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ORIGINAL RESEARCH

An Age–Period–Cohort Approach to the Incidence and Evolution of Overeducation and Skills Mismatch

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Abstract

This paper provides new evidence on the changes in the level and persistence of occupational mismatch across countries by investigating whether differences among generations (cohorts) are at the core of these changes. Using data from the 1994–1998 International Adult Literacy Survey, the 2003–2008 Adult Literacy and Life Skills Survey, and the 2011–2012 OECD Survey of Adult Skills, we estimate an age–period–cohort model in three European countries to examine the extent to which younger cohorts face a greater (smaller) risk of being occupationally mismatched in their jobs than their older counterparts. Two definitions of occupational mismatch are used, focusing on both educational attainment and literacy skills. Results indicate that countries present different patterns in the evolution of occupational mismatch from older to younger generations according to the definition employed (overeducation or skills mismatch). Different macro-economic and educational contexts may be at the core of these results, suggesting that tailored policy responses are desirable for effectively addressing the occupational mismatch problem.

Keywords Educational mismatch · Skills mismatch · Labour market · Age–period–cohort effects · PIAAC · ALL · IALS

1 Introduction

The last few decades have witnessed an increase in the general level of education in all European countries as a result of government efforts to decrease the share of early school leavers while increasing the percentage of tertiary graduates.[1] This situation raises the

[1] For the European Union, see https://ec.europa.eu/education/policies/european-policy-cooperation/et2020-framework_en.

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question of whether labour market demand for more educated individuals has increased enough to meet the larger supply. The reality is that greater educational investment, but also socio-economic changes such as increasing global competition, skills-biased technological adjustments, and the ageing of the population have resulted in a labour market situation in which it is often difficult to find the right people for the right jobs. As a result, occupational mismatch understood to be a situation in which the level of education or the skills attained by an individual are greater than what is required for the job they are hired for, has become a major concern in developed economies. It is pervasive, widespread, and persistent, resulting in real costs for individuals, businesses, and society as a whole (see, e.g., Groot and van den Brink 2000; Cedefop 2010; Quintini 2011).

Whether educational expansion leads to more overeducation depends on how the labour market can react. Occupational mismatch emerges and risks becoming persistent if the growth in the educational level of the individuals affected is systematically greater than the growth of the educational quality of jobs (Groot 1996). In contrast, in highly-skilled, demanding labour markets, the risks of permanent overeducation should be less important. In this case, overeducation might be more prevalent among younger workers, due to more difficult entry conditions, but it should diminish over their working life as workers move along in their careers (Sicherman 1991; Alba-Ramírez 1993). According to this view, we would expect that different generations (cohorts) of individuals experience overeducation or skills mismatch mostly at the beginning of their working lives. However, its evolution and, more importantly, its persistence within cohorts will differ depending on the contextual conditions (educational and labour market circumstances, or other macro-economic shocks) uniquely experienced by these individuals particularly during the first phase of their working lives.

This paper aims to provide new evidence on the changes in the level and persistence of occupational mismatch across countries by investigating whether differences among generations (cohorts) are at the core of these changes. Thus, we hope to contribute to the ongoing research systematizing generation dynamics in occupational mismatch. When studying change, one can focus on change over the life course (age effects), change over generations (cohort effects), and change over time (period effects) (Firebaugh 1997; Glenn 2005). According to the definition given by Blanchard et al. (1977), an ageing effect is a change in variable values that occurs among all cohorts independently of the time, as each cohort grows older. Age effects could arise since individuals may gain job experience as they get old and may find a job that better fits their educational level or skill. Similarly, a cohort effect is a change that characterizes populations born at a particular point in time but which is independent of the process of ageing. Cohort effects could include educational policies affecting specific generations (for example, policies increasing the number of compulsory schooling years or facilitating access to tertiary education: only some cohorts would be affected). Last, a period effect is a change that occurs at a particular time, affecting all age groups and cohorts uniformly. Factors that might cause period effects in occupational mismatch, for example, include a global economic crisis or high levels of unemployment, which could induce highly educated people to accept low-skill jobs.

One of the main issues when studying age–period–cohort models arises from the fact that each of the three can be always identified by knowing the other two. For example, knowing the age of a person and the current year-period, the cohort of birth is simply the

Footnote 1 (continued)

For Norway, see https://www.regjeringen.no/en/topics/european-policy/areas-cooperation/Education/id686144/.

year minus the year of birth. The interest in this paper is to identify cohort effects, which go beyond the simple linear combination of age and period. This is useful to understand whether there exist some cohorts that are systematically more exposed to the risk of overeducation and skills mismatch, once these linear relationships have been taken into account. To do so, we make use of the Age–Period–Cohort Detrended (APCD) methodology to detect cohort nonlinearities pertaining specifically to the cohort variable and which cannot be explained by the simple combination of age and period (Chauvel and Schröder 2014). To our knowledge, this is the first paper to perform cross-country comparisons to analyze differences between generations in the risk of being occupationally mismatched using both measures of overeducation and skills mismatch and relying on age–period–cohort models. This approach may contribute to a better understanding of the phenomenon and, more importantly, identify the role different governments might play through their educational systems but also their labour market policies in adjusting cohort characteristics, especially before their entrance into the labour market.

This research contributes to the existing literature in two main ways. First, we pool three cross-sectional datasets with comparable data on individuals' skills, educational attainment, employment status, and other socio-demographic characteristics to explore the existence of cohort effects in three European countries. More specifically, using three surveys offers an exceptional opportunity to perform an APCD analysis, able to detect generational differences (cohort effects) beyond age and period effects. Furthermore, knowing whether the process of occupational mismatch in a country occurs during the lifetime of an individual or, rather, over several generations makes an important difference and flags a possible need for targeted policy interventions in specific countries to better handle long-lasting determinants of occupational mismatch.

Second, taking advantage of the availability of cognitive skills (literacy scores) comparable across countries and between the three surveys, we extend our analysis to a measure of overeducation and a measure of overskilling.[2] Thus, we hope to cover better the occupational mismatch concept and uniquely contribute further empirical evidence on the topic. Flisi et al. (2017) show the sensitivity of results to the definitions chosen. They claim that although education mismatch and skills mismatch are related concepts within the framework of occupational mismatch, they are far from equivalent as education and skills do not have a one-to-one correspondence. Similarly, McGuinness et al. (2018a) show that overeducation and overskilling are weakly correlated. They also show that the incidence of overeducation and overskilling is heterogeneous across countries. The analysis of occupational mismatch faces significant challenges that make it a complicated endeavour (for a review, see Choi et al. 2020) but being able to measure both overeducation and overskilling can help shed further light on the issue.

Our main results can be summarized as follows: we find that in Italy and Norway, some cohorts are more likely to be overeducated than others. Specific characteristics of the educational system and labour markets circumstances affecting these particular cohorts may be at the core these results. Hence, it is reasonable to think that, in Italy, this may be due to two particular reforms that exogenously increased the educational attainment of the cohort born around 1950, without the market being ready to absorb this significant increase in education. Similarly, in the 1980s, Norway experienced a massive increase in the number

[2] An overeducated worker is an individual whose educational attainment exceeds the educational requirements of their workplace, whereas an overskilled worker is an individual whose skills and competences exceed those required to perform their job.

of individuals with tertiary education (with rates much above the OECD average), not fully needed in the labour market, which led to people ending up in jobs with lower educational requirements. However, further explanations cannot be excluded, as we are not able to empirically test if educational expansion was the real and only driver of our finding. More in-depth research of the mechanisms underlying these cohort effects would be desirable. We also find that in Italy, most cohorts deviate from the linear trend of mismatch measured using skills. Finally, as reported by Flisi et al. (2017), we also find that results are highly sensitive to the specific definition of occupational mismatch selected (overeducation or skills mismatch, in our case). Accordingly, policymakers need to be cautious when interpreting overeducation and skills mismatch figures.

This paper is organised as follows. The next section provides a review of the occupational mismatch literature and the role played by tertiary education expansion. Section 3 describes the data and the definitions of occupational mismatch used. The empirical approach followed to study the evolution and persistence of occupational mismatch among different cohorts of workers in the observed countries is presented in Sect. 4. Results are provided in Sect. 5, and Sect. 6 offers some concluding remarks.

2 Literature Review

The rapid expansion of tertiary education in the second half of the twentieth century (OECD, 2016) has been accompanied by several academic contributions from various disciplines that try to explain the phenomenon. Thus, economic theory suggests that tertiary education growth is the result of an increase in the demand for skilled labour (Keep and Mayhew 1996; Béduwé and Planas 2003). Greater global competition, together with the appearance of new information technology (IT)-related occupations and industries (a.k.a. skills-biased technological adjustments) have increased the labour demand for highly educated workers.

However, sociological theories place greater emphasis on non-economic factors, undermining the role played by the labour markets. They claim that tertiary education growth has been driven by direct public policy rather than by the free market (Witte 2006; Välimaa et al. 2007): governments have been able to accelerate the development of tertiary education institutions by increasing the number of available higher education opportunities, decreasing tuition fees, encouraging student enrolment and, in some cases, changing the degree structure. A second strand of the literature suggests that this expansion has been the result of a political struggle between classes and other social groups who fought to expand educational opportunities to ensure better mobility for younger generations (Collins 1971). Last, social researchers also focus on the role played by institutional changes (Schofer and Meyer 2005): democratization and the increased demand for civil rights or the scientization of society are some of the changes that can explain this tertiary education expansion.

