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The return to education and skills in Italy

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Abstract

Purpose – The purpose of this paper is to estimate the incidence of educational mismatch in Italy and the return to investment in education, controlling for employees' ability. Contrary to most existing studies, the heterogeneity of individual performance is measured directly through the assessment of required and provided skills.

Design/methodology/approach – Based on original data including over 3,600 face-to-face interviews, this paper appraises the incidence of self-assessed educational mismatch in the Italian private sector and estimates wage models of the economic returns to educational mismatch, skill requirements and provided skills.

Findings – In Italy, under-educated employees outnumber over-educated ones and returns to required education and over-education are lower than in other industrialised countries. Individual heterogeneous ability, as captured by individual skills, is a significant determinant of wage, although the inclusion of direct measures of required and provided skills does not substantially affect the estimated coefficients of the return to investment in education.

Practical implications – The omission of controls for the heterogeneous ability of employees biases the results of traditional ordinary least squares (OLS) estimates of wage models. However, the bias may be small enough to make simple OLS estimates on existing cross-sectional data an acceptable compromise to provide policy makers with reasonably accurate and up-to-date information.

Originality/value – The paper provides a direct appreciation of individual heterogeneity that other studies can capture only through sophisticated indirect econometric techniques. In addition, the paper extends the set of available cross-country comparisons by estimating the educational mismatch and the returns to educational and skill mismatches in the overall Italian private labour market.

Keywords Italy, Skills, Education, Private sector organizations, Pay, Educational mismatch, Return to education, Return to skills, Empirical analysis

Paper type Research paper

1. Introduction

International data show that educational mismatch has long been endemic to the labour markets of industrialised countries. The debate dates back to the contribution by Freeman (1976), who discusses how the declining wage premium for US post-graduates in the 1970s could discourage investment in higher education. In the subsequent decades, over- and undereducation have been constant concerns for economists and policy makers. Overeducation signals an inefficient allocation of resources to the education system and potential frustration among affected employees, whereas undereducation threatens economic development. Appropriate policy measures may reduce the economic and social costs of educational mismatch, yet

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their effects still unfold in the long run, and their undesired outcomes are difficult to correct (Shaw, 1987).

Educational mismatch has gained renewed attention in recent years. On one hand, governments increasingly recognise citizens' education and lifelong learning as keys to economic growth and catch-up (European Commission (EC), 2010). On the other hand, increased off-shoring of high value-added jobs to newly industrialised countries (Lewin *et al.*, 2009) and signals of overeducation in fast-growing economies such as China (Yue and Yang, 2006) call into question the possibility that all qualified employees will find a job commensurate with their investment in education. At the same time, researchers have expressed increasing dissatisfaction with education as an appropriate measure of individual skills and potential productivity as education reflects, at best, the explicit and codified share of individual capabilities (Bauer, 2002; Green *et al.*, 2002; Wasmer *et al.*, 2005).

The identification of the causes of educational mismatch is a requirement to balance demand and supply in labour markets. This need is apparent in Italy, which has been characterised by the paradox of recurrent claims of insufficient graduates and the parallel "talent drain" of young professionals to foreign countries. Nonetheless, the return to education and the effects of educational mismatch in Italy have not been thoroughly examined, and the quantitative evidence for the overall national labour market remains limited (Brunello and Miniaci, 1999; Flabbi, 1999; Istat, 2005; Wasmer *et al.*, 2005; Brynin and Longhi, 2009; Cainarca and Sgobbi, 2009). An opportunity to fill this gap and extend the set of available cross-country comparisons was provided by the OAC archive[1] developed by Isfol, the Italian Institute for Vocational Education and Training (Tomassini, 2006). Based on subjective evaluations by employees, the data of the OAC archive permit the determination of both the incidence of educational mismatch in Italy and the return to investment in education. In addition, the OAC archive provides the opportunity to control for employees' ability as it includes several measures of required and provided skills. Consequently, OAC allows for direct appreciation of individual heterogeneity that other databases can capture only indirectly through sophisticated econometric techniques based on panel data (see, e.g. Abowd *et al.*, 1999; Guimarães and Portugal, 2009).

