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Wages and labour mismatch in Italy: An investigation with PIAAC data

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Abstract

This paper provides new evidence on the returns to education and ability in Italy by employing the two cycles (2011 and 2022) of the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills. We employ Mincer-type equations to quantify the impact of required education, overeducation and undereducation (expressed in number of years) on Italian employees' wages. We also estimate the impact of both overskilling and underskilling (in the form of dummy variables) on wages. Our results show that returns to required and surplus education are positive and significant in all our model specifications, while returns to deficit education are significantly negative. As for over- and under-skilling, we find a wage premium for overskilled workers and no penalty for underskilled ones.

Keywords: Education mismatch, Overeducation, Skills mismatch, PIAAC.

JEL Classification: J24, J31, C21, C25.

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1. Introduction

The latest data (2022) from the Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills reveal that in Italy, as well as in OECD countries, adults with the highest numeracy proficiency scores have significantly better employment outcomes compared to those at the lowest level. These individuals experience higher participation rates, lower unemployment rates, and higher wages. However, a significant number of workers are mismatched in their jobs, with their qualifications, skills, or fields of study not aligning with the demands of their current positions. For instance, in Italy the percentage of under-qualified workers (18%) is higher than the OECD average (9%), while that of the over-qualified is lower (15% and 23% in Italy and the OECD, respectively) as well as the share of underskilled workers (6% in Italy vs 10% in the OECD). This suggests there is room to enhance the efficiency of human capital allocation in both Italy and OECD countries. Mismatches may arise from an inefficient distribution of workers to jobs, but they can also indicate that workforce skills and qualifications are not keeping up with structural changes in the economy, driven by factors such as digitalisation, an ageing population, and the green transition.

In an ageing population such as that of Italy, ranked second only to Japan (see, for instance, Prometeia, 2023), a possible source of mismatch is the level of education of those entering and leaving the labour market: older workers now reaching retirement age generally have lower levels of education than younger ones (Prometeia, 2024). For instance, in 2020, the proportion of individuals with only primary education was around 13% in the age bracket 60-64, but only around 1% in the age bracket 25-29; in addition, between 2004 and 2020 the number of individuals completing tertiary educations almost doubled and the trend is projected to continue. These disparities may result in gaps between inflows and outflows that are different for low-educated workers and high-educated ones, making it difficult for employers to find the appropriate matches among the pool of available workers and causing labour market shortages (see Camussi et al., 2024 for an analysis on the Italian labour market). In addition, in the literature there is evidence that overeducation and undereducation affect wages.

A wide strand of the literature has studied the impact of overinvestment in education on wages and our paper fits within it. The quantification of the returns to overeducation is relevant from a policy perspective, since it is important to know whether education investments pay off, especially in countries, such as Italy, where education is heavily subsidized (Leuven and

Oosterbbek, 2011) and the phenomenon of highly skilled young people emigrating abroad is becoming increasingly important. However, the empirical evidence of the existence of a price premium for education has received little policy response despite showing that overeducation and low skills utilisation impose substantial costs on workers and firms (McGuinness et al., 2018a). The costs are both economic and social, such as underemployment (individuals are working in roles that do not require the level of skill or education they possess), wage compression (workers are paid less than they would in an economy with full utilization of human capital), and social strain (the inability to properly use a highly educated or skilled workforce can result in social issues like job dissatisfaction and frustration). Moreover, large shares of overeducated and overskilled workers "may reflect an overall inefficiency of the labour allocation process, leading to a less productive job market equilibrium" (McGuinness et al., 2018a, p. 987). Finally, skill mismatch can slow down economic growth, because underskilled workers may be less able to adapt to technological changes (Perry et al., 2014).

In this paper, we explore mismatch in Italy along two different dimensions, education and skills, using individual level data taken from the two cycles (2011 and 2022) of the PIAAC Survey of Adult Skills. The recent release of the 2022 data allows us to provide updated evidence on the returns to education and skills in Italy, a country that, as documented in Prometeia (2023; 2024), suffers from high levels of labour mismatch and for which there is little empirical evidence. We contribute to the literature by providing estimates of the Duncan and Hoffman (1981) wage equation, which decomposes attained years of education employed by Mincer (1974) into years of required education, years of overeducation and years of undereducation. Moreover, we estimate the impact of both overskilling and underskilling on wages.

The estimation of the wage equations reveals that returns to required and surplus education are positive and significant in all our model specifications, while returns to deficit education are significantly negative. However, marginal returns to overeducation and those to required education differ in size: marginal returns to surplus education are about half the size of those to required education, imposing a cost on overeducated workers compared to well-matched ones. These findings suggest that educational mismatch has a significant impact on workers' earnings. We also find that the Duncan and Hoffman (1981) equation fits the data better compared to a standard Mincerian specification. Finally, we find a wage premium for overskilled workers and no penalty for underskilled ones.

The outline of the paper is the following. Section 2 reviews the literature, Section 3 describes and discusses the mismatch indicators, Section 4 presents descriptive statistics of the data employed in the analysis. The econometric models are outlined in Section 5, Section 6 presents and discusses the empirical results, and finally the main findings are summarised in Section 7.

2. Literature review

Individual labour mismatch is a broad concept including different types of mismatches, i.e. educational or skills, horizontal or vertical, objective or subjective, and it relates to the degree to which workers have skill or education levels that are above, below or inadequately connected to those required by their current job. Mismatch measures can be grouped into measures of surplus and deficit human capital. Surplus human capital is usually measured in terms of overeducation or overskilling, while deficit human capital is typically captured by undereducation and underskilling.