Whatever the rationale behind tertiary education expansion, empirical evidence shows that rapid growth in educational attainment may result in an occupational mismatch between a highly educated labour supply and the demand available, raising concern about whether occupational mismatch is a transitory or permanent state for workers. From a theoretical point of view, Sicherman and Galor (1990) and their career mobility theory argue that young individuals might be voluntarily willing to take up a job below their competence level at the beginning of their careers. By doing so, they acquire job experience, which then results in greater possibilities for promotion. Thus, occupational mismatch is a temporary phenomenon that disappears with job experience. In contrast, Thurow's job competition theory (Thurow 1975) states that jobs are ranked and workers lined up to get high-ranked jobs. Better-educated workers get positions higher in the ranking, while workers with lower education levels are left lower in the ranking. This theory implies that occupational mismatch is a more permanent state. At an aggregate level, on-the-job search and matching models suggest that a higher proportion of skilled workers induces firms to create more skilled vacancies (e.g., Dolado et al. 2009). The introduction of on-the-job search stimulates the creation of skilled jobs since mismatched workers stay in the pool of job seekers, which facilitates filling these jobs. This transitory skills mismatch of overeducated workers is more harmful to the prospects of less-educated workers than permanent mismatch as it reduces their stability, given the shift in the demand towards skilled jobs. Similarly, alternative models suggest that rising overeducation has induced rapid skill-biased technical change (Acemoglu 1998) with similar effects.

Interestingly, empirical evidence on the persistence of occupational mismatch at the individual level is mixed. Several papers support the career mobility hypothesis (Sicherman 1991; Robst 1995; Frei and Sousa-Poza 2012). However, other authors more numerous, suggest that occupational mismatch is a persistent state (Dolton and Vignoles 2000; Rubb 2013; Büchel and Mertens 2004; Mavromaras and McGuinness 2012; Baert et al. 2013; Kiersztyn 2013; Clark et al. 2017; Meroni and Vera-Toscano, 2017; Wen and Maani 2019).

Various studies provide interesting results at the country level suggesting that occupational mismatch (particularly overeducation) is becoming a more widespread phenomenon. Green and Zhu (2010) report an increase in overeducation incidence in the UK between 1992 and 2006. Korpi and Tåhlin (2009) show that the average number of years of overeducation (excess education) steadily increased in Sweden between 1974 and 2000. In Poland, Kiersztyn (2013) reports a rising incidence of overeducation for the period of 1988–2008. She finds that the increase in overeducation is associated with an upward shift in overeducation risk between cohorts. Her results are in line with Baran's (2019) work.

Studies investigating the evolution and possible persistence of occupational mismatch across countries are less common, mainly due to the lack of comparable data. In their work, Mavromaras et al. (2010) and Pouliakas (2013) conclude that the levels of overeducation across countries may vary with macro-economic conditions and the business cycle. Using a multi-level model with a cross-country graduate cohort database for Europe, Verhaest and Van der Velden (2013) find that differences in overeducation are related to variations in the quality and orientation of the educational system (general versus specific), business cycle effects, and the relative oversupply of highly skilled labour. Croce and Ghignoni (2012) use annual data from the European Community Household Panel (ECHP) to examine differences in graduate overeducation in 26 European countries between 1998 and 2003. They report that overeducation tends to be influenced by business cycle variables and is higher in countries with a lower wage gap between graduates and workers with upper secondary education. Similarly, Davia et al. (2017) highlight the importance of educational oversupply as a crucial driving force. More recently, McGuinness et al. (2018b) use a time-series approach to examine the extent to which youth and adult overeducation move together within countries and the degree to which long-run relationships exist in the rates of overeducation between countries. They find that while overeducation has tended to increase over time in some European countries, this is by no means a universal pattern as it has remained static and has even declined in others. Thus, results are indicative of a situation where overeducation within European countries is highly systemic of imbalances in the demand and supply of workers (e.g., unemployment rates, share of temporary workers, or share of graduates in the labour force). Last, Bar-Haim et al. (2019) estimate an age–period–cohort effect model on the return to education. They show that educational expansion is in most countries associated with decreasing returns to tertiary education, where the labour market is not able to create jobs for the newly educated.

The studies mentioned solidly document the negative relationship between age and the risk of occupational mismatch, providing evidence of the increase in mismatch over time in some economies as a result of macro-economic conditions and the business cycle. However, none of them examines whether cohort differences can explain the differences in the level and evolution of occupational mismatch across countries. We aim to do so in this paper, in the context of an age, period, and cohort effects analysis.

3 Data and Definitions

3.1 Data

We rely on data from the 1994–1998 IALS (International Adult Literacy Survey), the 2003–2008 ALL (Adult Literacy and Life Skills) survey, and the 2011–2012 PIAAC (OECD Survey of Adult Skills).[3] The IALS survey provided the world's first comparable estimates of the levels and distributions of cognitive foundation skills in the adult population. Three separate data collections spanning four years were conducted in 24 countries or regions (1994, 1996, and 1998). A few years later, the ALL survey measured the literacy and numeracy skills of a nationally representative sample of 16–65-year-olds in participating countries, in two rounds: first in 2003 and then again between 2006 and 2008. Similarly, the PIAAC survey measured key cognitive and workplace skills. In particular, the survey assessed three domains of cognitive skills, namely literacy, numeracy, and problem-solving in technology-rich environments. The three surveys—IALS, ALL, and PIAAC—were designed to be comparable regarding literacy skills. The IALS and ALL data on prose and document literacy have been re-scaled to be comparable with the PIAAC measure of literacy, which combines both prose and document literacy. In this paper, we use the rescaled data. In addition to information on the cognitive skills of the adult population, these surveys also contain comparable information about educational attainment, employment, occupation, and other socio-demographic characteristics.

This paper focuses on the countries that participated in all three surveys, namely Italy (IT), the Netherlands (NL), and Norway (NO).[4] Although this may seem limited, these countries are good examples of the very different labour market and educational systems, namely: the continental one (The Netherlands), the Scandinavian one (Norway), and the southern European one (Italy) (see the papers by Esping-Andersen (2013) and Esping-Andersen and Regini (2000) for a discussion of these).[5]

[3] Further information about these Surveys can be found at:
https://nces.ed.gov/statprog/handbook/pdf/ials.pdf (for IALS Survey).
https://nces.ed.gov/surveys/all/ (for ALL Survey).
https://www.oecd.org/skills/piaac/ (for PIAAC Survey).

[4] The USA and Canada also participated in all of the surveys, but we exclude them as the variable *age* is not reported as continuous in the original dataset, which does not allow us to build the right cohorts.

[5] The Netherlands represents a peculiar situation as in some features, it resembles the Scandinavian regime.

3.2 Definitions

This research focuses on occupational mismatch—either educational or skills mismatch. More specifically, our interest is in occupational mismatch, referred to as the situation in which a worker's educational attainment (skill level) exceeds the educational qualification (skill level) required for their job.

Educational attainment is a reasonable candidate to proxy individuals' competences. However, individuals' skills arise as a superior and more reliable approach to measure occupational mismatch given the greater demand for more information-processing and high-level cognitive skills that do not necessarily need to be acquired through the educational system. Flisi et al. (2017) provide an extensive review of the existing methods for measuring occupational mismatch and investigate the differences between education and skills mismatch, building several indicators available from PIAAC data. Their results show that education and skills mismatch are two distinct phenomena.

Based on the information contained in the three surveys, we were able to build the following two indicators related to occupational mismatch:

1. ***Education mismatch*** using the level of education. In each survey, we compare the level of education of the individual with the modal level of education of all individuals in the same country and occupation. Occupations are identified following the International Standard Classification of Occupations (ISCO) at 1-digit level.[6] We define an individual as mismatched (overeducated) if his level of education is higher than the modal level of occupation in his occupation and country.[7]
2. ***Skills mismatch*** using skill level for literacy. Individuals are considered overskilled if they are overskilled according to at least one of the following two definitions:
a. In each survey, we compare the skill level of the individual in literacy (as measured by the first plausible value) with the average skill level in literacy of all individuals in the same country and ISCO 1-digit occupation. We define an individual as mismatched

[6] ISCO 1-digit occupations have been used for the estimation of occupational mismatch variables. The ISCO 1-digit occupation divides jobs into ten major groups. Although a 2-digit or larger ISCO classification would have been preferred to reduce the heterogeneity in the entry requirements to the occupations included, this is not possible as ISCO 2-digit is only available in the PIAAC sample. Nonetheless, we conduct two checks using only PIAAC data, where the two classifications are available. First, we build two measures of overeducation using both the ISCO 1-digit and ISCO 2-digit classifications, and we estimate the correlation between these two, which is as high as 0.98. Second, we check how many individuals would have been classified as overeducated using one measure and not the other. In the PIAAC sample, only 6% of the working individuals do not overlap when using the two different measures. We believe that these two checks indicate that using the ISCO 1-digit or ISCO 2-digit categories to build the measure of overeducation is equivalent in this paper. Moreover, Mavromaras et al. (2010), McGuinness et al. (2018b) or Bar-Haim et al. (2019) also rely on ISCO 1-digit to calculate their overeducation variable providing results in line with other empirical evidence in this field, which reassures our approach. Nevertheless, it should be kept in mind that this does not refute the argument that there might still be a problem of heterogeneous requirements among the ten occupations used, being this issue probably more relevant in some countries than others. More information about using ISCO classifications and national features can be found at https://www.ilo.org/public/english/bureau/stat/isco/docs/publication08.pdf (last accessed September 2020).