The OAC data show that the Italian case mirrors the general findings of the international literature: educational mismatch is a non-negligible phenomenon that significantly impacts the earnings of affected employees. However, the Italian case also presents important peculiarities: undereducation rates are higher than overeducation rates, and the economic return to investment in education is significantly lower in Italy compared to other industrialised countries. In addition, individual heterogeneous ability, as captured by individual skills, is a significant determinant of wage, although the inclusion of direct measures of required and provided skills does not substantially affect the estimated coefficients of the return to investment in education.

The remainder of this paper is divided into four sections. Section 2 surveys the international literature on educational mismatch and the main empirical problems of assessing the return to education. Section 3 presents the OAC archive, discusses the peculiarities of educational mismatch in Italy and outlines the empirical methodology followed to estimate the returns to education and skills for Italian employees. Section 4 presents the results of the empirical estimates and Section 5 summarises the main results and provides some concluding remarks.

2. Literature background

Educational mismatch can be assessed through subjective criteria based on self-assessment and through objective criteria based on the opinions of external observers. Subjective criteria ask an employee to quantify his or her own educational mismatch or to identify the qualifications required for effective performance in his or her job (Allen and van der Velden, 2005). In the latter case, educational mismatch is identified by comparing required and attained educational qualifications[2]. Objective criteria quantify the mismatch by comparing actual schooling with the educational attainment required for a similar job by job analysts or job directories, e.g. the UK Standard Occupational Classification or the US Dictionary of Occupational Titles. A more controversial measure is proposed by Verdugo and Verdugo (1989), who identify a mismatch when the attained education is more than one standard deviation above or below the mode of a sample of employees in the same job.

All of the above approaches present specific pros and cons (see Kiker *et al.*, 1997; Hartog, 2000; Allen and van der Velden, 2005), and the scientific community has not yet agreed upon any solution as superior. Hartog (2000) argues that objective criteria are "conceptually superior" (p. 133) because subjective criteria suffer from the risk of manipulation, whether voluntary or involuntary. However, the high measurement costs and the unavailability of reliable and up-to-date objective information make self-assessment a more viable option. In addition, self-assessment enables the inclusion of information that is otherwise inaccessible to an external observer and careful planning of data collection reduces the risk of manipulation (Allen and van der Velden, 2005).

Despite significant quantitative and qualitative differences in its form, educational mismatch has been identified in all industrialised countries[3]. A meta-analysis by Groot and Maassen van den Brink (2000) shows that, when measured according to subjective criteria based on skill requirements, overeducation affects on average 26.2 per cent of a nation's workforce, while 15.4 per cent are undereducated. Overeducation is always significantly higher in the USA, the UK and Canada (between 22 and 50 per cent) compared with Germany, the Netherlands and Spain (between 11 and 26 per cent). Undereducation, a much less investigated phenomenon compared to overeducation, is particularly high in Spain, where it affects an estimated 23 per cent of employees (Alba-Ramirez, 1993). A positive relation between experience, tenure, competence level and undereducation has often been reported, with opposite results in the case of overeducation[4] (Alba-Ramirez, 1993; Sloane *et al.*, 1999).

Several researchers have reported that overeducation is more common among early-career workers (Hartog, 2000), which is consistent with the hypothesis of educational mismatch as a transient disequilibrium between labour demand and supply that is solved when employers and employees acquire the information needed to optimise their matching. The theory of career mobility explains the higher occurrence of overeducation at entry into the labour market through the better promotion opportunities offered to overqualified people. The initial acceptance of a job with lower returns to the attained qualification represents a sort of investment in higher future earnings (Sicherman, 1991). However, empirical tests have mostly confuted the theory of career mobility (Büchel and Mertens, 2004). The persistence of overeducation and undereducation among older employees supports the hypotheses of heterogeneity among individuals with the same educational qualification (Green *et al.*, 2002) or malfunctioning of regulating mechanisms in labour markets.