The economic literature has investigated the topic extensively since the 1980s. In their pioneering study, Duncan and Hoffman (1981) decomposed attained years of schooling of Mincer's (1974) wage equation into three components – required years of education, years of overeducation and years of undereducation – that can have different effects on wages. Since then, most of the literature has dealt with overeducation and has consistently found the existence of a wage penalty, that is a lower salary of the overeducated compared to those with the same level of education but who work in a well-matched job. By employing US census data, Verdugo and Verdugo (1989) find that overeducated workers often earn less than "their adequately educated and undereducated counterparts". However, their approach differs from Duncan and Hoffman's in three aspects: first they employ the "mean method" to get the required amount of education, second they identify the over and undereducated workers by means of dummy variables instead of years of schooling, and third they control for completed years of schooling instead of required ones.[1] Following the approach of Duncan and Hoffman, Alba-Ramirez (1993) finds that in Spain overeducated workers have less experience, decreased on-the-job training and higher turnover than other comparable workers. Bauer (2002) estimates both the Verdugo and Verdugo (1989) model and Duncan and Hoffman (1981) one on a panel dataset of German workers over the period 1984-1998 and finds results coherent with those of

[1] In the "mean method" a worker's required amount of schooling is retrieved from the mean of completed years of schooling of all workers with the same occupation. Specifically, overeducated workers are those whose actual years of education are greater than one standard deviation above the mean of required education for their specific occupation.

the reference works. Unlike most studies, McGuinness (2007) uses Propensity Score Matching (PSM) techniques to assess to what extent the costs of overeducation are over-estimated when using standard Ordinary Least Squares (OLS) regressions: the result is that the PSM estimates are in line with those generated by OLS, suggesting that the overeducation phenomenon is likely to be imposing real and significant wage and productivity costs on individuals and the economy.

McGuinness (2006), Leuven and Oosterbeek (2011) and McGuinness et al. (2018b) provide thorough reviews and discussion of the topic both from a theoretical point of view and from an empirical one, while Groot and van der Brink (2000b) perform a meta-analysis and find that only the definition of overeducation based on variation in years of education within occupational groups yields lower-than-average rates of overeducation.

From an aggregate country level perspective, McGuinness et al. (2018a) perform a comparative analysis of overeducation across 28 European Union (EU) countries building a panel dataset from the European Labour Survey and find overeducation rates converging at a yearly rate of 3%. In Manacorda and Petrongolo (1999) there is evidence that there has been some increase in skill mismatch in a few OECD countries over the 1980s and 1990s and that the rise in mismatch cannot explain much of the rise in unemployment in continental Europe. Other studies of overeducation at aggregate level are those of Croce and Ghignoni (2012), Verhaest and Van der Velden (2013) and Davia et al. (2017), which all point to the potential importance of aggregate level variables in explaining international differences in overeducation. Comparative analysis is also provided in Morgado et al. (2016) who employ labour survey data to measure labour mismatch in 30 European countries between 1993 and 2011.

A strand of the literature has investigated whether there is coherence between subjective and objective indicators of mismatch. Most of the studies find that the percentages of overeducated workers vary remarkably (see, for instance, McGoldrick and Robst, 1996; Groot and van den Brink, 2000a) and that the indicators identify different pools of people (Battu et al., 2000). Both Sloane (2003) and McGuinness (2006) find that while the correlation between the two approaches tends not to be particularly high, they generate very similar results with respect to both the incidence and impacts of overeducation.

Without claiming to be exhaustive, we review some works that have used PIAAC to study overeducation or skills mismatch. One example is Perry et al. (2014) who, working on 2011 data for Austria, Germany and the US, find that the importance of skill mismatch for individual earnings differs greatly, depending on the measure of mismatch used. Hanushek et al. (2015) estimate an instrumental variables (IV) model to obtain that returns to skills are systematically lower in countries with higher union density, stricter employment protection, and larger public-sector shares. The unconditional quantile regressions employed by Paccagnella (2015) show that formal education is found to have a larger impact on inequality, given that returns to education are in general much higher at the top that at the bottom of the distribution. Nieto and Ramos (2017) estimate wage equations for Spain following the approaches of Duncan and Hoffman (1981) and Verdugo and Verdugo (1989), extending the latter by including a skill level variable that is built following the approach of Pellizzari and Fichen (2013; 2017) and OECD (2013) by combining workers' self-assessment questions and their skill proficiency score. Rebollo-Sanz and De la Rica (2022) address the empirical relationship between cognitive skills and gender gaps in labour market performance. Kawaguchi and Toriyabe (2022) suggest new indicators of skills and skills use and demonstrate that the proposed indices explain the wage gap between males and females, as well as the gap between immigrants and natives. McGowan and Andrews (2017) match PIAAC data with industry-level data of 19 OECD countries and find that higher skill and qualification mismatch is associated with lower labour productivity, with over-skilling and underqualification accounting for most of these impacts. Finally, descriptive analysis is provided by Flisi et al. (2017) and Choi et al. (2020).

As far as Italy is concerned, there is little empirical evidence on overeducation or overskilling/underskilling. Among others, Brynin and Longhi (2009) and Johnes (2019) find evidence of a relatively low incidence of overeducation in Italy in PIAAC data. Esposito and Schicchitano (2022) investigate the relationship between educational mismatch and individual unemployment risk by employing the Participation, Labour and Unemployment Survey (PLUS) and the Survey of Professions (ICP), both developed by the National Institute for Public Policy Analysis (INAPP).

3. Mismatch indicators

In this paper, we explore mismatch along two different dimensions, education and skills, using individual level data taken from both rounds of the PIAAC Survey of Adult Skills. The survey provides data on adults' cognitive skills in literacy, numeracy, and problem-solving, as well as on a range of information providing insight on the link between skills, education, and employment and the role skills play in improving the employment and life prospects of the adult population. The survey covers individuals aged 16-65 years old in 38 OECD countries, providing harmonised data for international comparisons.

Using both dimensions of mismatch is important, since there need not be a one-to-one correspondence between an individual's level of education and her ability (Leuven and Oosterbeek, 2011). For both dimensions of mismatch, we define at least one objective and one subjective indicator, as both objective and subjective measures might be biased. Subjective measures may be prone to bias as workers might have the tendency to overstate job requirements to upgrade their position (Hartog, 2000). Objective measures based on realized matches, on the other hand, might capture demand and supply forces, rather than job requirements alone, and ignore variation in requirements across jobs within an occupation (Leuven and Oosterbeek, 2011).

