absolute value of the difference between attained and effective schooling	Observed educational mismatch	Effective educational mismatch
Belgium	12.54	12.79	1.02	0.40	0.68
Czechia	13.32	13.26	0.89	0.65	0.61
Denmark	12.87	12.93	1.05	0.67	0.80
Estonia	12.19	12.26	0.93	0.74	0.81
Finland	12.57	13.00	1.06	0.24	0.73
Ireland	15.03	14.03	1.29	0.77	−0.22
Italy	11.79	11.43	1.05	−0.01	−0.43
Japan	13.30	13.73	0.97	1.04	1.46
Netherlands	13.25	13.41	0.99	0.01	0.18
Norway	14.31	14.20	1.04	0.62	0.56
Republic of Korea	12.89	12.61	0.90	0.78	0.44
Slovakia	13.12	13.11	0.93	0.93	0.97
Spain	11.36	10.77	1.07	0.94	0.41
United Kingdom	13.23	12.92	1.08	0.51	0.29
Full sample	12.99	12.89	1.02	0.60	0.55

Source: Own calculations based on PIAAC data.

Figure 1. Observed educational mismatch vs effective educational mismatch.



Source: Own calculations based on PIAAC data.

Lastly, table 8 presents the values for observed and effective educational mismatch focusing particularly on mismatched individuals. We find that Ireland, followed by the Mediterranean countries, has the highest value for the difference between attained and effective schooling for overeducated workers. This indicates that undereducation is exacerbated in these countries – as well as in the Republic of Korea – when effective schooling is considered. By contrast, and in line with the results reported in tables 6 and 7, Japan and Finland have higher effective than observed over- and undereducation figures, suggesting that overeducated (undereducated) workers in the two countries have, on average, a higher-than-expected skill level given their education and experience.

The values reported in tables 7 and 8 and in figure 1 are in line with the findings reported by Flisi et al. (2017). They put Ireland, Italy and Spain in the category of countries with high levels of overeducation whose workers do not, however, possess extra skills. This is consistent with the sizeable difference between observed and effective overeducation that we find for these countries. Flisi et al. (2017) also find that workers in Finland have the right educational level required by their jobs but possess a high level of skills, which is consistent with our figures for the effective educational mismatch being higher than the observed educational mismatch.

An analysis of the reasons for the disparate educational mismatch figures by country is beyond the scope of this article and is available in other studies (see table 9). Nonetheless, we would like to point out that, as stated by Flisi et al. (2017), a plausible explanation would lie in the idiosyncrasy of national educational systems. Thus, schooling in Ireland, Italy and Spain provides very little tracking and a high level of general education, meaning that students are poorly matched to labour market opportunities. By contrast, Scandinavian educational systems are more stratified and offer solid vocational education tracks, resulting in less overeducation.

Table 8. Observed vs effective educational mismatch (mismatched workers)

Country	Observed over-education	Effective over-education	Absolute value of the difference between attained and effective schooling	Observed under-education	Effective under-education	Absolute value of the difference between attained and effective schooling
Belgium	3.85	3.77	0.99	−3.10	−2.49	1.07
Czechia	3.12	2.90	0.90	−2.49	−2.35	0.93
Denmark	3.77	3.60	1.11	−2.76	−2.27	1.13
Estonia	2.75	2.68	0.90	−2.25	−1.97	1.02
Finland	3.32	3.85	1.09	−2.75	−2.12	1.10
Ireland	3.36	2.22	1.38	−2.84	−3.61	1.12
Italy	4.57	3.75	1.24	−4.13	−4.21	0.98
Japan	3.24	3.62	0.91	−2.69	−2.17	1.11
Netherlands	3.16	3.16	1.00	−2.67	−2.23	1.01
Norway	3.37	3.15	1.05	−2.23	−2.11	1.01
Republic of Korea	4.34	3.74	1.03	−3.89	−4.00	0.88
Slovakia	2.32	2.37	0.90	−2.36	−2.06	0.90
Spain	3.92	3.24	1.08	−3.16	−3.41	1.00
United Kingdom	3.44	3.05	1.07	−3.00	−2.75	1.05
Full sample	3.35	3.13	1.05	−2.83	−2.63	1.03

Source: Own calculations based on PIAAC data.