[7] Note that to guarantee sufficient variability to compute the indicators, the identification of matched and mismatched individuals is performed for each measure only when the number of sample observations on which the indicator is based is at least 20. This minimum threshold is a standard procedure in European surveys such as the European Union Statistics on Income and Living Conditions (EUSILC) and the Labour Force Survey (LFS).

(overskilled) if his literacy skills level is more than 1 standard deviation higher than the average in his ISCO 1-digit occupation and country.

b. In each survey, following Krahn and Lowe (1998), we identify individuals with literacy surplus if they have *high* literacy skills and *low* literacy requirements in their job. More specifically, we divide the working population into 3 skill-level groups—low, medium, and high—according to the value of their skills in the percentile of the distribution of skills in the working population (Level 1: individuals whose skills level, measured by the first plausible value is below the 33rd percentile of the distribution of skills in the working population in the country; Level 2: between the 33rd and 66th percentile; and Level 3: above the 66th percentile). For their skills use, we rely on the question about how often they perform certain tasks related to reading and writing at work, with answers ranging from "rarely or never" to "every day" and which we also re-group into three levels. Although the operational definition of literacy surplus is necessarily somewhat arbitrary, as discussed in Kranh and Lowe (1998), we consider as overskilled those individuals whose measured literacy ability level is at least one category above the literacy requirements of their job.[8]

While the indicators defined above were built for each survey individually and results reported in this paper are based on this specification, we conduct some robustness exercises by pooling the three surveys together and then calculating the indicators. That is, the overeducation indicator compares the level of education of each individual with the modal level of education of all the individuals in the same country and ISCO 1-digit occupation considering the overall sample: the IALS, ALL, and PIAAC pooled. Results with this alternative specification are equivalent to the main results and are not reported for the sake of brevity.

4 Methods

We aim to determine whether individuals born in different cohorts are systematically more/less exposed to the risk of overeducation and skills mismatch. Hence, we consider the binary dependent variable [*yiapc*], observed in all three surveys, which denotes whether individual I of age a in period p and belonging to cohort $c=p\text{-}a$ is overeducated/skills mismatched ($yiapc=1$) or not ($yiapc=0$).[9] A key challenge in identifying cohort or generational effects is that they are confounded by age or period effects. In particular, since there is a linear dependency among the three effects (period—age = cohort), the conventional age-period-cohort (APC) analysis is unable to identify the independent effects of age, period, and cohort (Yang et al. 2008). However, the Age–Period–Cohort Detrended (APCD) model, developed by Chauvel and Schröder (2014), based on the former one proposed by Holford (1983), solves this identification problem. More specifically, the model is designed to retrieve nonlinear cohort effects.[10] According to Chauvel and Smits (2015a,

[8] Further details about the construction of this variable are reported in the Appendix (Tables 3 and 4).

[9] The working sample is composed of currently working individuals. This may generate sample selection since being mismatched or unemployed may not be independent decisions. However, many of the papers studying overeducation simply focus on the working individuals and do not consider these sample selection issues (some examples are Bar-Haim et al. 2019; McGuinness et al. 2018b; McGuinness 2006; Mavromaras et al. 2010). We also follow this approach.

[10] The corresponding nonlinear age and period effects are also simultaneously estimated.

b), cohort effects, as well as age and period effects, consist of both a linear dimension and a nonlinear dimension. To give an example, the former indicates a long-term increase in education that younger cohorts may have attended, whereas the latter indicates cohorts that are above or below the linear trend. Due to the perfect linearity among age, period, and cohort effects, the APC literature shows that it is not possible to simultaneously estimate the linear dimension and attribute it to cohort (age or period) effects (see Bell and Jones 2015, 2018). However, the nonlinear dimension of cohort (age or period) effects, if it exists, can be detected in the Age–Period–Cohort Detrended (APCD) model, which shows which cohorts (age groups or periods) deviate from the trend ("fluctuation"). The eventual cohort bumps identified to express the specificity of some cohorts compared to others. Therefore, our interest is not to estimate a trend in overeducation or overskilling per se; rather, we focus on the nonlinear effects of cohort around a linear trend using the APCD model. This innovative approach has been used in recent studies on political participation (Chauvel & Smits 2015a, b), earning opportunities (Chauvel and Schröder 2014; Freedman 2017; Kim 2015; Karonen and Niemela 2019), suicide research (Chauvel et al. 2016), and attitudes towards marriage (Yoonjoo Lee 2019).

Given the binary nature of the dependent variables, we rely on the specification used by Chauvel and Smits (2015a, b), who apply a logit function rather than OLS.

In more detail, the dependent variable y_i^{apc} denotes whether individual i of age a in period p and belonging to cohort $c=p\text{-}a$ is mismatched (we run two separate regressions, one where y takes a value of 1 if the individual is overeducated and a second one where y is equal to 1 if the individual is skills mismatched). The APCD model is expressed as follows:

$$\begin{cases} \Pr\left(y_i^{apc}=1\right)=\alpha_a+\pi_p+\gamma_c+\alpha_0 rescale(a)+\gamma_0 rescale(c)+\beta_0+\sum_j \beta_j x_{i,j}+\underset{i}{\int} \\ \qquad \begin{cases} \sum_a \alpha_a=\sum_p \pi_p=\sum_c \gamma_c=0 \\ slope_a\left(\alpha_a\right)=slope_p\left(\pi_p\right)=slope_c\left(\gamma_c\right) \\ with\, p=c+a\, and\, restricted\, to\, c_{\min}<c<c_{\max} \end{cases} \end{cases} \tag{1}$$

where $x_{i,j}$ are control variables, $\alpha_a, \pi_p, \gamma_c$ are, respectively, age, period, and cohort effect vectors, which reflect the nonlinear effect of age, period, and cohort as they come with two main constraints: each vector sums up to 0 and has a slope of 0. This implies that these vectors are null when the age, period, or cohort effects are linear. $\alpha_0 rescale(a)$ and $\gamma_0 rescale(c)$ absorb the linear trends. The detrended cohort effect coefficients are γ_c. These are zero when cohort effects are absent. In this case, cohorts do not deviate from age and period characteristics; then the APCD model provides no improvement compared to a simple age and period model (AP) with the first and last cohorts omitted. For further details regarding this model, refer to Chauvel (2013), Chancel (2014), and Chauvel and Schröder (2014).

We estimate the model both with and without control variables. A comparison of the results between these two models delivers a diagnosis on the degree to which cohort effects are the consequence of changes in population characteristics. Variables used as controls are individual educational level categorised as low–medium (ISCED 0–4) or high (ISCED 5 or higher), gender, and immigration status. The regressions are estimated separately by country.

The analysis is based on three periods, corresponding to the three survey years. However, since the periods must be equally spaced to be able to fit the model, we recoded

1994–2007–2011 as 1995–2005–2010 for the Netherlands and 1998–2003–2011 as 2000–2005–2010 for Italy and Norway. Available cohorts range between 1935 and 1980 and are grouped into 5-year brackets (1935–1939, 1940–1944, etc.); however, since the first and last cohorts are present only in one of the three surveys (the oldest age group of the first period and the youngest of the last one), they are excluded from the analysis of the APCD. Furthermore, individuals are aged between 25 and 65 and grouped in 5-year brackets. The data are structured in a pseudo-panel design similar to the one suggested by Verbeek and Vella (2005). In a pseudo-panel cohort design, which is also referred to as a Lexis table (Carstensen 2007), it is possible to follow different cohorts over their life course, even if the individual responses are drawn from different samples.

5 Results

5.1 Descriptive Statistics

First, we start by providing some descriptive statistics on the extent of occupational mismatch (both overeducation and overskilling) by cohort (Fig. 1). Results show that in Norway, the share of overeducated individuals remained stable across cohorts. However, some increase is observed for the Netherlands, where younger cohorts seem more likely to be overeducated. This trend is even more pronounced in Italy. Regarding skills mismatch (overskilling), similar patterns emerge in the three countries, with younger cohorts reporting higher shares of skills mismatch. We move on to test whether these differences are unique to the idiosyncratic characteristics of younger generations or are the result of countries' other socio-economic characteristics.

Next, to study the evolution and persistence of overeducation and skills mismatch during the working life of different cohorts of workers, we begin by providing some results based on "synthetic cohort" and "cohort diagram" analyses. The "synthetic cohort" tool shows the development of overeducation and skills mismatch for different birth cohorts, given a certain period. This helps to examine the degree of mobility (or immobility) over the working life of these cohorts. Alternatively, "cohort diagrams" compare different cohorts when they have the same age, making it possible to see differences between birth cohorts given certain ages. Thus, while the APCD model allows us to detect nonlinear cohort effects, these descriptive analyses provide us with some insights about the actual trends.

5.2 Overeducation

Figure 2 provides the results for the "synthetic cohort" analysis of overeducation for the three countries investigated. For Italy, results indicate that younger cohorts are more likely to be overeducated. Thus, for example, individuals born in 1975 are twice more likely to be overeducated than those born in 1950. This graph further confirms that the share of overeducated individuals within a given cohort slightly decreases over time. However, this trend is not so clear for the younger cohorts born in 1970 and 1975. Interestingly, the cohort-relative ranking is generally stable over time. This result may indicate that in Italy, recent cohorts face a greater overeducation risk and have difficulties "catching up" to their older counterparts. Overeducation rates of younger cohorts in Italy do not decrease as they age.