For educational mismatch, the subjective indicator is based on a comparison between the highest level of education obtained by an individual (e_i)[2] and the self-reported level of education required to perform her job (r_i). Formally, an individual is (subjectively) over-qualified if $e_i > r_i$, (subjectively) under-qualified if $e_i < r_i$, and (subjectively) well-matched if $e_i = r_i$. The objective indicator is built by comparing the highest level of education obtained by an individual (e_i) to the 25th and 75th percentiles of education obtained by individuals employed in the same industry as the respondent. Call e_{nc}^{25} and e_{nc}^{75} the 25th and 75th percentile of educational attainment, where n represents the industry ISIC Rev.4 one-digit code the respondent is employed in, and $c \in \{1,2\}$ identifies the cycle. One individual is (objectively) over-qualified when $e_i > e_{nc}^{75}$, (objectively) under-qualified when $e_i < e_{nc}^{25}$ and (objectively) well-matched if $e_{nc}^{25} \leq e_i \leq e_{nc}^{75}$.

In addition to these categorical variables, we also calculate two variables of (subjective) educational mismatch which compare respondent's attained years of education to the years of schooling required to perform the respondent's job. Let S_i^a be attained years of education for respondent i and S_i^r the years of education necessary to perform her job. Following Duncan and Hoffman (1981), we define years of surplus education (or overeducation) as $S_i^o = max(0, S_i^a - S_i^r)$ and years of deficit education as $S_i^u = max(0, S_i^r - S_i^a)$.

Turning to skill mismatch, the subjective indicator is based on individual answers to the PIAAC questionnaire. Due to differences in the wording of questions across cycles, however, the

[2] Individual-level variables are not indexed by cycle, as the two rounds of PIAAC survey cannot be used to build a panel dataset.

definition is slightly different between Cycle 1 and Cycle 2. In Cycle 1, an individual is (subjectively) over-qualified if she answered affirmatively to the question "Skill use work – Not challenged enough", while she is (subjectively) under-qualified if she answered affirmatively to the question "Skill use work – Need more training". In Cycle 2, she is (subjectively) over-qualified if she chose the option "My skills are higher than what is required by my job" for the question "Skills in relation to what is required", and (subjectively) under-qualified if she chose the option "Some of my skills are lower than what is required by my job and need to be further developed" in the same question.

We calculate the objective ability mismatch measure for both literacy and numerical skills. To do so, we first define the individual ability level as the individual average across ten plausible values scores (s_i), where $s \in \{Literacy, Numerical\}$. Then, we calculate the 25th and 75th percentile of each skill within ISIC Rev.4 one-digit code industry and cycle, s_{nc}^{25} and s_{nc}^{75}. An individual is (objectively) overskilled along dimension s when $s_i > s_{nc}^{75}$, underskilled when $s_i < s_{nc}^{25}$, and well-matched if $s_{nc}^{25} \leq s_i \leq s_{nc}^{75}$.

Finally, an individual is (objectively) generally overskilled whenever she is overskilled along at least one dimension, i.e. $s_i > s_{nc}^{75}\ for\ s\ =\ Literacy$ or $s_i > s_{nc}^{75}\ for\ s\ =\ Numerical$, (objectively) generally underskilled if she is not overskilled and she is underskilled along at least one dimension, and (objectively) generally well-matched if she is well-matched along both the numerical and literacy dimension. In case an individual is not employed or is out of the labour force, her reference category is the pool of unemployed or out of the labour force respondents, respectively. In addition, we calculate a general measure of ability a_i as the maximum between the average literacy score and the average numerical score.

Both objective measures are built so that the reference to which individuals are compared to are survey cycle specific. This implies that two individuals with the same level of education or skills across cycles can be categorized differently, depending on education and skills dynamics over time within a given industry. We believe that this approach reflects changing working environments, structural and technological changes, and the need to update individual qualifications and skill levels over time.

PIIAC data also allow for a categorization of each industry sector in terms of skills required to perform a job in the sector. We categorize each industry sector into high or low skill requirements (along both numeracy and literacy dimensions) by comparing the average skill level of those employed in each sector to the overall skill distribution. Formally, given the industry median $\overline{m}_{nc}, for\ s \in \{Literacy, Numerical\}$, sector n has high (low) skill requirements if $\overline{m}_{nc} > \overline{m}_c$ ($\overline{m}_{nc} < \overline{m}_n$), where $\overline{m}_c$ is such that $F_{s_c}(\overline{m}_c) = 0.5$ and F_{s_c} is the cumulative distribution function of either literacy or numerical skills in cycle c.[3]

4. Data and descriptive statistics

PIAAC survey has been run over two cycles, the first conducted between 2011 and 2018, while the second has been completed in 2022-2023.[4] In Italy, 4,621 and 4,847 respondents participated to the first and the second round of the survey, respectively, for a total of 9,468 respondents.[5] To perform our analysis, we exclude unemployed individuals (3,796 observations) and self-employed workers (1,248 observations) from the original sample. In addition, we exclude individuals with foreign qualifications (10 observations) and younger than 25 (456 observations). Finally, we drop observations for which the monthly earnings variable and the subjective skill mismatch variable are missing (562 and 2 observations, respectively). The final sample is made of 3,394 observations, 1,742 of which participated to the first survey Cycle and 1,652 to the second one.

The core of the survey is a set of skill measurements obtained through a series of computer-based adaptive tests. In addition, the survey collects a rich set of socio-economic and demographic information for each respondent, as well as characteristics related to the current respondent's occupation. We use demographic information (age and gender), whether the respondent has at least one child younger than 11 years old, the highest education level attained by the respondent, her health status, both parents' education, whether the respondent is native born, and whether she is a manager. If the respondent is employed, we use educational requirements of current occupation.

Summary statistics of selected variables are reported in **Table 1**. Panel A and B reports descriptives statistics for respondents who participated to the first and second cycle of PIAAC, respectively. Notably, in Cycle 2, we observe a worsening in the level of both numerical and literacy skills in our sample. Both skill types dropped by around 3%. Similarly, subjective

[3] Given the importance of numerical cognitive skills, we focus on sectoral categorization based on numeracy levels. Using cycle 2 as a reference, sectors with low numeracy requirements are E (water supply; sewerage, waste management and remediation activities), F (construction), H (transportation and storage) and I (accommodation and food service activities).
[4] INAPP (2025) presents the main findings from the second cycle of the PIAAC for Italy in the international context.
[5] The survey does not follow respondents over time, instead it consists of two cross-sections.

measures of skill mismatch dropped consistently, although we cannot exclude that the reason for this is the difference in wording across survey cycles.