Table 9. Selected references regarding the differences in observed educational mismatch among countries

Authors	Data	Countries covered by the study	Educational/skill mismatch(es) measures	Main conclusions
Allen, Levels and van der Velden (2013)	PIAAC, 2012	22 OECD countries	Skill mismatch measure based on a comparison between individuals' skill levels and skill use at work	▪ Overskilling is positively related to higher wages and job satisfaction. Overskilled workers engage in more on-the-job training. Underskilling (overskilling) and undereducation (overeducation) are only weakly related. ▪ At an individual level, participating in vocational vs general secondary education favours higher skill use relative to one's skill level. By contrast, at a country level, educational systems with poor vocational training tracking show the highest skill use relative to individuals' skill levels.
Davia, McGuinness and O'Connell (2017)	European Union Survey on Income and Living Conditions, 2004–09	28 European countries	Subjective measure of overeducation	▪ Overeducation is mainly driven by an excess of supply relative to the distribution of skilled jobs, and it tends to be higher in those countries whose individuals are more likely to enrol in tertiary education. ▪ Institutional factors have an influence on overeducation rates at a country level. Trade union density and employment protection legislation seem to be helpful mechanisms for preventing overeducation.
Di Pietro and Urwin (2006)	Italian National Institute of Statistics (ISTAT), 2001	Italy	Subjective measure of overeducation and skill mismatch based on both employee and employer perception regarding the educational level and the skills needed to properly perform the job	▪ A non-negligible proportion of overeducated Italian graduate workers report a proper use of their skills, while one third of adequately educated graduate workers report skill underutilization. Graduate workers constitute a heterogeneous group in terms of skills. ▪ Overeducation does not imply skill underutilization. Contrary to the assumptions of the assignment theory, skill underutilization does not explain the pay penalty due to overeducation in the Italian labour market.
Flisi et al. (2017)	PIAAC, 2012	17 European countries	Occupational mismatch indicators based on education and skill variables	▪ Education and skill mismatches are two distinct phenomena, and the vast majority of mismatched workers are mismatched with respect to either education or skills. Policies aimed at alleviating only one type of mismatch might fail to help a non-negligible part of the mismatched workers. ▪ Educational mismatch and skill mismatch are negatively correlated at a country level: those countries showing higher (lower) levels of overeducation tend to show lower (higher) proportions of overskilled workers.

(*Cont.*)

Table 9. Selected references regarding the differences in observed educational mismatch among countries (*concl.*)

Authors	Data	Countries covered by the study	Educational/skill mismatch(es) measures	Main conclusions
Jauhiainen (2011)	Finnish census data, 2001	Finland	Statistical measure of overeducation	▪ The spatial dimension of the job search area affects the probability of overeducation. In particular, living in a small (large) regional labour market increases (decreases) the probability of being overeducated. ▪ The influence of spatial factors on the probability of being overeducated is stronger for women living in spatially constrained job search areas and weaker for mobile individuals.
Kucel, Fuentes Molina and Raya (2016)	REFLEX, 2005	Japan	Subjective measure of overeducation	▪ Overeducation affects a large proportion of workers in Japan, and it has a strong negative effect on wages. ▪ Working in large firms reduces the probability of being overeducated thanks to better chances of internal promotion. Performing high-skilled occupations also reduces the probability of overeducation for Japanese men and women.
McGuinness, O'Shaughnessy and Pouliakas (2017)	European Skills and Jobs Survey, 2014	Ireland and 27 other European countries	Subjective measure of overeducation	▪ Overeducation rates in Ireland are higher than the EU average, especially for young people and elementary workers. ▪ The overeducated workers suffer a higher pay penalty in Ireland than in the rest of the EU countries. An Oaxaca-Blinder decomposition reveals that only about one third of this pay penalty can be explained by the better attributes of matched workers. Job skill requirements play an important role in the explained part of the pay gap. The evidence gives support to the qualification inflation hypothesis.
Pellizzari and Fichen (2017)	PIAAC, 2012	23 OECD countries	Skill mismatch measure combining information on skill proficiency, self-reported skill mismatch and skill use	▪ Overskilling incidence greatly varies by country, ranging from about one quarter of workers in Spain to barely 6 per cent of workers in France. ▪ Overskilling affects men more heavily than women and graduate workers are less likely to be underskilled. Foreign workers are much more likely to be underskilled than native workers.

Source: Own compilation.