In the Netherlands, there is no such clear ranking among cohorts. We can still say that people born from 1960 to 1965 show higher levels of overeducation than those born

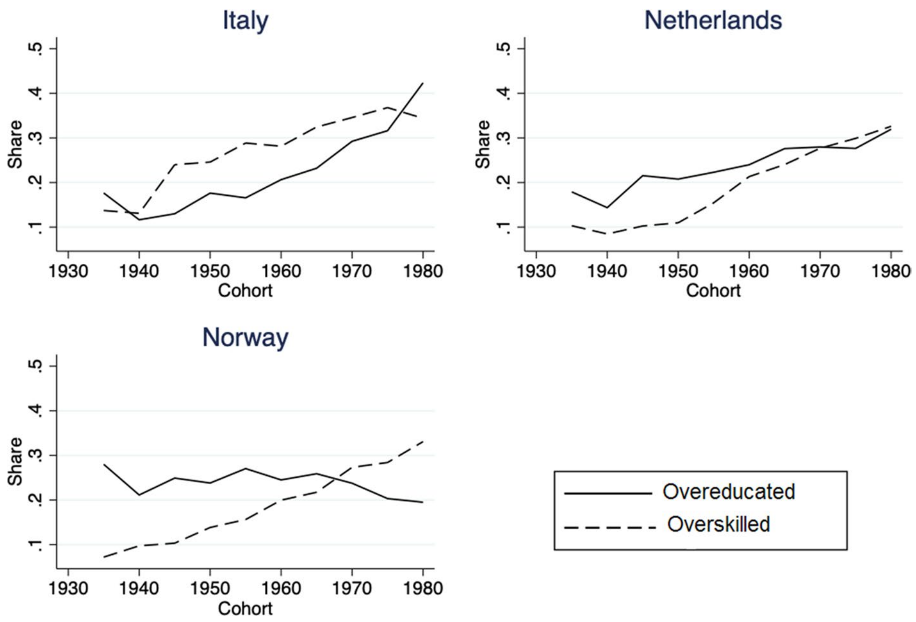

Fig. 1 Cohort change in occupational mismatch (overeducation and overskilling). *Note:* The figure plots the shares of individuals in the working population who are overskilled and overeducated, by birth cohort. Source: Own calculations pooling IALS, ALL, and PIAAC data

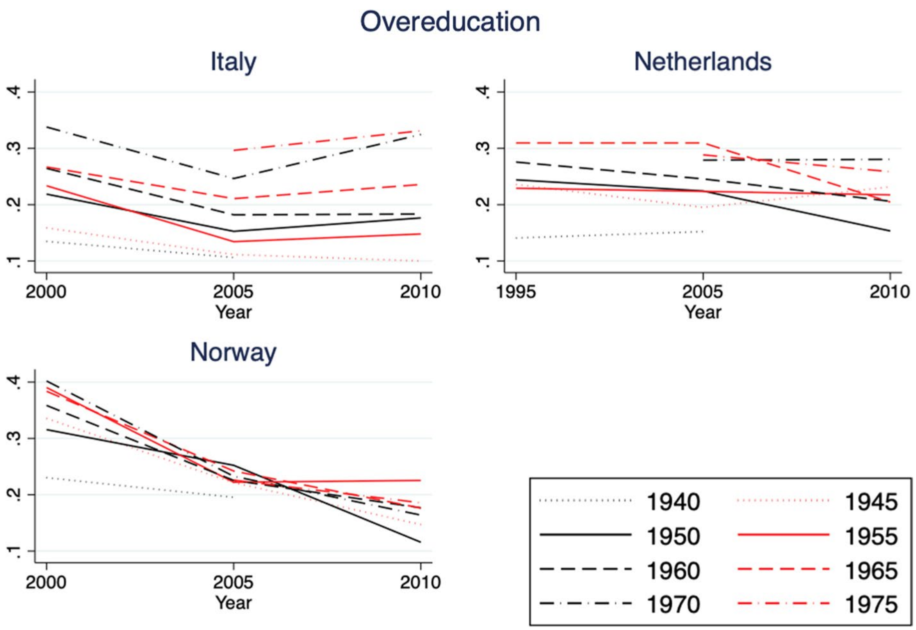

Fig. 2 Overeducation in Italy, the Netherlands, and Norway—synthetic cohort analysis. *Note* The Y-axis shows the proportion of overeducated people in each country; the X-axis shows the periods; the lines represent birth cohort groups. Source: own calculation using PIAAC, ALL, and IALS data

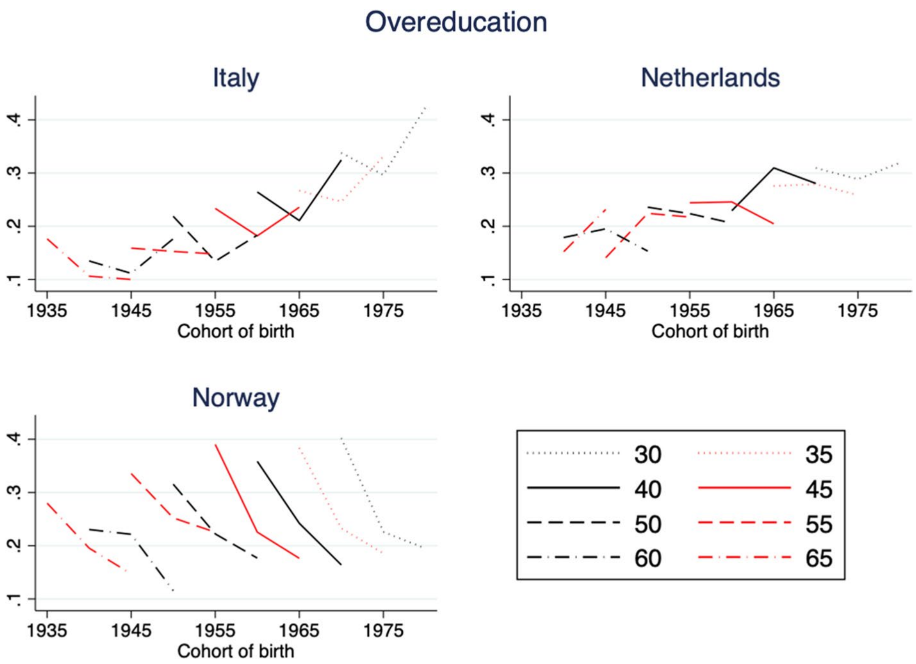

Fig. 3 Overeducation in Italy, the Netherlands, and Norway—Cohort Diagram. *Note* The Y-axis shows the proportion of people overeducated in each country; the X-axis shows the year of birth; the lines represent age groups. Source: own calculation using PIAAC, ALL, and IALS data

between 1940 and 1955. However, this is true only in the first two periods. Most of the cohorts show a relatively similar overeducation level of around 20% in 2010, the exception being those born in 1970 and 1975, who are stable around 30%. Last, for Norway, the share of overeducated workers decreases over time. Moreover, all cohorts exhibit a similar level of overeducation. We might conclude that the linear cohort trend in Italy is negative (the younger cohorts show a higher level of overeducation) and that the period trend is slightly positive (no big difference over the three periods, but relatively lower values in the last year). In the Netherlands, the linear cohort trend is somehow negative (younger cohorts show higher levels of overeducation) and the period effect is slightly positive (especially in the last year, the values are lower). In Norway, we see a flat cohort trend (no difference between the different cohorts) but a very positive period trend, as the level of overeducation decreases over time for all cohorts.

In the "cohort diagrams" (Fig. 3), we can see differences between birth cohorts given certain ages. For example, what age group 30 looks like when born in 1970 compared to being born in 1975 or 1980, etc. Again, the pictures drawn are different across the three countries. Thus, for Italy, we already saw in Fig. 1 that younger cohorts had a greater risk of overeducation. Now we see that if you are born after 1955, for any given age group (50 or younger), the most recent generations are equally and even more likely (especially those aged 40 or younger) to be overeducated. For those born after 1955 in the Netherlands, we observe a mix of stagnation (age group 30) and soft decline (age groups 50, 45, and 35). Last, a significant decline in overeducation is observed for any age group (among more recent cohorts) in the case of Norway. This points to a

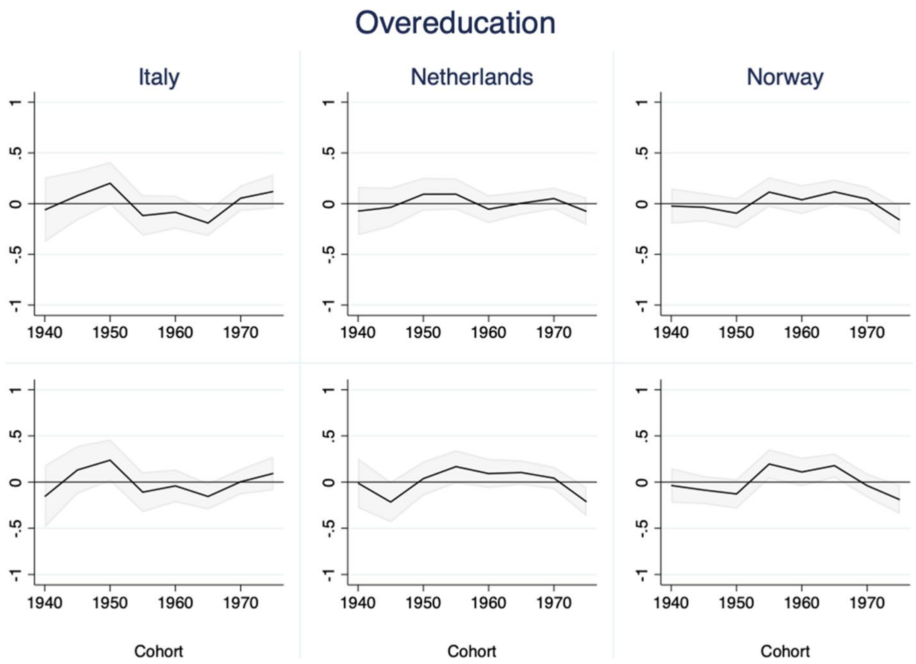

Fig. 4 Effect of cohort (APCD) on the risk of overeducation in Italy, the Netherlands, and Norway. *Note* Solid lines are estimates, while the grey area represents 90% confidence intervals. Results reported in the first row do not include control variables, while results reported in the second row include control variables (education, gender, and immigration status). Source: own calculation using PIAAC, ALL, and IALS data

clear positive age trend (for all cohorts, the older you get, the less likely you are to be overeducated).