	N	Mean	SD	Min	Max
Panel A: Cycle 1					
Age	1742	42.629	9.311	25	65
Gender	1742	1.48	0.5	1	2
Monthly earnings	1742	2198.234	1538.409	11	20833.33
Skills not challenged	1742	0.87	0.336	0	1
Skills need more training	1742	0.305	0.461	0	1
Mother education <_ISCED 4	1742	0.809	0.393	0	1
Father education <_ISCED 4	1742	0.751	0.432	0	1
Literacy skills	1742	260.608	41.147	97.714	378.226
Numerical skills	1742	261.818	45.43	97.775	381.937
Years of completed education	1742	12.258	3.294	0	22
Panel B: Cycle 2					
Age	1652	42.953	11.356	25	65
Gender	1652	1.474	0.499	1	2
Monthly earnings	1652	2125.75	3333.566	75.167	90583.34
Skills not challenged	1652	0.186	0.389	0	1
Skills need more training	1652	0.047	0.212	0	1
Mother education < ISCED 4	1652	0.685	0.465	0	1
Father education < ISCED 4	1652	0.655	0.476	0	1
Literacy skills	1652	252.378	49.259	98.092	385.857
Numerical skills	1652	253.374	50.493	69.923	386.83
Years of completed education	1652	12.535	3.652	0	22

***Table 1*: Summary Statistics.** *Source: Authors' elaborations on PIAAC data.*

	Well-Matched		**Over-Qualified**		**Under-Qualified**	
Age	Cycle 1	Cycle 2	Cycle 1	Cycle 2	Cycle 1	Cycle 2
25-29	84.56	78.27	11.47	18.53	3.97	3.20
30-34	83.94	85.17	13.46	13.87	2.61	0.96
35-39	87.23	79.31	8.43	15.58	4.34	5.11
40-44	80.26	80.67	7.89	13.90	11.85	5.42
45-49	84.17	80.44	5.33	14.33	10.50	5.23
50-54	77.84	77.37	2.70	9.17	19.46	13.46
55-59	64.10	78.54	4.71	7.93	31.19	13.53
60-65	56.98	69.97	4.71	11.27	38.31	18.76

***Table 2:* Distribution of education mismatch**. Note: this table reports the percentage of well-matched, over-qualified and under-qualified workers, by PIAAC survey cycle and age cohort. *Source: Authors' elaborations on PIAAC data.*

The objective, categorical measures of education and skill mismatch can be used to analyse mismatch dynamics across survey cycles. Overall, in Cycle 1, 7.81% of individuals in our sample was overqualified according to the objective educational mismatch measure, while 11.34% was underqualified. The percentage of overqualified individuals increased to 12.75% in Cycle 2, while that of underqualified decreased to 8.11%: this is concerning because it looks like, despite rising education levels, people are securing jobs that do not fully utilize their skills. **Table 2** shows the percentage of individuals who are well-matched, over, or underqualified in both cycles, across age groups. Within each survey cycle, younger cohorts are more likely to be overqualified, compared to older ones, and the incidence of overqualification (underqualification) decreases (increases) with age. Over cycles, the share of overqualified workers increased across all age groups, while that of underqualified markedly decreased. The demographic effect may be a factor here: older generations, who were often in positions above their level of education (typically low and largely learned on the job), are leaving the workforce.

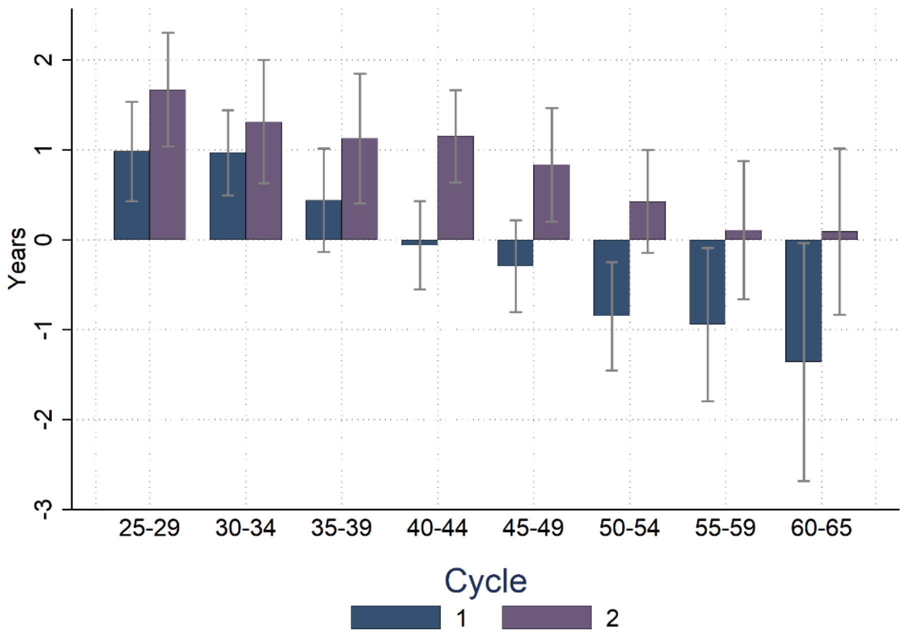

Figure 1: **Surplus or deficit years of education by age group and cycle.** *Note: positive y-axis values suggest educational surplus, while negative ones suggest educational deficit. 95% confidence bands on top of bars. Source: Authors' elaborations on PIAAC data.*

The qualification shift is clear when looking at the surplus or deficit average years of education across age groups, as shown in Errore. L'origine riferimento non è stata trovata., where positive values in the y-axis indicate surplus years of education and negative values indicate deficit years. In Cycle 1, a worker, on average, was characterized by an educational deficit from the age of 40 onwards. In Cycle 2, however, there is, on average, educational surplus at any age group. In addition, in Cycle 1 there was an overall surplus of 0.051 years of education, while in Cycle 2 there is an average surplus of 0.811 years of education. This shift is significant, considering that our sample is made up of employed individuals only.