6. Conclusions

The issue of educational mismatch has been studied at length in the literature. Typically, researchers identify mismatched workers by comparing individuals' formal education with the level required to do or to get a job. However, the empirical evidence shows that the years of attained schooling do not accurately reflect individuals' actual skills. New trends in the literature on labour mismatches suggest that the wage effects of educational mismatch might be associated with workers having different skills to those that are expected given their level of education. Our article has built upon these trends, aiming to shed light on the question of whether individuals might compensate for a deficit (surplus) in skills with an excess (shortage) of education. The objective was to analyse whether at least some of the observed educational mismatch is down to apparent rather than actual overeducation (undereducation) considering that mismatched workers may have different skills to those expected.

The PIAAC's Survey of Adult Skills provides data on both individuals' attained years of education and their observed skills. We have used these data to implement an objective method to compare formal education with the expected skills that individuals should have acquired through schooling. The skill mismatch is calculated by comparing individuals' observed skills with those expected given their human capital. We then explicitly measure the compensation between educational and skill mismatches in terms of wages in the labour market and define a new indicator of educational mismatch taking into account this substitution between educational and skill mismatches. We apply this methodology to study the level of effective – or real – educational mismatch in a sample of countries included in the PIAAC database.

We have found that, overall, observed competencies are frequently lower than expected, especially in certain countries where overeducation is, thus, more apparent than real. Therefore, overeducation figures tend to decrease when the compensation between surplus schooling and deficient skills is considered, with some countries declaring overeducation for effectively undereducated individuals. By contrast, other countries have populations whose average skills surpass the competencies that can be expected based on human capital. As the inputs considered in our study to approximate expected skills are the years of formal education and the years of labour market experience, a skill shortage can be attributed to either ineffective knowledge transmission or a production process of goods and services that does not properly exploit employee potential.

Although the topic of educational and skill mismatches has been extensively analysed in the literature, some aspects still remain underdeveloped and warrant further research. This is the case of the analysis of the substitution between education and skills. As McGuinness, Pouliakas and Redmon (2018) emphasize, the incidence and effects of labour mismatch strongly depend on how it is measured (e.g. in terms of schooling or skill mismatches). How accurately labour mismatch is defined is even more important, since the concept of educational mismatch could play a different role if it is compensated for, to some extent, by skill mismatches.

Being able to measure educational mismatch reliably is also significant from an economic policy perspective. If overeducation truly exists, it suggests an inefficient allocation of resources, where overeducated workers fail to take full advantage of the capabilities provided by their formal education. Thus, from both an individual and a societal standpoint, these resources are misallocated. In this regard, it is essential to take skill heterogeneity among workers with similar schooling into account when designing effective policies. Policymakers should acknowledge that overeducation does not necessarily imply skill underutilization and tailor interventions accordingly.

Our findings suggest that it is crucial to enhance the effectiveness with which educational systems transform schooling into skills, especially in countries such as

Ireland or Italy, where effective educational mismatch is capable of turning the observed overeducation figures around. Policies focusing on enhancing the quality of education and training programmes should be a priority to ensure that graduates have the skills and knowledge needed to perform their jobs. Promoting programmes that meet the evolving needs of the labour market and provide individuals with key skills can help reduce overeducation by bringing education into line with job requirements. Furthermore, addressing the informal sector and promoting formal employment opportunities can help reduce overeducation by providing workers with jobs that match their skills and educational levels. Closing the gap between actual and expected competencies, together with a better match between individuals' education and changing labour market needs, would maximize both individual and social returns to education. As stated by Brunello and Wruuck (2021), this challenge is a responsibility not only for individuals and schools but also for firms and governments.

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Competing interests

The authors declare that they have no competing interests.