The empirical tests of the return to educational mismatch are usually based on the ORU model (Over, Required and Undereducation) by Duncan and Hoffman (1981), which discriminates between the returns of required and attained qualifications. The model explains the natural logarithm of wage ($\ln w$) with the drivers of individual productivity, namely education and experience:

$$\ln w_i = \beta_0 + \beta_1 S_i^r + \beta_2 S_i^o + \beta_3 S_i^u + \beta_4 Exp_i + \beta_5 Exp_i^2 + X_i' \beta + \varepsilon_i \tag{1}$$

For each employee i, S^r is the educational qualification required by his or her job; S^o and S^u measure the extent of overeducation and undereducation, respectively; *Exp* appraises the employee's experience in the labour market; X is a vector of individual-specific and job-specific features; and ε is the error term. The ORU model collapses into the wage equation proposed by Mincer (1974) when $\beta_1 = \beta_2 = \beta_3$, i.e. when, reflecting the assumptions of the Human Capital Theory, labour is rewarded according to provided education (McGuinness, 2006).

The international literature usually recognises a significant and positive impact of required education (coefficient β_1 in Equation (1)). Overeducation is also rewarded by employers, yet the lower value usually assumed by coefficient β_2 compared to coefficient β_1 signals the penalisation of overqualified individuals compared with employees with the same educational attainment in an appropriate job. The negative sign usually displayed by coefficient β_3 signals the penalty suffered by undereducated employees compared to workers in similar jobs who hold the required qualification.

In recent years, researchers have reported increasing dissatisfaction with the ordinary least squares (OLS) estimates of the ORU model with cross-sectional data. First, the values estimated by OLS regressions may be biased due to self-selection among respondents (Heckman, 1979). Second, OLS estimates of ORU models have been proven to be biased and inconsistent due to the omission of regressors on the employee's ability, which makes the investment in education endogenous to the expected growth rate of earnings with education (Card, 1999).

One way to account for the effect of heterogeneous ability on wage is to use panel data in models with fixed individual effects. Bauer (2002) demonstrates that the impacts of overeducation and undereducation on wage shrink when individual heterogeneity is accounted for. Dolton and Silles (2008) use panel analysis to show that unobserved heterogeneous ability causes an upward bias in the return to overeducation in standard OLS estimates of ORU models. However, the authors also show that the upward bias is balanced by a similar downward bias caused by measurement errors.

While desirable, panel estimates are rare due to the paucity of suitable data. Among alternative solutions to the problem of endogeneity of education with wage, instrumental variables in two-step least square models have gained significant attention among researchers. Most studies instrument education with proxies of employees' family background, assuming that the latter affects schooling decisions but not individual ability (see, e.g. Brunello and Miniaci, 1999; Di Pietro and Urwin, 2006). However, since the seminal study by Coleman *et al.* (1966), this assumption has repeatedly been questioned by empirical studies. Given the difficulty of finding valid instruments (i.e. correlated with schooling but not with individual ability), some authors suggest that additional controls should be added to regressors in the wage function rather than used to instrument the variable(s) suspected of endogeneity (Flabbi, 1999).

A further source of criticism regarding the estimation of ORU wage equations is rooted in the awareness that years of schooling are at best a partial proxy for the effectiveness of provided skills and, consequently, for individual productivity (García-Aracil and van der Velden, 2008). Allen and van der Velden (2001), Green *et al.* (2002), Chevalier (2003), Green and McIntosh (2007), Robst (2008), Chevalier and Lindley (2009) and Green and Zhu (2010) question to various extents the "genuine" nature of education-based measures of skill mismatch. An apparent mismatch could result from a different distribution of either skills or individual preferences among employees with the same educational qualification (Robst, 2008). This stream of literature suggests that information on schooling should be complemented by additional measures of the effectiveness of the labour effort provided by employees, such as information on skill shortages and overskilling (Allen and van der Velden, 2001; Green and McIntosh, 2007; Green and Zhu, 2010) or information on employees' satisfaction about the match between their education and job (Chevalier, 2003; Chevalier and Lindley, 2009).

3. Data and methodology

In 2004, Isfol promoted a survey among the employees of Italian private firms[5] in order to explore the relation between labour organisation, education, training and skills (Tomassini, 2006). Over 3,600 people in paid jobs participated in one-hour face-to-face interviews with trained personnel in accordance with a Computer-Assisted Personal Interviewing technique. The resulting database provides information on the jobs of interviewed employees, the organisational models of their employers and the employees' skills, autonomy and training.