Cycle	Avg.	t	P>|t|	Obs.
1	0.051	0.461	0.645	1742
2	0.811	6.566	0.000	1652

***Table 3*: One-sample t-test on surplus/deficit education.** Note: this table reports the average surplus/deficit of years of education across cycles, as well as the results of a one-sample t-test testing H_0: average = 0. *Source: Authors' elaborations on PIAAC data.*

We formally test whether the average deficit/surplus years of education are significantly different from 0 in each survey cycle by regressing, for each cycle, the number of deficit/surplus years of education on a constant only and testing whether the constant is different from 0. Results are reported in **Table 3**. While we cannot reject the null hypothesis that the surplus in education years is different from 0 in Cycle 1, we reject the same null hypothesis for surplus education years in Cycle 2. This suggests that we moved from a situation of general absence of educational mismatch to one where educational mismatch is a relevant phenomenon.

	Well-Matched		**Overskilled**		**Underskilled**	
Age	Cycle 1	Cycle 2	Cycle 1	Cycle 2	Cycle 1	Cycle 2
25-29	33.85	36.46	44.44	38.70	21.71	24.84
30-34	33.35	33.53	37.86	50.57	28.79	15.91
35-39	37.62	39.91	32.61	37.74	29.77	22.35
40-44	40.47	35.57	26.43	36.61	33.10	27.82
45-49	38.02	42.10	28.42	33.68	33.56	24.22
50-54	43.11	39.32	25.90	31.74	30.99	28.94
55-59	36.75	34.26	19.01	34.80	44.25	30.94
60-65	44.24	42.57	6.17	19.63	49.58	37.79

***Table 4:* Distribution of skill mismatch.** Note: this table reports the percentage of well-matched, overskilled and underskilled workers, by PIAAC survey cycle and age cohort. *Source: Authors' elaborations on PIAAC data.*

Turning to skill mismatch, the proportion of objectively overskilled workers in Cycle 1 was 22.32%, while that of underskilled workers 27.76%. In Cycle 2, these proportions were inverted, with 27.07% of workers being overskilled and 23.26% underskilled. **Table 4** shows the distribution of skill mismatch, again across cycles and age groups. The dynamics are similar to those that characterise education mismatch. Except for the youngest cohort (i.e. workers between 25 and 29 years of age), the percentage of overskilled individuals increased markedly from Cycle 1 to Cycle 2 across all age groups, with older cohorts experiencing a larger increase compared to younger ones. This increase has been accompanied by a corresponding decrease in the percentage of underskilled workers. In addition, the incidence of overskilling decreases with age in both cycles.

These trends might be driven by both demand and supply forces. On the supply side, we observe a generalized increase in the number of years of education attained by employed individuals across cycles (in the left panel of **Figure 2**), except for the younger cohort. However, the level of workers' ability (defined as the maximum value between literacy and numerical scores) decreased across all age groups when moving from Cycle 1 to Cycle 2 (right panel of **Figure 2**). That is, increased educational levels do not translate into better workers ability.

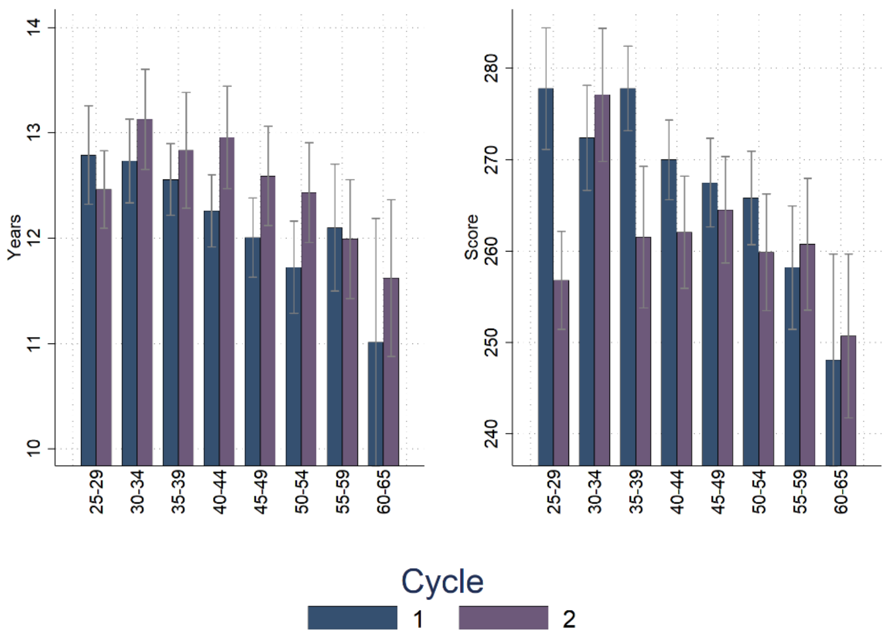

Figure 2**: Distribution of years of education and ability levels.** Note: this figure shows the distribution of completed years of education (left panel) and a measure of ability (right panel) across cycles and age groups. 95% confidence bands on top of bars. *Source: Authors' elaborations on PIAAC data.*

On the demand side, we can match sectoral skill requirements to sectoral information on labour demand, to characterize its dynamics over time. As a measure of labour demand, we use Istat data on sectoral vacancy rates. The vacancy rate is defined as the ratio of open job positions over the sum of open and total job positions and is an indicator of market tightness. **Figure 3** shows the dynamics of the vacancy rate by required skill level. Sectors requiring a relatively lower level of ability have driven labour demand dynamics since 2015, with higher vacancy rates in these sectors.