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Appendix 1

Table A1. Descriptive statistics by country

	Belgium		Czechia		Denmark		Estonia		Finland		Ireland		Italy	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Log of hourly wage	2.92	0.40	2.08	0.45	3.06	0.44	2.09	0.60	2.84	0.40	2.93	0.56	2.58	0.47
Age	41.18	11.17	40.22	11.30	40.42	12.91	40.37	12.33	41.20	12.41	37.98	11.64	40.53	10.32
Experience	19.73	11.47	18.71	11.59	20.94	12.74	18.85	12.39	18.59	12.35	16.61	11.07	17.41	10.70
Schooling	12.98	2.61	13.36	2.52	12.92	2.65	12.58	2.60	13.02	2.91	15.46	2.87	11.43	3.82
Overeducated	0.2226	0.4161	0.3041	0.4601	0.2598	0.4386	0.4100	0.4919	0.2675	0.4427	0.3964	0.4892	0.2100	0.4074
Undereducated	0.1584	0.3652	0.1473	0.3545	0.1285	0.3347	0.1762	0.3810	0.2306	0.4213	0.2013	0.4010	0.2706	0.4444
Adequately educated	0.6190	0.4857	0.5486	0.4977	0.6117	0.4874	0.4139	0.4926	0.5020	0.5001	0.4023	0.4905	0.5195	0.4997
Mathematical skills	574.27	90.67	557.28	80.74	571.29	89.13	554.54	81.36	583.52	88.17	529.73	92.87	509.72	94.44
Standardized maths skills	0.35	0.93	0.17	0.83	0.32	0.92	0.14	0.84	0.44	0.91	−0.11	0.96	−0.32	0.97
Literacy skills	563.94	84.53	553.30	75.52	554.89	81.99	559.37	80.14	593.82	85.05	548.64	83.83	507.98	86.17
Standardized literacy skills	0.18	0.95	0.06	0.85	0.08	0.92	0.13	0.90	0.51	0.96	0.01	0.94	−0.45	0.97
Women	0.4795	0.4997	0.4643	0.4988	0.4969	0.5000	0.5494	0.4976	0.5142	0.4999	0.5314	0.4991	0.4241	0.4943
Number of observations	2 758		2 635		4 669		4 026		3 310		2 793		1 984	
	Japan		Netherlands		Norway		Republic of Korea		Slovakia		Spain		United Kingdom	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Log of hourly wage	2.58	0.59	2.87	0.53	3.11	0.43	2.57	0.71	1.98	0.57	2.50	0.52	2.77	0.54
Age	41.38	12.51	39.04	12.81	40.04	12.97	39.48	11.26	40.45	11.36	40.17	10.63	38.76	12.34
Experience	18.65	12.02	18.21	11.72	18.73	12.26	12.86	9.94	18.55	11.67	17.14	10.96	18.88	12.15
Schooling	13.30	2.36	13.50	2.58	14.41	2.45	13.36	3.02	13.68	2.60	12.31	3.45	13.21	2.29
Overeducated	0.3820	0.4860	0.2447	0.4299	0.3218	0.4672	0.2643	0.4410	0.4604	0.4985	0.3715	0.4833	0.2370	0.4253
Undereducated	0.1015	0.3020	0.2512	0.4338	0.2088	0.4065	0.1209	0.3261	0.0602	0.2379	0.1494	0.3566	0.1084	0.3109
Adequately educated	0.5165	0.4998	0.5041	0.5001	0.4694	0.4991	0.6148	0.4867	0.4794	0.4997	0.4790	0.4997	0.6547	0.4755
Mathematical skills	585.28	80.14	575.54	87.78	571.45	95.77	535.33	82.15	569.96	76.62	515.36	90.44	547.82	93.90
Standardized maths skills	0.46	0.83	0.36	0.90	0.32	0.99	−0.05	0.85	0.30	0.79	−0.26	0.93	0.07	0.97
Literacy skills	600.17	70.40	583.77	84.34	567.70	84.25	550.20	75.86	559.56	66.10	523.18	87.30	565.67	84.43
Standardized literacy skills	0.58	0.79	0.40	0.95	0.22	0.95	0.02	0.85	0.13	0.74	−0.28	0.98	0.20	0.95
Women	0.4363	0.4960	0.4815	0.4997	0.4918	0.5000	0.4226	0.4940	0.4821	0.4998	0.4731	0.4994	0.4881	0.4999
Number of observations	3 286		3 204		3 609		3 156		2 521		2 463		4 486	

Note: SD = standard deviation.

Source: Own calculations based on PIAAC data.

Table A2. Wage equation estimations incorporating demand-side variables

	Coef.	*t*
Attained schooling	0.0795***	23.25
Educational mismatch	−0.0427***	−11.06
Skill mismatch	0.0688***	10.8
Experience	0.0226***	10.41
Experience^2	−0.0004***	−7.59
Women	−0.1623***	−5.96
Agriculture	0.0521	1.43
Industry	0.0087	0.89
Construction	0.0833***	3.02
50–249 employee firm	0.0639***	10.71
>250 employee firm	0.1481***	14.25
Public firm	0.0063	0.27
Indefinite contract	0.0865***	5.52
Constant	1.5677***	25.5
Country dummies	Yes	
R^2	0.562	
F	–	
N	48 781	

*** indicates significance at the 1per cent level.
Note: Medium firms = 50–249 employees; large firms = >250 employees.
Source: Own calculations based on PIAAC data.