In order to gather information that would otherwise be inaccessible to an external observer (Allen and van der Velden, 2005), the Isfol survey prioritised data collection via self-assessment. The risk of biased answers typical of self-assessment was reduced by exploiting the experiences of other large-scale surveys, such as the periodical skills survey run in Britain by SKOPE (see Felstead *et al.*, 2002). The stratification strategy adopted by Isfol controls for gender, age group at the time of the interview, area of residence, type of occupation and employer sector of the interviewed workers. The interviewees were chosen from lists maintained by Istat for its periodical statistical survey on the Italian workforce. An *ex post* analysis performed by Isfol confirmed the alignment between OAC respondents and the corresponding participants in the Istat workforce survey (Centra and Falorsi, 2006). The *ex post* analysis also assigned a weight to each survey respondent to represent the whole Italian private sector. Table I reports some summary statistics for the examined universe.

The OAC database provides information on the attained educational level of employees, while the required qualification to get the current job is derived from the answer to the following question: "What educational qualification should be required if someone applied for your job?"[6] Educational mismatch, calculated as the gap between required and attained education, is consequently based on a subjective evaluation of skill requirements to get the examined job.

To assess educational mismatch in Italy, interviewed employees were classified as overeducated when their educational attainment on a five-level scale[7] was higher than the required attainment and as undereducated if their educational attainment was lower, all else matched. Descriptive statistics on educational mismatch in Italy are presented in Table II. The 68.8 per cent of matched employees is much higher than the 60 per cent average reported for other industrialised countries (Hartog, 2000).

Variable	Per cent
Education	
Primary school certificate	3.5
Compulsory school certificate	27.0
Vocational school certificate	18.2
High-school diploma	42.5
University graduates and post-graduates	8.8
Age group	
15-29	25.4
30-44	49.3
45-64	25.2
Gender	
Male	61.4
Female	38.6
Qualification	
Blue-collars	56.5
White-collars	36.5
Managers	7.0
Employment contract	
Part-time employment	12.5
Fixed-term employment	8.6
Firm size (employees)	
1-49	56.0
50-99	7.6
100-499	15.4
⩾500	14.8
na	6.2
Area of residence	
Northwest	34.6
Northeast	24.4
Centre	19.7
South	21.3
Total	100.00

Notes: Weighted data; observed universe: 9,182,953 employees

Table I.
Employment in the Italian private sector: descriptive statistics

Mismatch	Undereducation (%)	Match (%)	Overeducation (%)
Total	17.12	68.80	14.08
By gender			
Males	17.67	67.43	14.90
Females	16.25	70.99	12.76
By age group			
15-29 years old	11.66	69.31	19.03
30-44 years old	17.40	68.66	13.94
45-64 years old	22.08	68.57	9.35

Notes: Weighted data; observed universe: 9,182,953 employees

Table II.
Educational mismatch in Italy

The incidences of overeducation and undereducation significantly change with age, with overeducation prevailing among employees younger than 35 years. Nevertheless, the reported figures for every age group in Table II are about half as large as those reported by Dekker *et al.* (2002) in the case of the Netherlands based on a subjective criterion. The progressive shift from overeducation to matching and from matching to undereducation suggests that labour demand and supply adjust over time as training and experience support job enlargement and job enrichment processes. However, the non-negligible percentage of overeducated people among older employees (6.7 per cent over 55 years of age) shows that at least a share of overeducation is permanent rather than temporary in nature.