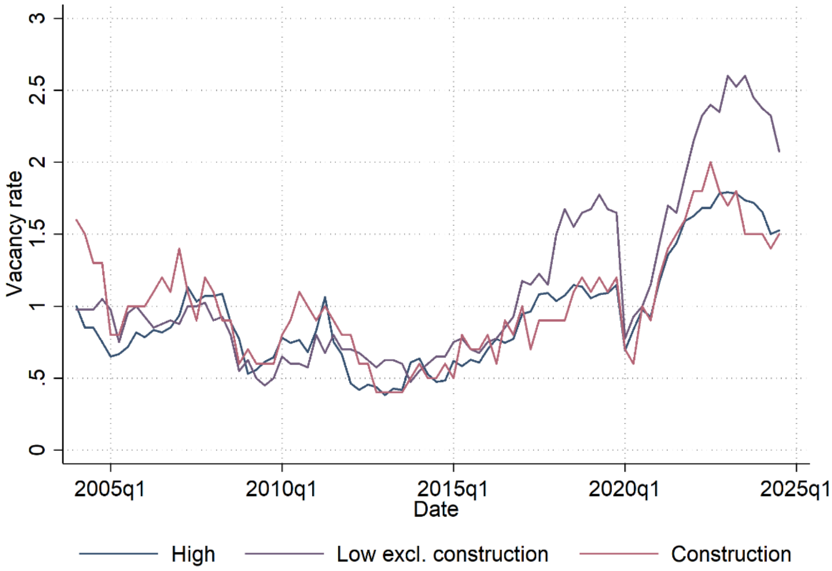

***Figure 3*: Vacancy rate by skill level.** Note: this figure shows the vacancy rate across sectors with high or low (numeracy) skill requirements, as well as the construction sector. Construction is categorized as a sector with low (numeracy) skill requirements. *Source: Authors' elaborations on PIAAC and ISTAT data.*

5. Econometric models

5. 1 Overeducation

To estimate the impact of overeducation on individual wages, we employ the Mincer-type (Mincer, 1974) equation suggested by Duncan and Hoffman (1981), whose specification is the following:

$$ln\, w_i = \delta_r S_i^r + \delta_o S_i^o + \delta_u S_i^u + x_i' \beta + \varepsilon_i \qquad \text{for } i = 1, \dots, N \qquad (1)$$

where $ln\, w_i$ is log of individual monthly wages (including bonuses), S_i^r is years of education required to perform the job, S_i^o is years of surplus education (i.e. overeducation), and S_i^u is years of deficit education (i.e. undereducation), as detailed in Section 3, and δ_r, δ_o and δ_u are the returns to required education, overeducation and undereducation, respectively. x_i' contains individual and household level socio-economic characteristics and ε_i is the error term.

Equation (1) allows us also to test whether the Duncan and Hoffman specification fits the data better than the standard Mincer equation $ln\, w_i = \delta_a S_i^a + x_i' \beta + \varepsilon_i$ (where S_i^a is attained years of education) by imposing the restriction $\delta_r = \delta_o = -\delta_u$. In addition, testing the restrictions $\delta_o = \delta_u = 0$ is equivalent to test whether only the job requirements affect workers' wage.

In our analysis, the regressors in x_i are:

(i) *Individual*: age and age squared, gender (male is the reference category), education (primary education is the reference category), manager (not being a manager is the reference category), health (poor/average health is the reference category), native (immigrant is the reference category), and ability (defined as the maximum between literacy and numerical scores).

(ii) *Household-level*: whether in the household there is at least one child below 11 years of age and three dummy variables on whether parents (mother, father and mother and father jointly) have a low level of education (primary or lower secondary).

(iii) *Other*: a dummy variable identifying cycle 2.

Equation (1) is estimated via OLS (Ordinary Least Squares) on the two repeated cross sections of cycles 1 and 2 and on two sets of data: one corresponding to the subsample of industrial sectors (restricted sample), i.e. Mining, Manufacturing, Energy supply, and Water supply (Section 6) and one including all the economic sectors (unrestricted sample) (Appendix A).[6] The rationale for restricting the estimation sample to the industry sector lies in the fact that there may be structural differences in how wages are set in different sectors, especially construction and agriculture that are characterised by temporary and seasonal jobs. In general, this problem may not be solved using sector fixed effects, as there might be selective sorting across sectors.

5.2 Overskilling/underskilling

The estimation of the returns to over-skilling and under-skilling are obtained by running the following OLS regression:

$$ln\, w_i = \gamma_o G_i^o + \gamma_u G_i^u + x_i'\beta + \varepsilon_i \qquad \text{for } i = 1, \dots, N \qquad (2)$$

where $ln\, w_i$ is log of individual monthly wages (including bonuses), G_i^o is a dummy variable for overskilling, G_i^u is a dummy capturing underskilling, γ_o and γ_u are their returns, x_i' contains individual and household level socio-economic characteristics as detailed above and ε_i is the

[6] Mining, Manufacturing, Energy supply, and Water supply are the B, C, D and E sectors of the ISIC Rev.4 classification.

error term. As before, Equation (2) is estimated on both cycles of PIAAC data and on the two sets of data, restricted and unrestricted.

6. Empirical results

6.1 Overeducation

Table 5 reports the estimation results of Equation (1) on the subsample of employees working in the industry sectors (restricted sample). Column (i) shows the estimates of a basic model including a smaller set of control variables. Returns to required and surplus education are positive and significant: keeping everything else constant, an additional year of required education increases wages by 6.77%, while an additional year of surplus education increases wages by 4.32%. Returns to deficit education, on the other hand, are negative and significant and amount to a 3.72% decrease in wages for each deficit year. In column (ii), we augment the base model including a wider set of covariates. Returns to education are smaller in magnitude, compared to the estimates in column (i), but their sign and significance still hold. Finally, column (iii) also includes a measure of ability, which is positively and significantly correlated with wage. However, the coefficients associated with returns to education maintain their significance and sign.

We formally test the null hypothesis $\delta_r = \delta_o = -\delta_u$ and cannot reject it, implying that the augmented Mincerian wage equation fits the data better compared to the standard specification. In addition, we test whether only job requirements affect a worker's wage by imposing the null $\delta_o = \delta_u = 0$. We reject the null hypothesis at 1% confidence level and conclude that undereducation and overeducation have a significant, albeit different, impact on workers' earnings.