Overall, this analysis suggests that in Italy, we see a cohort effect as younger cohorts are systematically more likely to be overeducated. However, in Norway, there seems to be an age effect since all cohorts show a decrease in overeducation as they age. The picture seems less clear for the case of the Netherlands.

Now we turn to the APCD model[11] to know more about the significances of the cohort effects identifying the nonlinearities in the three variables (age, period, and cohort).[12] Figure 4 shows the cohort effects with the confidence intervals for the three countries independently. The deviation of the cohorts from the linear trends is shown. In the first row, we provide the results without including control variables and in the second one those after the inclusion of gender, level of education, and immigrant status. Descriptive statistics on the working sample used are provided in Table 5 in the Appendix. The regression estimates are reported in Table 2.

Looking at the estimates without controls, we see that only for Italy, the 1965 cohort is below the linear trend, while for the Netherlands and Norway, none of the cohorts

[11] Estimates are done in STATA using the APCD command.

[12] Notice that the APCD method identifies deviations from the linear trends of age, period, and cohort: it can identify specific cohorts defined by higher/lower overeducation rates, but it cannot identify the actual linear trend.

significantly deviate from the linear trend. However, one advantage of the APCD method is that we can include controls for relevant variables that could a priori better disentangle possible fluctuations. Thus, we proceed and control for education, gender, and immigration status (see Table 1).

Regarding the control variables, we see the same picture in all countries: as expected, the most educated people are the most likely to be overeducated. The differences between educational categories are significant at a p value < 0.10, with the biggest differences observed in the Netherlands, followed by Italy and then Norway. As for gender, women are significantly less likely to be overeducated in Italy and the Netherlands, with the former reporting a much larger coefficient, and not significant results found for Norway. For immigrant status, migrants are more at risk of being overeducated.

Interestingly, controlling for gender, education, and immigration status only slightly changes the cohort effects for Italy. Even if the coefficient associated with the 1965 cohort is now smaller, it is still significant at the 10% significance level. Besides, those born in 1950 have a greater risk of being overeducated. Italy is characterized by a relatively low percentage of people with tertiary education compared to other European countries (even though it has experienced some growth). Also, the crisis of scientific vocations that characterizes most European countries is particularly strong in Italy. There, the prevalence of humanistic disciplines in secondary school and the diffused perception of the difficulty of scientific degrees leads to a reduced number of students enrolling in a scientific "laurea" compared to one in humanities and social sciences. This is likely to affect an ever more highly specialized labour market in the face of Skill–Biased Technological Change—SBTC (Ghignoni 2012; OECD 2017). Moreover, the structure of the economy based on the overwhelming presence of family-managed small enterprises is also likely to affect the demand for graduates. Bernardi and Ballarino (2016) found that occupational returns to post-secondary education holders decreased in several countries, including Italy. Having said this, in Italy, some policy reforms in the 1960s contributed to education expansions. In 1963, junior high school became mandatory and the number of compulsory years of schooling increased by three years (from 5 to 8 years). The first cohort potentially affected by this reform is the cohort born in 1949 (Law 1859, 1962). Similarly, between 1961 and 1968, a new education reform (Law 685, 1961) allowed children coming from vocational education high schools to enrol in some universities (before this reform, access to higher education for pupils from these secondary schools was very limited; see Bianchi, 2020). Later, in 1969, another education law gave students the possibility of entering any university department from any upper secondary school, making Italian universities progressively become "mass universities" (Law 910, 1969). Again, the cohort fully affected by this law was that born around 1950. The combination of these labour demand and supply facts may be driving the results: a greater risk of overeducation for the cohort born in 1950 that initiated a period of increasing educational attainment (both at medium and high education levels) and low demand for high education levels when entering the labour market.

For Norway, cohort nonlinearities are found for cohorts born in 1955 and 1965, who are more likely to be overeducated; and cohort born in 1975, who are less likely to be overeducated. The evidence to support these results is twofold. First, Kahn (1998) and Salvanes and Forre (1999) showed that for both men and women, demand for workers with tertiary education, relative to workers with primary education, increased in Norway from the early to the late 1980s and 1990s. This is primarily due to reduced demand for low-education workers, as has been observed in most OECD countries. However, on the supply side, Norway experienced an increase in the relative supply of highly educated workers throughout the 1980s, for both men and women, leading to a noticeable increase in the relative supply

Table 1 APCD models of risk of overeducation without and with controls, for Italy, the Netherlands, and Norway

	Italy				The Netherlands				Norway			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Without controls		With controls		Without controls		With controls		Without controls		With controls	
	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val
1940 Cohort	− 0.061	0.753	− 0.157	0.446	− 0.073	0.616	− 0.011	0.946	− 0.024	0.822	− 0.037	0.745
1945 Cohort	0.079	0.595	0.131	0.41	− 0.037	0.758	− 0.216	0.106	− 0.035	0.682	− 0.087	0.35
1950 Cohort	0.201	0.118	0.237	0.087	0.093	0.352	0.037	0.744	− 0.094	0.298	− 0.129	0.188
1955 Cohort	− 0.117	0.336	− 0.109	0.408	0.093	0.323	0.167	0.124	0.114	0.203	0.195	0.045
1960 Cohort	− 0.084	0.397	− 0.042	0.701	− 0.055	0.515	0.092	0.34	0.039	0.659	0.109	0.249
1965 Cohort	− 0.191	0.016	− 0.156	0.071	0.004	0.956	0.103	0.202	0.116	0.118	0.177	0.028
1970 Cohort	0.054	0.486	0.003	0.969	0.05	0.44	0.043	0.569	0.045	0.537	− 0.039	0.627
1975 Cohort	0.12	0.246	0.093	0.403	− 0.076	0.366	− 0.214	0.027	− 0.161	0.071	− 0.19	0.047
Age 30	− 0.106	0.374	0.05	0.695	0.067	0.423	0.186	0.056	0.214	0.018	0.268	0.006
Age 35	− 0.059	0.472	− 0.163	0.066	− 0.022	0.739	− 0.008	0.917	− 0.072	0.317	− 0.085	0.275
Age 40	0.157	0.049	0.103	0.238	0.091	0.187	0.072	0.367	− 0.142	0.059	− 0.157	0.055
Age 45	0.096	0.378	0.06	0.61	− 0.08	0.343	− 0.187	0.052	− 0.12	0.17	− 0.198	0.036
Age 50	− 0.018	0.892	− 0.021	0.887	− 0.067	0.485	− 0.167	0.131	− 0.071	0.452	− 0.069	0.497
Age 55	0.006	0.97	− 0.001	0.996	− 0.046	0.656	− 0.127	0.287	0.235	0.009	0.261	0.007
Age 60	− 0.028	0.871	− 0.061	0.743	− 0.181	0.137	− 0.107	0.439	− 0.129	0.156	− 0.105	0.284
Age 65	− 0.047	0.852	0.033	0.902	0.238	0.133	0.338	0.061	0.086	0.441	0.085	0.479
1995 Period	–	–	–	–	0.037	0.063	0.083	0.000	–	–	–	–
2000 Period	0.05	0.039	0.021	0.422	–	–	–	–	− 0.044	0.03	-0.104	0.000
2005 Period	− 0.1	0.039	− 0.043	0.422	− 0.073	0.063	− 0.165	0.000	0.088	0.03	0.209	0.000
2010 Period	0.05	0.039	0.021	0.422	0.037	0.063	0.083	0.000	− 0.044	0.03	− 0.104	0.000
Rescacoh	0.038	0.914	− 0.174	0.652	0.597	0.034	− 1.042	0.004	− 0.663	0.015	− 2.087	0.000

Table 1 (continued)

	Italy				The Netherlands				Norway			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Without controls		With controls		Without controls		With controls		Without controls		With controls	
	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val
Rescaage	− 0.797	0.000	− 1.058	0.000	0.029	0.841	− 0.852	0.000	− 0.495	0.000	− 1.089	0.000
Female	–	–	− 0.379	0.000	–	–	− 0.228	0.001	–	–	− 0.028	0.658
High educ	–	–	2.352	0.000	–	–	2.524	0.000	–	–	1.971	0.000
Immigrant	–	–	0.77	0.000	–	–	0.358	0.001	–	–	0.507	0.000
Constant	− 1.729	0.000	− 2.133	0.000	− 1.278	0.000	− 2.477	0.000	− 1.405	0.000	− 2.404	0.000

In this table, we report the estimates of the APCD model for overeducation without controls—columns 1, 3, and 5—and with controls—columns 2, 4, and 6—as explained in Eq. (1). The controls included are education (reference = lower than tertiary education), gender (reference = male), and immigration status (reference = native) of workers with college/university education. Tertiary education attainment in Norway in the early 2010s was higher than the OECD average (47% of those 25–34 years of age attained this level in 2011, compared with the OECD average of 39%).[13] This evidence may support the greater risk of overeducation among the 1955 and 1965 cohorts, which vanishes as the demand for workers with tertiary education increased to reach to the situation where the youngest cohort (1975) has a lower risk of overeducation. Second, as argued by Liu et al. (2012), overeducation may be an important mechanism behind the persistent career loss for generations graduating in recessions. That is, workers who are hired under poorer labour market conditions could be exposed to long-term career loss. This could be the case for those born in 1965 and likely to graduate and enter into the labour market around 1991 when the third global recession after World War II hit. Finally, after the 1970s, some existing post-secondary schools (for teacher training, engineering, and nursing) were transformed into higher education institutions. This meant that for individuals from the 1950 cohort to be employed in a given profession (e.g., nursing), they would need a higher level of education compared to the older cohorts (Pinheiro and Stensaker 2018).