While confirming that overeducation in Italy is in line with the figures for continental Europe, the Isfol data show the prevalence of undereducation, which affects 17.1 per cent of employees, compared to overeducation (14.1 per cent)[8]. This pattern, which has been observed elsewhere only in the cases of Spain (Alba-Ramirez, 1993) and the Netherlands (Hartog and Oosterbeek, 1988), underlines the importance of testing the determinants of wage via an ORU specification, which separately identifies the impacts of required education, overeducation and undereducation. However, mainly due to the lack of suitable data, the existing estimates of the return to education for the overall Italian labour market do not separate the wage effect of required schooling from overeducation and undereducation (see, e.g. Brunello and Miniaci, 1999; Flabbi, 1999). It must also be noted that most of the existing analyses focus on the limited segment of the labour market for university graduates and post-graduates (see, e.g. Boero *et al.*, 2001; Checchi *et al.*, 2004; Di Pietro and Urwin, 2006; Cutillo and Di Pietro, 2006). Despite representing the most "valuable" share of the labour market, evidence on this segment cannot be extended to the whole national labour market due to the inclusion of only a small share of Italian employees (about 12 per cent) and to biases towards younger individuals and higher value-added jobs.

Besides allowing the estimation of ORU models by providing separate information on required education, overeducation and undereducation, the OAC archive also offers detailed information on job skill requirements as well as on the effectiveness of provided skills. With the aim of attenuating the endogeneity of the educational choice in the OLS estimate of the ORU model, the latter information was used to elaborate different proxies for employees' ability, which enter the wage equation as additional independent variables.

The assessment of individual skill requirements is based on six different self-reported measures of task variety and responsibility to which employees responded on a Likert scale ranging from 1 to 7. The diversification of skill requirements across jobs can be witnessed in the dispersion of the answers provided by survey participants. Only 38 per cent of employees recognised significant autonomy in task execution and scheduling, whereas slightly more than 30 per cent reported limited or very limited variety in their tasks.

Due to partial overlap in the analytical constructs and significant correlations among the observed measures, the original data were manipulated to provide a reduced number of immediately explainable measures. A factor analysis run on the six individual skill requirements outlined two main components, which jointly explain 71.25 per cent of the variance observed in the sample (Table III). The first component, which is positively correlated with the responsibility attached to the job, has been labelled "vertical scope" because it reflects the degree of vertical specialisation of the observed organisational roles (Mintzberg, 1979). The other component reflects the

Table III.
Vertical span and horizontal span

Original variables (answers on a 1-7 Likert scale)	Component Vertical scope	Horizontal scope
How do you rate your own decisional power?	0.671	0.336
What is your decision power over time and effort extent?	0.831	0.094
What is your decision power over tasks and task scheduling?	0.889	0.154
What is your decision power over task execution?	0.863	0.146
How often do you execute short and repetitive tasks?	−0.023	−0.891
How varied is your job?	0.365	0.711

Notes: Load factors from the rotated component matrix; extraction method: principal component analysis; rotation method: varimax with Kaiser normalization; 3,605 observations

variety of tasks in the employee's job and has consequently been labelled as "horizontal scope". The degrees of vertical and horizontal specialisation of a job proxy for required ability because roles characterised by higher responsibility and variety will presumably demand higher skills.

To assess the effectiveness of provided skills, the empirical analysis exploits self-evaluations of 44 tasks and organisational behaviours listed by the Isfol questionnaire. For each item relevant for their job, interviewees were asked to rate the frequency of their effective performance on a scale from 1 (seldom) to 7 (almost always). The accomplishment of those tasks requires both general and specific skills, which span from operational practices and techniques to physical capabilities, relationship management, planning and control, leadership and autonomy. Skill deficiency was often recognised by the interviewed employees. Only 31.2 per cent of the sample claimed that their performance in all of the organisational behaviours relevant for their jobs was "almost always", "quite often" or at least "often" effective.

A factor analysis run on the 44 variables accounting for organisational behaviours identified seven main components, which jointly explain 55.93 per cent of the variance observed in the sample[9]. As is apparent in Table IV, the seven components reflect the degrees of proficiency in different areas, including literacy and numeracy (Numeliteracy), working out viable solutions and establishing agreement (Proactivity), job-specific skills and techniques to complete the assigned tasks in a proper and timely manner (Reliability), counselling and advising capabilities (Consulting), working with other people (Teamwork), physical capabilities (Physical skills) and autonomous decision making (Autonomy).