	log(monthly wages)		
	(i)	(ii)	(iii)
Required education	0.0677***	0.0496***	0.0427***
	[0.0065]	[0.0065]	[0.0068]
Surplus education	0.0432***	0.0305***	0.0253**
	[0.0093]	[0.0086]	[0.0087]
Deficit education	-0.0372***	-0.0276**	-0.0225*
	[0.0091]	[0.0087]	[0.0090]
Female	-0.2956***	-0.2406***	-0.2450***
	[0.0473]	[0.0447]	[0.0444]
Age	0.0589***	0.0583***	0.0570***
	[0.0171]	[0.0161]	[0.0162]
Age squared	-0.0006**	-0.0006**	-0.0005**
	[0.0002]	[0.0002]	[0.0002]
Manager		0.2758***	0.2670***
		[0.0381]	[0.0384]
Excellent, very good, good health		-0.0613	-0.0633
		[0.0670]	[0.0668]
>= 1 child below 11 years of age		-0.0328	-0.0288
		[0.0443]	[0.0431]
Mother < ISCED 4		-0.0063	-0.0085
		[0.0698]	[0.0689]
Father < ISCED 4		-0.0083	-0.0091
		[0.0830]	[0.0844]
Both parents < ISCED 4		-0.1523	-0.1295
		[0.1048]	[0.1058]
Native born		-0.0779	-0.0994
		[0.0525]	[0.0521]
Ability			0.0012**
			[0.0004]
No. of obs.	767	763	763
R-Squared	0.288	0.3615	0.3703
Cycle FE	Yes	Yes	Yes

Table 5: **Returns to schooling.** Note: *, **, and *** represent significance level at 10%, 5% and 1% confidence level, respectively. Robust standard errors are reported in brackets. *Source: Authors' elaborations on PIAAC data.*

6.2 Overskilling/Underskilling

Table 6 reports the estimation results of Equation (2), where we investigate the impact of over- and under-skilling on workers' earnings. Across columns, a smaller or wider set of control variables has been included in the regression. However, the results are similar: we find a wage premium for overskilled workers ranging from 12.62% to 10.06% and no penalty for underskilled workers (coefficients are not statistically significant). These results are consistent with the human capital theory, which postulates that in equilibrium wages correspond to marginal productivity and that overskilled workers should be inherently more productive (McGowan and Andrews, 2017).

	log(monthly wages)	
	(i)	(ii)
Overskilled	0.1262**	0.1006*
	[0.0404]	[0.0392]
Underskilled	-0.0843	-0.0395
	[0.0511]	[0.0497]
Female	-0.3202***	-0.2558***
	[0.0498]	[0.0472]
Lower secondary education	0.1137	0.1463
	[0.0872]	[0.0787]
Upper secondary education	0.3214***	0.3025***
	[0.0859]	[0.0755]
Post secondary/tertiary education	0.6447***	0.5131***
	[0.0981]	[0.0862]
Age	0.0638***	0.0594***
	[0.0177]	[0.0165]
Age squared	-0.0006**	-0.0006**
	[0.0002]	[0.0002]
Manager		0.2927***
		[0.0381]
Excellent, very good, good health		-0.0771
		[0.0670]
At least 1 child below 11 years of age		-0.0313
		[0.0425]
Mother's education < ISCED 4		-0.0598
		[0.0706]
Father's education < ISCED 4		-0.0382
		[0.0869]
Both parents' education< ISCED 4		-0.0833
		[0.1093]
Native born		-0.0448
		[0.0486]
No. of obs.	775	771
R-Squared	0.2801	0.3586
Cycle FE	Yes	Yes

Table 66: **Returns to skills.** Note: *, **, and *** represent significance level at 10%, 5% and 1% confidence level, respectively. Robust standard errors are reported in brackets. *Source: Authors' elaborations on PIAAC data.*

6.3 Discussion

Overall, educational mismatch has a significant impact on workers' earnings, in addition to the positive impact coming from one's job educational requirement. Marginal returns to required years of education are positive and equal to 6.77%, 4.96% and 4.27% per year, depending on the model specification of **Table 5**. Each educational year in surplus compared to the level required by a respondent's job increases wages by 4.32%, 3.05% and 2.53%, while each deficit year decreases wages by 3.72%, 2.76% and 2.25%. This implies that when looking at returns to education, whether additional years are required or surplus matters: marginal returns to surplus years are about half as much as those to required years.[7] In other words, keeping everything else constant, marginal returns to education are not equalized across workers with the same level of education, and overeducated ones effectively incur a cost, compared to those who are well-matched. If individuals internalise this cost when making educational choices, it could contribute to shortages of highly educated workers.

Our estimates are consistent, albeit smaller in magnitude, with those found by Duncan and Hoffman (1981), who estimated returns to job requirements of 0.063, returns to overeducation of 0.029, and returns to undereducation of -0.042.[8] An important difference is that we control for "ability" (defined as the maximum between literacy and numerical scores). When comparing models which do and do not include this control (i.e. column (iii) and (ii) in **Table 5**), individual ability absorbs a significant portion of returns to over- and undereducation. Ability has two effects. First, it reduces returns to overeducation, suggesting that educational surpluses do not fully offset negative productivity effects of low ability. Second, it reduces the wage penalty for undereducation, indicating that it is possible, to some extent, to compensate for educational deficits with higher ability.

Overskilled workers, relatively to other workers in the same economic sector, seem indeed more productive. This is suggested by the fact that their wage is significantly higher than that of well-matched workers. However, underskilled workers do not face a wage penalty, relative to well-matched ones. On average, overskilled workers have a smaller surplus of education years, compared to underskilled workers. It is therefore possible that overeducation is a tool to compensate for lack of skills and this is enough to offset the negative impact of low ability on wages.

These findings speak to the policy importance of addressing qualification mismatches, which can lead to underemployment and human capital misallocation, reducing productivity, as well

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[7] We test the null hypothesis $\delta_r = \delta_o$ in each of the specifications reported in **Table 5**: we reject it with p-values 0.004, 0.027 and 0.043 for models in column (i), (ii) and (iii), respectively.

[8] The difference in magnitude is explained by the different dataset employed and its composition, as Duncan and Hoffman use a cross-section of white males in the US in 1976, while our sample refers to Italian workers, both male and female, in 2022.

as shortages of high educated workers, if low marginal returns to surplus education are internalised when making educational choices. Overeducation may also exacerbate labour market inequalities and obscuring genuine skill shortages. This misalignment can contribute to long-term sectoral shortages. Policies should prioritize aligning education with labour market needs, promoting diverse educational pathways, and addressing systemic inequalities while enhancing workforce adaptability to economic shifts.

7. Conclusions

In this paper we provide new evidence on the returns to education and skills in Italy by employing the 2011 and 2022 PIAAC data, with the aim of testing whether labour mismatch, measured by over- and undereducation or by over- and underskilling, affects wages and to what extent.