Finally, for the Netherlands, cohort nonlinearities are found for the youngest ones born in 1975, who are less likely to be overeducated. This means that an individual aged 45 and born in 1975 is less likely to be overeducated than a peer his/her age but born earlier. As in Norway, we argue that this is because the impact of educational expansion (likely to increase overeducation) was diminished by the experience of SBTC (which increased the demand for highly skilled labour), exposing this cohort to lower levels of overeducation. Davia et al. (2017) and Crivellaro (2016) found similar results in an international comparison of 25 European countries, but they did not directly measure overeducation in terms of economic returns.

5.3 Skills Mismatch

We focus now on the descriptive statistics to illustrate the actual trends in skills mismatch in the three countries (see Figs. 5 and 6).

First, let us focus on changes in skills mismatch over the working life for the different cohorts studied ("synthetic cohort" analysis). As opposed to overeducation, the results in Fig. 5 provide a more homogenous (and perhaps more challenging to interpret) picture across the three countries for skills mismatch. While skills mismatch, on average, seems to be slightly larger in Italy for almost all birth cohorts, in all countries we observe that in the year 2000, younger cohorts are more likely to be overskilled. Then, as individuals age, the share of skills-mismatched workers slightly decreases or remains steady in most of the cohorts, but this is not a general trend. For example, in Italy, cohorts born in 1940, 1945, and 1955 increase their share of skills mismatch, while for the Netherlands and Norway, individuals decrease their risk of skills mismatch as they age. Because of a different pace in the evolution of skills mismatch as cohorts age, the relative ranking is not stable over time and a new one in terms of overskilled individuals by cohort is found in 2010. Overall, in all countries, we observe a relatively flat linear trend.

Second, results for the "diagram cohort" analysis (Fig. 6) for the Netherlands show that younger age groups are more likely to be overskilled, while there are no large

[13] OECD (2013), Education at a Glance 2013: OECD Indicators, OECD Publishing, Paris, https://dx.doi.org/10.1787/eag2013-en.

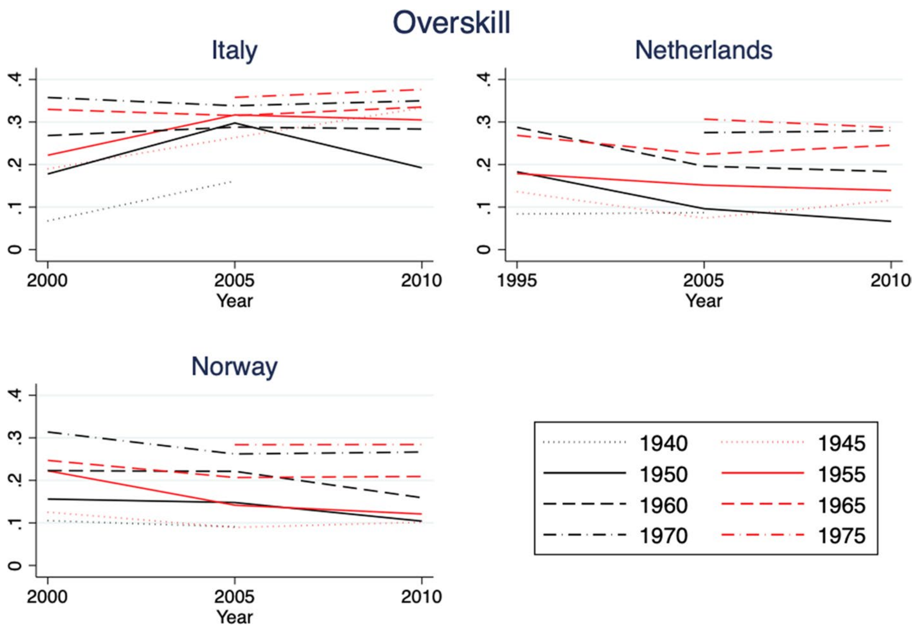

Fig. 5 Birth cohort and skills mismatch: synthetic cohort analyses (Italy, the Netherlands, and Norway). *Note* The Y-axis shows the proportion of overskilled people in each country; the X-axis shows the periods; the lines represent birth cohort groups. Source: own calculation using PIAAC, ALL, and IALS data

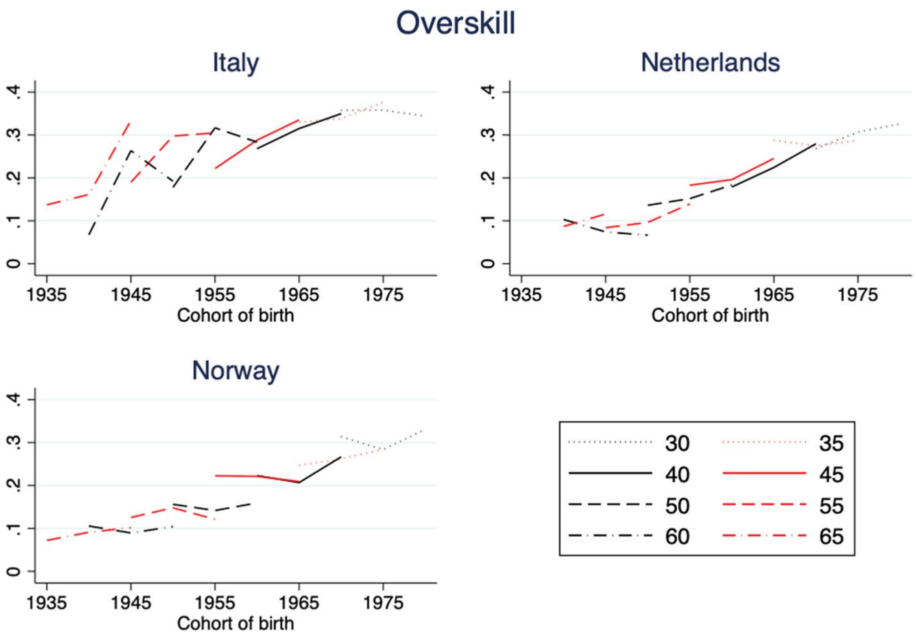

Fig. 6 Birth cohort and skills mismatch: cohort diagram analyses (Italy, the Netherlands, and Norway). *Note* The Y-axis shows the proportion of overskilled people in each country; the X-axis shows the year of birth; the lines represent age groups. Source: own calculation using PIAAC, ALL, and IALS data

differences between different age groups observed in the same birth cohort (look at three lines, keeping fixed the year). Moreover, on average, younger cohorts of the same age group are more overskilled than older cohorts. The picture is very similar for Norway, with the exception that the trend of younger cohorts of the same age group being more likely to be overskilled is more intense in this country for those born in 1965 and later. This points to a flat age trend and a negative cohort trend. For Italy, we observe a much steeper slope for the different age groups, meaning that younger cohorts of the same age group are much more likely to be overskilled, particularly among those born between 1935 and 1970. However, the trend stabilizes between 1970 and 1980 when younger cohorts of the younger age group (30 years) are less likely to be overskilled.

To better identify nonlinear cohort effects across the three countries, we now undertake the same APCD analysis for skills mismatch, the results of which are reported without and with control variables in Table 2.

We first discuss the effects of the control variables and then look to the cohort diagnosis. For overskilled individuals, we observe the same picture as for the risk of overeducation: people with tertiary education are more likely to experience skills mismatch. The most significant differences are observed in the Netherlands and Norway. For gender, women are more likely to be skills mismatched in Norway, while no significant difference is found for Italy or the Netherlands. Migrants are also less likely to be overskilled, particularly in the Netherlands (largest coefficient reported). Regarding potential deviations from the linear trends among the different cohorts studied, results are also reported in Fig. 7.

For Italy, we see that cohorts born between 1950 and 1965 are more likely to experience skills mismatch, even though no differences between cohorts were found for overeducation in this country. This heterogeneity in the results is largely due to the sensitivity to the definition used to measure occupational mismatch (it is also important to remember that there is a very small overlap between overeducated and overskilled individuals, so we are talking about different population characteristics). Also, qualifications in Italy are typically poor predictors of a person's true skills and competences (OECD 2017). The skill-signalling power of qualifications is low, and education titles may diverge considerably from the true skills of the workers; this could be the reason why we find such a difference in the estimates for skills mismatch and overeducation in Italy.