The availability of skill assessments to gauge the otherwise unobserved heterogeneity in individual abilities represents a source of value added for our analysis. However, skill appraisal based on self-assessment by employees may introduce further endogeneity to the estimated wage equations. Satisfactory earnings may indeed induce the perception that one's skills fit with job requirements[10]. This risk is reduced by the survey design, which, contrary to other surveys (see, e.g. Allen and van der Velden, 2001; Wasmer *et al.*, 2005; Green and McIntosh, 2007; Green and Zhu, 2010), focuses the attention of interviewees on specific organisational behaviours rather than asking for overall assessments of individual overskilling or underskilling. The reference to "objective" job features such as decision power over task execution or frequency of short and repetitive tasks (Table III) limits the scope for instinctive rather than rational judgement in the assessment of required skills. In addition, the analysis

Table IV. Skill proficiency

Source variables	Numeliteracy	Proactivity	Reliability	Consulting	Teamwork	Physical skills	Autonomy
	Component						
Writing long documents in a correct way	0.666	0.254	−0.085	0.042	0.127	−0.021	0.160
Writing short information such as forms in a correct way	0.708	0.105	0.094	0.106	0.171	−0.185	0.178
Reading short documents such as short reports, letters or memos	0.712	0.217	0.170	0.142	0.196	−0.256	0.112
Reading long documents such as long reports, manuals, articles or books	0.726	0.259	0.035	0.120	0.181	−0.088	0.135
Reading written information such as forms notices or signs	0.626	0.088	0.267	0.129	0.148	−0.096	0.066
Using a computer, PC or other types of computerised equipment	0.629	0.172	0.230	0.139	0.030	−0.368	−0.045
Calculations using decimals, percentages or fractions	0.666	0.188	0.175	0.136	−0.061	−0.086	−0.073
Calculations using advanced mathematical or statistical procedures	0.672	0.252	0.111	0.077	−0.063	0.047	−0.096
Making speeches or presentations	0.392	0.386	−0.156	0.376	0.152	0.109	0.122
Analysing complex problems in depth	0.454	0.553	0.198	0.135	0.114	−0.002	0.045
Organising your own time	0.093	0.507	0.356	0.018	0.094	−0.282	0.214
Persuading or influencing others	0.219	0.495	−0.034	0.429	0.238	−0.006	0.123
Taking initiatives	0.176	0.668	0.188	0.208	0.139	−0.116	0.168
Knowledge of how your organisation works	0.254	0.349	0.264	0.228	0.288	−0.182	0.063
Thinking ahead	0.201	0.594	0.245	0.149	0.117	−0.214	0.080
Planning your own activities	0.184	0.600	0.305	0.057	0.093	−0.280	0.178
Planning the activities of others	0.250	0.627	−0.035	0.168	0.360	0.048	0.066
Managing difficult situations	0.197	0.490	0.362	0.211	0.114	−0.091	0.204
Thinking of solutions of problems or faults	0.271	0.579	0.387	0.159	0.132	−0.082	0.127
Strategic decision making	0.293	0.614	−0.073	0.279	0.090	0.161	0.024
Instructing, training or teaching people	0.228	0.519	0.049	0.113	0.417	0.186	0.007
Working out the causes of problems or faults	0.192	0.444	0.438	0.039	0.136	0.212	0.111

(*continued*)

Table IV.