The motivation for this work stems from the evidence contained in the newly released 2022 PIAAC data suggesting that in Italy, as well as in OECD countries, many workers are not well-matched to their jobs, meaning that their qualifications, skills, or fields of study do not align with the requirements of their current roles. These mismatches can arise from inefficient job allocation, but they may also indicate that the skills and qualifications of the workforce are not evolving in line with structural shifts in the economy, driven by factors like digitalization, an ageing population, and the green transition.

This paper fits within the literature on vertical mismatch in education and skills and employs wage equations to estimate the returns to education and skills of Italian employees. To this end we employ two sets of equations, one for under/overeducation and one for under/overskilling. To investigate the returns to education we estimate three specifications that differ in the covariates used by employing the Duncan and Hoffmann (1981) approach in which attained years of education of the standard Mincerian equation is decomposed into years of required education, years of overeducation and years of undereducation. To investigate the return to skills, we employ two specifications in which wages are regressed on two dummy variables capturing overskilling and underskilling, in addition to other covariates.

Our findings show that returns to both required and surplus education are positive and significant across all model specifications, while returns to deficit education are significantly negative, indicating that educational mismatch notably affects workers' earnings, in line with Duncan and Hoffmann’s (1981) results. Similarly to their results, we find that returns to required education are about twice those to surplus education, implying a cost in terms of lower wages for overeducated employees compared to well-matched ones. Additionally, we observe that the Duncan and Hoffmann specification provides a better fit for the data than the standard Mincerian one. In the third specification we introduce the variable "ability" (i.e. the maximum between literacy and numerical scores), which has a positive and significant impact on wages and has also the effect of reducing both the wage premium for overeducation and the wage penalty for undereducation. The latter result may imply that undereducation can be partially compensated by increased ability. Lastly, we also identify a wage premium for overskilled workers and no wage penalty for underskilled workers. We find that, on average, overskilled workers have fewer excess years of education compared to underskilled workers. This suggests that overeducation may serve as a means to compensate for a lack of skills, potentially offsetting the negative effect of low ability on wages.

These findings are significant from a policy standpoint, as the mismatch between individuals' qualifications and job requirements can result in underemployment, where highly educated workers are placed in positions that don't fully utilise their skills. Specifically, overeducation can lead to inefficient use of human resources, wasting valuable assets like time, money, and effort spent on education, all of which can negatively impact productivity. Overeducation may also hide genuine skill shortages in certain sectors, with workers possessing excess qualifications filling roles that could otherwise be taken by those with the appropriate skillsets, potentially leading to long-term labour shortages in specific industries. Therefore, it is advisable that policies focus on aligning educational outcomes with labour market needs, encouraging a variety of educational paths, and tackling systemic inequalities. Furthermore, policies should support workforce adaptability to navigate economic changes.

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Appendix A - Estimation results on the unrestricted sample

	log(monthly wages)		
	(i)	(ii)	(iii)
Required education	0.0621***	0.0486***	0.0448***
	[0.0036]	[0.0039]	[0.0040]
Surplus education	0.0396***	0.0301***	0.0273***
	[0.0051]	[0.0049]	[0.0049]
Deficit education	-0.0166*	-0.0130*	-0.0103
	[0.0067]	[0.0063]	[0.0063]
Female	-0.2313***	-0.1909***	-0.1891***
	[0.0258]	[0.0260]	[0.0258]
Age	0.0520***	0.0448***	0.0444***
	[0.0089]	[0.0087]	[0.0087]
Age squared	-0.0005***	-0.0004***	-0.0004***
	[0.0001]	[0.0001]	[0.0001]
Manager		0.2527***	0.2469***
		[0.0224]	[0.0225]
Excellent, very good, good health		-0.1260***	-0.1215***
		[0.0328]	[0.0328]
>= 1 child below 11 years pf age		0.0216	0.0229
		[0.0270]	[0.0269]
Mother < ISCED 4		-0.0941*	-0.0919*
		[0.0435]	[0.0436]
Father < ISCED 4		-0.0065	-0.0098
		[0.0415]	[0.0417]
Both parents < ISCED 4		-0.0181	-0.0085
		[0.0554]	[0.0555]
Native born		-0.0441	-0.0589
		[0.0324]	[0.0328]
Ability			0.0007**
			[0.0002]
No. of obs.	3338	3309	3309
R-Squared	0.3351	0.3757	0.3782
Cycle FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes

Table A.1: **Returns to schooling in the unrestricted sample.** Note: *, **, and *** represent significance level at 10%, 5% and 1% confidence level, respectively. Robust standard errors are reported in brackets. The estimation sample includes all industry sectors. *Source: Authors' elaborations on PIAAC data.*

	log(monthly wages)	
	(i)	(ii)
Overskilled	0.0935***	0.0652**
	[0.0234]	[0.0227]
Underskilled	-0.0466	-0.0329
	[0.0257]	[0.0255]
Female	-0.2346***	-0.1897***
	[0.0264]	[0.0262]
Lower secondary education	0.1172	0.1188
	[0.0710]	[0.0649]
Upper secondary education	0.3113***	0.2669***
	[0.0714]	[0.0648]
Post secondary/tertiary education	0.5211***	0.4211***
	[0.0749]	[0.0683]
Age	0.0531***	0.0451***
	[0.0090]	[0.0088]
Age squared	-0.0005***	-0.0004***
	[0.0001]	[0.0001]
Manager		0.2876***
		[0.0224]
Excellent, very good, good health		-0.1306***
		[0.0330]
>= 1 child below 11 years of age		0.0149
		[0.0271]
Mother < ISCED 3-4		-0.1192**
		[0.0437]
Father < ISCED 3-4		-0.0414
		[0.0416]
Both parents < ISCED 3-4		0.0273
		[0.0560]
Native born		-0.0166
		[0.0328]
No. of obs.	3373	3343
R-Squared	0.3099	0.3619
Cycle FE	Yes	Yes
Sector FE	*Yes*	*Yes*

***Table A.2*: Returns to skills in the unrestricted sample.** Note: *, **, and *** represent significance level at 10%, 5% and 1% confidence level, respectively. Robust standard errors are reported in brackets. The estimation sample includes all industry sectors. *Source: Authors' elaborations on PIAAC data.*