The range of skills mismatch measures is large, and no clear criteria have yet been defined to distinguish the most accurate among them while new proposals continue to be generated (see, for example, Flisi et al. 2017; McGuinness et al. 2018a; or Choi et al. 2020). Yet, we can interpret these results in the face of the existing evidence on the evolution of literacy skills (Barrett and Riddell 2016; Paccagnella 2016; Flisi et al. 2019), the variable used here to define skills mismatch. Indeed, in Italy, younger cohorts have progressively shown significantly higher literacy levels (Barrett and Riddell 2016). These results may justify the higher risk of experiencing skills mismatch for the 1950–1965 cohorts when the market was not ready to absorb and fully use the skills gained by the population. Indeed, we see that the 1965 cohort bump is smaller and the 1975 cohort is actually below the linear trends, suggesting that at one point the labour market adapted to the new skills of the working population in terms of jobs that could fit those skills. The 1950–1965 generations are the Italian "baby boomers", who had more opportunities to study and acquire skills than their parents.

Moreover, in the Netherlands, younger cohorts have shown an increase in skills, although it is modest in size. This might explain the significant difference found for the cohort born in 1965. In contrast, in Norway, literacy skills seem to have been falling across

Table 2 Logistic APCD models of the risk of skills mismatch without and with controls, for Italy, the Netherlands, and Norway

	Italy				The Netherlands				Norway			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Without controls		With controls		Without controls		With controls		Without controls		With controls	
	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val
1940 Cohort	− 0.521	0.002	− 0.501	0.002	0.337	0.053	0.353	0.043	0.174	0.175	0.187	0.146
1945 Cohort	0.118	0.314	0.114	0.328	− 0.092	0.534	− 0.111	0.457	− 0.063	0.561	− 0.075	0.492
1950 Cohort	0.235	0.026	0.223	0.035	− 0.331	0.01	− 0.357	0.006	0.065	0.524	0.054	0.597
1955 Cohort	0.268	0.006	0.256	0.008	− 0.026	0.815	− 0.026	0.814	− 0.208	0.036	− 0.203	0.042
1960 Cohort	0.192	0.021	0.187	0.025	− 0.127	0.164	− 0.1	0.281	− 0.052	0.546	− 0.038	0.655
1965 Cohort	0.129	0.052	0.134	0.045	0.115	0.1	0.14	0.049	− 0.157	0.025	− 0.155	0.028
1970 Cohort	− 0.146	0.03	− 0.151	0.026	0.105	0.116	0.102	0.132	0.136	0.044	0.105	0.124
1975 Cohort	− 0.276	0.002	− 0.263	0.003	0.019	0.833	− 0.001	0.992	0.104	0.224	0.125	0.15
Age 30	0.199	0.038	0.199	0.039	− 0.081	0.399	− 0.067	0.487	− 0.202	0.026	− 0.221	0.015
Age 35	0.073	0.28	0.065	0.342	0.023	0.729	0.026	0.705	− 0.032	0.638	− 0.031	0.659
Age 40	− 0.012	0.862	− 0.019	0.777	− 0.012	0.862	− 0.021	0.773	0.031	0.662	0.057	0.432
Age 45	− 0.249	0.004	− 0.235	0.006	0.151	0.098	0.131	0.154	0.337	0.000	0.33	0.000
Age 50	− 0.152	0.133	− 0.141	0.163	0.138	0.237	0.133	0.259	0.069	0.499	0.08	0.434
Age 55	− 0.092	0.411	− 0.092	0.413	− 0.129	0.34	− 0.13	0.341	0.072	0.504	0.07	0.517
Age 60	− 0.139	0.259	− 0.134	0.276	− 0.272	0.089	− 0.244	0.13	− 0.249	0.027	− 0.253	0.025
Age 65	0.371	0.036	0.358	0.043	0.183	0.357	0.172	0.387	− 0.026	0.847	-0.033	0.812
1995 Period	–	–	–	–	0.03	0.151	0.04	0.053	–	–	–	–
2000 Period	− 0.073	0.000	− 0.071	0.000	–	–	–	–	0.034	0.101	0.026	0.224
2005 Period	0.146	0.000	0.142	0.000	− 0.059	0.151	− 0.081	0.053	− 0.069	0.101	− 0.052	0.224
2010 Period	− 0.073	0.000	− 0.071	0.000	0.03	0.151	0.04	0.053	0.034	0.101	0.026	0.224
Rescacoh	2.4	0.000	2.447	0.000	0.975	0.003	0.84	0.011	0.266	0.344	− 0.063	0.826

Table 2 (continued)

	Italy				The Netherlands				Norway			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Without controls		With controls		Without controls		With controls		Without controls		With controls	
	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val	Coeff	*p* val
Rescaage	0.736	0.000	0.753	0.000	− 0.241	0.162	− 0.296	0.089	− 0.618	0.000	− 0.761	0.000
Female	–	–	0.109	0.055	–	–	0.124	0.04	–	–	0.169	0.005
High educ	–	–	0.325	0.000	–	–	0.626	0.000	–	–	0.656	0.000
Immigrant	–	–	− 0.429	0.005	–	–	− 0.87	0.000	–	–	− 0.48	0.000
Constant	− 1.048	0.000	− 1.118	0.000	− 1.543	0.000	− 1.777	0.000	− 1.646	0.000	− 1.961	0.000

In this table, we report the estimates of the APCD model for overskilling without controls—columns 1, 3, and 5—and with controls—columns 2, 4, and 6—as explained in Eq. (1). The controls included are education (reference = lower than tertiary education), gender (reference = male), and immigration status (reference = native)

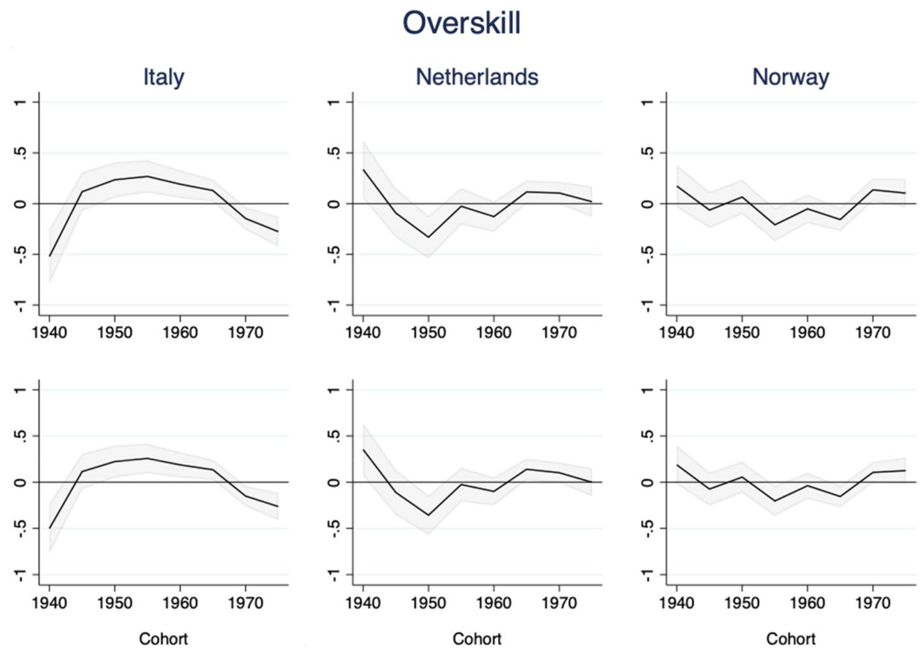

Fig. 7 Effect of cohort (APCD) on the risk of skills mismatch in Italy, the Netherlands, and Norway. *Note* The solid black lines are estimates, while the grey area represents 90% confidence intervals. Results reported in the first row do not include control variables, while results reported in the second row include control variables (education, sex, and immigrant status)

generations. This result may be the reason why Norway does not exhibit any risk of skills mismatch by cohort and, perhaps, for the lower risk for the 1955 and 1965 cohorts.

6 Conclusions

This paper describes and explains the differences between birth cohorts in the risk of overeducation and skills mismatch in Italy, the Netherlands, and Norway. Using descriptive tools for cohort analysis and APCD models, we found some differences across and within countries between cohorts concerning their risk of being overeducated or experiencing skills mismatch. The novelty of this paper is that we can detect deviation from a trend in cohort effects, which go beyond the simple linear combination of age and period, thanks to the use of the APCD model. This allows us to understand whether some cohorts are more likely to be mismatched than others. Results for Norway show that cohorts born between 1955 and 1965 are more likely to be overeducated, while there is a lower risk of overeducation for the most recent one born in 1975. The youngest cohort (born in 1975) is also less likely to be overeducated in the Netherlands. For Italy, overeducation is less likely among those born in 1965 and more likely among those born in 1950. Certain features of the country's educational system (e.g., the implementation of educational policies geared toward increasing educational attainment) but also labour markets circumstances affecting these particular cohorts may be at the core these results.

For skills mismatch, those born between 1950 and 1965 in Italy are more at risk of skills mismatch, and those born after 1970 are less exposed. Significant bumps are limited to those born in 1965 in the Netherlands, with a greater risk of being mismatched, while in Norway there is a lower risk of skills mismatch for the 1965 cohort. The most remarkable result may be that when significant, the cohort effects for the younger generation available in the data (1975) are negative. This happens for skills mismatch in Italy and overeducation in the Netherlands and Norway. This is, somehow, a positive finding. The youngest generations, those who are currently working and will work in the next decades may be less subject to the mismatch phenomenon.