Table A3. Stepped estimations of the wage equation

	(i)		(ii)		(iii)		(iv)		(v)	
	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Attained schooling	0.0835***	12.88	0.0743***	27.42	0.0855***	21.74	0.0736***	27.6	0.0841***	22.17
Educational mismatch					−0.0497***	−11.81			−0.0460***	−11.59
Skill mismatch							0.0938***	13.23	0.0725***	11.05
Experience	0.0386***	4.89	0.0289***	11.28	0.0264***	11.33	0.0283***	11.51	0.0261***	11.43
Experience^2	−0.0006***	−3.88	−0.0005***	−10.06	−0.0004***	−9.67	−0.0004***	−9.9	−0.0004***	−9.56
Women	−0.1814***	−4.08	−0.1868***	−6.21	−0.1843***	−6.21	−0.1840***	−5.92	−0.1823***	−5.98
Constant	1.1729***	7.96	1.7129***	26.17	1.6225***	22.54	1.7059***	26.69	1.6235***	23.11
Country dummies	No		Yes		Yes		Yes		Yes	
R^2	0.226		0.5148		0.5448		0.5266		0.5516	
F	88.01		–		–		–		–	
N	49 077		49 077		48 783		49 074		48 781	

*** indicates significance at the 1 per cent level.
Source: Own calculations based on PIAAC data.

Table A4. Skill mismatches for adequately educated workers (discrete option)

Country	Difference between observed and expected skills	Workers whose skills are as expected (%)	Underskilled workers (%)	Overskilled workers (%)
Belgium	0.2090	29.86	15.65	54.49
Czechia	0.0068	38.71	22.55	38.74
Denmark	0.1251	37.24	22.38	40.38
Estonia	0.0874	39.31	20.56	40.13
Finland	0.2612	34.41	14.95	50.64
Ireland	−0.6158	32.12	50.48	17.40
Italy	−0.2709	34.52	29.13	36.36
Japan	0.2765	34.12	12.22	53.66
Netherlands	0.0664	36.77	20.19	43.04
Norway	−0.0120	37.71	24.06	38.22
Republic of Korea	−0.1704	39.42	27.78	32.80
Slovakia	−0.0050	36.07	20.06	43.88
Spain	−0.3155	35.82	34.50	29.68
United Kingdom	−0.1475	31.69	28.81	39.50
Full sample	−0.0214	34.93	24.82	40.25

Source: Own calculations based on PIAAC data.

Appendix 2. Results using literacy skills to approximate skill mismatch

Table A5. Educational and skill mismatch wage effects

	I Only educational mismatch	II Only skill mismatch	III Educational and skill mismatches
Schooling	0.0859***	0.0739***	0.0849***
	(22.04)	(27.49)	(22.60)
Experience	0.0264***	0.02848***	0.0262***
	(11.40)	(11.66)	(11.62)
Experience^2	−0.0004***	−0.0004***	−0.0004***
	(−9.75)	(−9.82)	(−9.60)
Overeducation	−0.0478***		−0.0452***
	(−10.43)		(−9.95)
Undereducation	0.0543***		0.0501***
	(11.68)		(12.23)
Higher than expected skills		0.0897***	0.0754***
		(6.29)	(5.94)
Lower than expected skills		−0.0778***	−0.0533***
		(−10.82)	(−8.34)
Women	−0.1842***	−0.1838***	−0.1822***
	(−6.21)	(−6.04)	(−6.04)
Country dummies	Yes	Yes	Yes
R^2	0.5448	0.5242	0.5501
N	48 781	48 781	48 781