Source variables	Component						
	Numeliteracy	Proactivity	Reliability	Consulting	Teamwork	Physical skills	Autonomy
Paying close attention to details	0.061	0.099	0.638	0.063	0.056	0.016	0.034
Assessing the correct execution of tasks	0.092	0.154	0.711	0.048	0.106	−0.093	0.074
Spotting problems or faults	0.210	0.351	0.589	0.014	0.126	0.001	−0.047
How to use or operate tools/equipment/machinery	0.139	−0.090	0.497	0.007	0.081	0.409	−0.001
Physical stamina	0.016	−0.072	0.488	0.114	0.262	0.158	0.344
Specialist knowledge or understanding	0.336	0.362	0.430	0.103	−0.036	0.084	0.108
Assessing the correct execution of tasks	0.140	0.260	0.698	0.055	0.039	−0.013	0.018
Reliability in task execution	−0.047	−0.084	0.625	0.057	0.089	−0.094	0.300
Respecting due dates	0.031	0.082	0.483	−0.057	0.107	0.100	0.228
Dealing with people	0.196	0.126	0.226	0.500	0.273	−0.309	0.080
Counselling, advising or caring for other people	0.399	0.413	−0.006	0.454	0.194	−0.007	0.070
Selling a product or service	0.053	0.177	−0.022	0.837	−0.039	−0.026	0.004
Knowledge of particular products or services	0.165	0.190	0.373	0.527	0.113	−0.070	0.024
Counselling, advising or caring for customers or clients	0.203	0.188	0.076	0.794	0.028	−0.077	0.049
Working with a team of people	0.086	0.211	0.162	0.053	0.753	0.100	0.046
Helping team members	0.076	0.218	0.205	0.047	0.772	0.120	−0.021
Listening carefully to colleagues	0.205	0.244	0.239	0.114	0.584	−0.143	0.031
Skill or accuracy in using hands or fingers	−0.261	−0.040	0.145	−0.127	0.060	0.716	0.049
Physical strength	−0.356	−0.025	0.014	−0.060	0.106	0.679	0.126
Working without directions or suggestions	0.046	0.191	0.160	0.022	−0.139	−0.008	0.690
Working hard also without supervision	0.066	0.141	0.261	0.048	0.127	0.146	0.587
Problem management and solving without assistance	0.263	0.353	0.174	0.121	0.083	−0.018	0.504

Notes: Load factors from the rotated component matrix; extraction method: principal component analysis; rotation method: varimax with Kaiser normalization; 3,561 observations of the correlation indices between the factors measuring individual skill requirements and the proxies for provided skills supports the reliability of the latter measures. Vertical scope and horizontal scope are positively and significantly correlated with all factors based on provided skills except for "physical skills", which display a significant and negative correlation with job requirements[11].

4. The returns to education and skills for employees in Italy

In line with the literature, all of the estimated ORU models use the log of the net hourly wage as the dependent variable (Table V). Besides avoiding biases due to differences in working hours, this choice improves the international comparability of the provided results.

Table VI presents the results of four different estimates of the ORU model. Model 1 includes only "traditional" human capital variables, while Model 2 adds controls for training experience, employee-specific[12] and job-specific variables, occupation and industry. Whereas Models 1 and 2 replicate the standard models tested in the empirical literature, Models 3 and 4 explicitly address the role of individual ability. In particular, Model 3 tests the return to skill requirements (job vertical and horizontal scope), while Model 4 assesses the return to the effectiveness of provided skills. In the latter estimate, the factor numeliteracy was excluded from the regressors due to the high correlation with the years of required education ($\rho = 0.491$, $p < 0.001$). The complete list of the regressors used to estimate the ORU models is provided in Table V[13].

The initial sample of 3,605 observations shrinks to 2,835 due to 587 missing observations on individual wages, 33 observations with null variance in the scores of provided skills and 201 partially overlapped missing observations on employer size. *T*-tests for independent samples confirm that this sub-sample still represents the reference universe along the stratification variables of age class, gender, geographical area, industry and occupation type. Also, when significant, the correlation coefficients among explanatory variables are always low enough to exclude biases due to multicollinearity. Similarly, no risk is apparent based on the values calculated for variance inflation factors.

As expected, the determinants of the hourly wage for Italian employees confirm the findings of the international literature on the significances and signs of the coefficients that appraise the return to human capital. In all models reported in Table VI, the negative coefficient of *Undereducation* reflects the penalty attached to not attaining the required qualification, while the positive coefficient of *Overeducation* signals the wage premium for the skills and capabilities provided by additional years of schooling. However, the value recognised for excess education is only partially acknowledged by employers: the coefficient of *Overeducation* varies between one-third (Models 1 and 4) and one-quarter (Model 2) of the estimates for the coefficient of *Required_Edu*.