These results raise concern regarding the analysis of occupational mismatch: the sensitivity to the particular definition of occupational mismatch used. As mentioned earlier, the range of measures of occupational mismatch is large, with no clear direction on the most accurate one. More specifically, when looking at overeducation and skills mismatch, as McGuinness et al. (2018a) showed, overeducation and overskilling are weakly correlated. Our results further confirm this low correlation but also provide a different picture regarding the evolution of occupational mismatch depending on the approach followed (skills vs. educational attainment).

This research provides a good example of best practices for researchers interested in using skill surveys (e.g., IALS, ALL, and PIAAC) to undertake comparative studies of the incidence and evolution of occupational mismatch. Having said this, the analysis could usefully be extended and deepened beyond the scope of this paper. First, while we have hypothesized about the possible drivers of the identified cohort effects, including the significant educational expansion, other explanations cannot be ruled out. Further research of the mechanisms underlying these cohort effects could include to empirically test the extent to which these cohort differences are due to characteristics of the educational system or the labour market circumstances of the specific cohorts. With the limited number of countries available, we cannot test whether our hypotheses find hard evidence in the data. However, using the approach followed by Chauvel and Fransje (2015) in a paper studying the political participation of different cohorts across several countries, for example, this may be possible once more data will be available.[14] The forthcoming release of the second wave of the PIAAC Survey (foreseen in 2023) will allow extending this research beyond the three countries considered. More cohorts will also be included, in particular, younger cohorts, which should be the focus of eventual policies.[15] As more data of this type become available, more research on this field can be done, helping to improve our understanding of occupational mismatch and its dynamics. Second, the most obvious follow up to this paper could be to study the relationship between overeducation and skills mismatch and economic inequality (and eventually the impact): overeducation and skills mismatch represent an inefficient allocation of human capital resources such that they reduce allocative efficiency, productivity, and economic growth, increasing economic inequality (Thurow 1975). Future research could seek to provide empirical evidence on this matter.

[14] After having estimated the APCD, they implement post-estimation regression of the cohort APCD coefficients found in the model and regress them on variables that may explain those effects. They can do this because their analysis is based on 9 countries, for 12 cohorts, a much larger sample than the one available in our case which consisted of 3 countries, for 8 cohorts, making this analysis unfeasible.

[15] New waves of PIAAC data with detailed information of occupations at ISCO 2-digit level will also allow having a more precise measure of occupational mismatch overcoming the current limitation of ISCO 1-digit being the only classification available with the existing data.

Labour market mismatches are dynamic; therefore, static analyses drawing on cross-sectional data are unable to disentangle the effects of economic cycles and generational differences on overeducation and skills mismatch. Hence, our research is critical for analysing the size and relative severity of occupational mismatching. Some modest policy implications arise, suggesting the need for a more tailored policy response that considers the capacity of the different labour markets to absorb any given increase in educational/skills supply. Simultaneously, it implies taking specific account of both the level and composition of current and future labour demands. This is particularly important now, as most of developing economies are trying to increase the proportion of the population holding a tertiary education degree (See, for example, the Education and Training 2020 strategy[16] in Europe). While greater educational attainment is a desirable goal, a corresponding investment in the labour market should be made to ensure that new generations find a job that fits their level of education and skill.

Appendix

See Tables 3, 4 and 5

Details on how to build the skills mismatch indicator based on skill use

The skills mismatch measure is built following Krahn and Lowe (1998). In their paper, they build "workplace requirement indices" using the questions on how often respondents write or read documents of different types. Then, they build a measure of *Literacy fit and mismatch in the workplace*, combining the level of literacy skills and the literacy requirement in the workplace. They define a worker as having a literacy surplus if he has high literacy skills and low literacy requirements. We apply the same methodology to our data. However, since the surveys did not ask the exact same questions for workplace literacy requirements, we had to adjust the methodology to make it comparable across the three surveys.

First, we considered only common questions on workplace literacy requirements s to build the workplace requirement indices (see Table 3 below):

Second, we needed to adjust the scales as the list of possible answers regarding the frequency of the different tasks (workplace literacy requirements) was not the same in the three surveys. For example, as shown in Table 4 for low-frequency use in the PIAAC, respondents could choose between *Never* or *Less than once per month*, while in the IALS there was a single choice: *Rarely or never*. Therefore, we grouped some of the items as shown in Table 4.

In our indicator of skills mismatch, there are 3 possible frequencies of skills used at work for each of the 9 questions: 1. Rarely or never, 2. Less than once per week, 3. At least once per week/daily. Higher values indicate more frequent reading/writing requirements.

The average of these three-category "workplace literacy requirements" across the questions is taken for each individual (ranging from 1 to 3) and is compared to the 3 literacy levels, built as explained in the next paragraph.

[16] https://ec.europa.eu/assets/eac/education/policy/strategic-framework/.

Table 3 List of questions asked in the IALS, ALL, and PIAAC regarding skills used at work

IALS	ALL	PIAAC
Reading		
Read letters, memos, or emails	Read letters, memos, or emails	Read letters, memos, or emails
Read reports, articles, magazines, or journals	Read reports, articles, magazines, or journals	Read articles in newspapers, magazines, or newsletters
Read manuals or reference books, including catalogues or part lists	Read manuals or reference books, including catalogues	Read manuals or reference materials
Read bills, invoices, spreadsheets, or budgets	Read bills, invoices, spreadsheets, or budget tables	Read bills, invoices, bank statements, or other financial statements
Read diagrams or schematics	Read diagrams or schematics	Read diagrams, maps, or schematics
Writing		
Write letters, memos	Write letters, memos, or emails	Write letters, memos, or emails
		Write articles for newspapers, magazines, or newsletters
Write reports or articles	Write reports, articles, magazines, or journals	Write reports
Write forms or things such as bills, invoices, or budgets	Write bills, invoices, spreadsheets, or budget tables	Fill in forms

Table 4 Possible responses regarding the frequency of skills used at work as recorded in the IALS, ALL, and PIAAC and the proposed reclassification for the skills mismatch indicator built

IALS	ALL	PIAAC	Combined
–	Never	Never	1. Rarely or never
Rarely or never	Rarely	Less than once per month	
Less than once per week	Less than once per week	Less than once per week, but at least once per month	2. Less than once per week
A few times per week	At least once per week	At least once per week, but not every day	3. At least once per week/ every day
Once per week	–	–	
Every day	–	Every day	

Table 5 Descriptive statistics of the working sample

	Italy		Norway		Netherlands	
	Mean	sd	Mean	sd	Mean	sd
Low education	0.356	0.479	0.133	0.339	0.257	0.437
Medium education	0.458	0.498	0.336	0.473	0.339	0.473
High education	0.186	0.389	0.531	0.499	0.404	0.491
Female	0.442	0.497	0.473	0.499	0.493	0.500
Immigrant	0.045	0.207	0.089	0.285	0.072	0.259
Overeducated	0.221	0.415	0.242	0.429	0.247	0.431
Overskilled	0.294	0.456	0.194	0.395	0.205	0.404
Cohort of birth: 1935	0.007	0.085	0.014	0.120	0.012	0.110
Cohort of birth: 1940	0.040	0.195	0.057	0.232	0.024	0.153
Cohort of birth: 1945	0.075	0.264	0.107	0.309	0.077	0.266
Cohort of birth: 1950	0.121	0.326	0.124	0.330	0.125	0.331
Cohort of birth: 1955	0.147	0.354	0.139	0.346	0.148	0.355
Cohort of birth: 1960	0.174	0.379	0.141	0.348	0.171	0.377
Cohort of birth: 1965	0.174	0.379	0.157	0.364	0.172	0.378
Cohort of birth: 1970	0.145	0.352	0.132	0.339	0.121	0.326
Cohort of birth: 1975	0.081	0.273	0.081	0.273	0.103	0.304
Cohort of birth: 1980	0.036	0.186	0.047	0.212	0.046	0.210
Age: 25–30	0.095	0.293	0.106	0.308	0.144	0.351
Age: 30–35	0.150	0.358	0.137	0.344	0.152	0.359
Age: 35–40	0.185	0.388	0.157	0.364	0.170	0.375
Age: 40–45	0.176	0.381	0.145	0.352	0.163	0.370
Age: 45–50	0.151	0.358	0.145	0.352	0.142	0.349
Age: 50–55	0.126	0.332	0.133	0.340	0.123	0.328
Age: 55–60	0.078	0.268	0.112	0.315	0.088	0.284
Age: 60–65	0.039	0.192	0.066	0.248	0.018	0.133
Survey: IALS	0.229	0.420	0.242	0.429	0.204	0.403
Survey: ALL	0.480	0.500	0.410	0.492	0.448	0.497
Survey: PIAAC	0.291	0.454	0.348	0.476	0.348	0.476
Number of observations	6,931	–	8,622	–	7,868	–

The table reports the mean and standard deviation of the relevant variables in the working sample, by country

The literacy levels are built based on the distribution of skills in the working population. The population is divided into three groups according to where their level of skill falls compared to the 33rd and 66th percentile of the skill distribution in the population (Level 1: individuals whose skills level, measured by the first plausible value—variable PVLIT1—is below the 33rd percentile of the distribution of skills in the working population in the country; Level 2: between the 33rd and 66th percentile; Level 3: above the 66th percentile). A comparison of workplace literacy requirement to the skill level tells us whether an individual is overskilled or not: individuals whose literacy level is higher than the "workplace literacy requirement" category are considered to be overskilled.

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