*** indicates significance at the 1 per cent level.
Source: Own calculations based on PIAAC data.

Table A6. Relationship between educational mismatch and skill mismatch

	I Only educational mismatch	II Only skill mismatch	III Educational and skill mismatches
Schooling	0.0714***	−0.1705***	0.2325***
	(33.23)	(−62.10)	(11.23)
Experience	−0.0121***	0.0165***	−0.0283***
	(−24.89)	(29.71)	(−5.20)
Overskilled	−0.0691***	0.2159***	−0.2645***
	(−4.33)	(12.14)	(−3.20)
Underskilled	0.1827***	−0.1612***	0.4795***
	(16.23)	(−10.79)	(8.36)
Women	0.0017		0.0301
	(0.15)		(0.99)
Country dummies	Yes	Yes	Yes
(Pseudo)-R^2	0.0516	0.1592	0.1250
N	55 541	55 541	55 541

*** indicates significance at the 1 per cent level.
Source: Own calculations based on PIAAC data.

Table A7. Wage equation estimations

Dependent variable: log of hourly wage	Coef.	*t*
Attained schooling	0.0844***	22.26
Educational mismatch	−0.0466***	−11.45
Skills mismatch	0.0621***	9.56
Experience	0.0261***	11.54
Experience^2	−0.0004***	−9.55
Women	−0.1826***	−6.06
Constant	1.6333***	23.74
Country dummies: Yes		
R^2	0.5500	
N	48 781	

*** indicates significance at the 1 per cent level.
Source: Own calculations based on PIAAC data.

Table A8. Rate of substitution between educational mismatch and skill mismatch

Rate of substitution	Values
Mean	−1.3328***
Standard deviation	0.1354
t-statistic	9.84

*** indicates significance at the 1 per cent level.
Source: Own calculations based on PIAAC data.

Table A9. Skill mismatches for adequately educated workers

Country	Difference between observed and expected skills	Observed<Expected (%)	Observed>Expected (%)
Belgium	0.0326	44.38	55.62
Czechia	−0.1145	53.56	46.44
Denmark	−0.1358	52.72	47.28
Estonia	0.0427	45.56	54.44
Finland	0.3388	30.68	69.32
Ireland	−0.4894	72.70	27.30
Italy	−0.3857	65.46	34.54
Japan	0.3730	25.20	74.80
Netherlands	0.0971	40.37	59.63
Norway	−0.1315	51.41	48.59
Republic of Korea	−0.1171	55.37	44.63
Slovakia	−0.1943	59.57	40.43
Spain	−0.3540	64.25	35.75
United Kingdom	−0.0621	51.40	48.60
Full sample	−0.0609	49.85	50.15

Source: Own calculations based on PIAAC data.

Table A10. Skill mismatches for adequately educated workers (discrete option)

Country	Difference between observed and expected skills	Workers whose skills are as expected (%)	Underskilled workers (%)	Overskilled workers (%)
Belgium	0.0326	29.76	14.70	55.54
Czechia	−0.1145	38.61	21.29	40.10
Denmark	−0.1358	36.98	21.22	41.80
Estonia	0.0427	39.15	19.27	41.57
Finland	0.3388	33.69	14.06	52.25
Ireland	−0.4894	32.79	49.07	18.13
Italy	−0.3857	34.54	27.89	37.57
Japan	0.3730	33.55	11.46	54.98
Netherlands	0.0971	36.58	18.99	44.43
Norway	−0.1315	37.52	23.15	39.33
Republic of Korea	−0.1171	39.72	26.07	34.21
Slovakia	−0.1943	36.07	18.70	45.24
Spain	−0.3540	36.33	33.15	30.52
United Kingdom	−0.0621	31.80	27.52	40.68
Full sample	−0.0609	34.88	23.62	41.49

Source: Own calculations based on PIAAC data.

Table A11. Observed vs effective educational mismatch (all workers)

Country	Years of attained schooling	Years of effective schooling	Absolute value of the difference between attained and effective schooling	Observed educational mismatch	Effective educational mismatch
Belgium	12.54	12.49	0.86	0.40	0.40
Czechia	13.32	13.11	0.80	0.65	0.44
Denmark	12.87	12.56	0.91	0.67	0.43
Estonia	12.19	12.28	0.87	0.74	0.74
Finland	12.57	12.99	0.95	0.24	0.74
Ireland	15.03	14.33	1.01	0.77	0.07
Italy	11.79	11.35	0.92	−0.01	−0.53
Japan	13.30	13.80	0.86	1.04	1.55
Netherlands	13.25	13.38	0.86	0.01	0.19
Norway	14.31	14.09	0.86	0.62	0.42
Republic of Korea	12.89	12.73	0.74	0.78	0.55
Slovakia	13.12	12.93	0.76	0.93	0.73
Spain	11.36	10.81	0.97	0.94	0.44
United Kingdom	13.23	13.12	0.89	0.51	0.45
Full sample	12.99	12.86	0.88	0.60	0.51

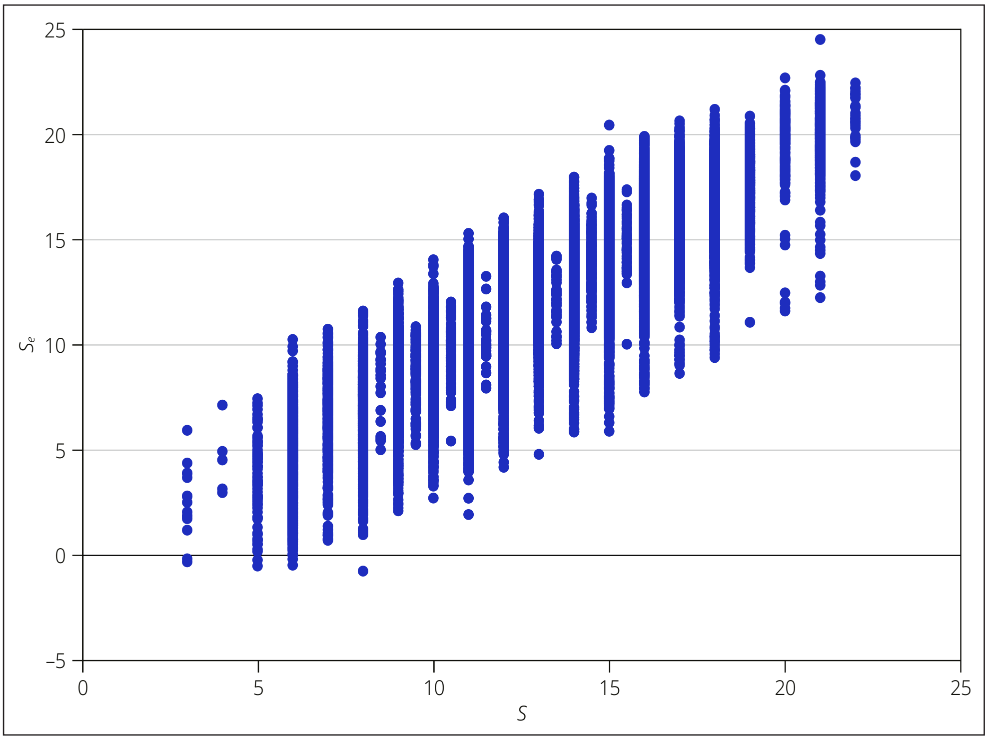
Source: Own calculations based on PIAAC data.

Table A12. Observed vs effective educational mismatch (mismatched workers)

Country	Observed overeducation	Effective overeducation	Absolute value of the difference between observed and effective schooling	Observed undereducation	Effective undereducation	Absolute value of the difference between observed and effective schooling
Belgium	3.85	3.56	0.91	−3.10	−2.84	0.83
Czechia	3.12	2.76	0.82	−2.49	−2.57	0.78
Denmark	3.77	3.29	1.01	−2.76	−2.72	0.85
Estonia	2.75	2.65	0.87	−2.25	−2.14	0.91
Finland	3.32	3.85	0.98	−2.75	−2.19	0.98
Ireland	3.36	2.52	1.05	−2.84	−3.35	0.88
Italy	4.57	3.67	0.95	−4.13	−4.35	0.85
Japan	3.24	3.76	0.86	−2.69	−2.14	0.94
Netherlands	3.16	3.17	0.88	−2.67	−2.26	0.90
Norway	3.37	3.05	0.92	−2.23	−2.26	0.80
Republic of Korea	4.34	3.86	0.78	−3.89	−3.90	0.73
Slovakia	2.32	2.14	0.78	−2.36	−2.39	0.71
Spain	3.92	3.30	1.00	−3.16	−3.48	0.93
United Kingdom	3.44	3.27	0.92	−3.00	−2.60	0.96
Full sample	3.35	3.12	0.91	−2.83	−2.73	0.87

Source: Own calculations based on PIAAC data.

Figure A1. Attained schooling (*S*) vs effective schooling (S_e)



Source: Own calculations based on PIAAC data.