Model 1, which includes among its regressors only human capital variables, allows the comparison of Italian data with international findings based on OLS estimates of ORU models. Although the signs and significances of the coefficients do not differ from international findings, our results suggest a reduced sensitivity of employees' wages to human capital. The average returns to an additional year of required education and overeducation are, respectively, 5.9 and 1.8 per cent, compared to 12 and 4.7 per cent estimated by Groot and Maassen van den Brink (2000) for self-reported educational requirements. On the contrary, our estimate of the wage penalty corresponding to each year of undereducation almost matches the 3 per cent assessed by Groot and Maassen van den Brink[14]. In line with the study by Brynin and Longhi (2009), our results show

Table V.
The variables in the econometric estimates

	Description	No of observations	μ	σ
Dependent variable				
Ln w	Natural log of the net hourly wage in €	3,018	1.949	0.352
Explanatory variables				
Human capital				
Required_Edu	Years of required education	3,605	12.296	3.480
Overeducation	Years of education above the required level	3,605	0.547	1.469
Undereducation	Years of education below the required level	3,605	0.799	1.773
Experience	Years in the labour market	3,605	17.194	10.479
Empl_training	Years of training with the current employer	3,605	0.148	0.485
Ability				
Vert_scope	Degree of vertical scope	3,605	0.000	1.000
Hor_scope	Degree of horizontal scope	3,605	0.000	1.000
Proactivity	Effectiveness in pro-activity	3,561	0.000	1.000
Reliability	Effectiveness in task reliability	3,561	0.000	1.000
Consulting	Effectiveness in consulting	3,561	0.000	1.000
Teamwork	Effectiveness in team working	3,561	0.000	1.000
Physical skills	Effectiveness in physical skills	3,561	0.000	1.000
Autonomy	Effectiveness in autonomy	3,561	0.000	1.000
Employee and job				
Gender	= 1 for females	3,605	0.375	0.484
Part_time	= 1 for part-time contracts	3,605	0.120	0.325
Temp	= 1 for temporary contracts	3,605	0.090	0.287
LnSize	Natural log of firm employees	3,605	0.068	0.251
North_West (baseline)	= 1 for localisation in northwest Italy	3,403	0.232	0.482
North_East	= 1 for localisation in northeast Italy	3,605	0.265	0.441
Centre	= 1 for localisation in Centre Italy	3,605	0.282	0.450
South	= 1 for localisation in South Italy	3,605	0.221	0.415
Occupation				
Managers	= 1 for managers and administrators	3,605	0.178	0.383
Professionals	= 1 for professional occupations	3,605	0.031	0.174
Associate professor	= 1 for associate professor and technical occupations	3,605	0.083	0.276
Skilled trades	= 1 for craft and related occupations	3,605	0.124	0.330
Personal services	= 1 for personal service occupations	3,605	0.264	0.441
Administrative	= 1 for administrative and secretarial occupations	3,605	0.007	0.083
Sales	= 1 for sales occupations	3,605	0.070	0.256
Plant&Machine	= 1 for plant and machine operatives	3,605	0.143	0.350
Elementary (baseline)	= 1 for elementary occupations	3,605	0.099	0.299
Industry				
Traditional mfg	= 1 for traditional manufacturing	3,605	0.162	0.368
Scale intensive mfg	= 1 scale intensive manufacturing	3,605	0.142	0.349
Science-based mfg	= 1 for science-based manufacturing	3,605	0.115	0.319
Hotels and restaurants	= 1 for hotels and restaurants	3,605	0.047	0.211
Transport	= 1 for transport and warehousing	3,605	0.079	0.269
Communications&ICT	= 1 for communications and ICTs	3,605	0.082	0.274
Finance&Insurance	= 1 for financial and insurance services	3,605	0.095	0.293
Others	= 1 professional, scientific and tech services, real estates, rental and leasing	3,605	0.103	0.304
Trade (baseline)	= 1 for wholesale and retail trade	3,605	0.177	0.381

	Model 1		Model 2		Model 3		Model 4	
	β	SE	β	SE	β	SE	β	SE
Constant	0.9710	0.0254***	1.2270	0.0329***	1.2548	0.0331***	1.2515	0.0331***
Required_Edu	0.0587	0.0017***	0.0334	0.0021***	0.0314	0.0021***	0.0308	0.0021***
Overeducation	0.0181	0.0036***	0.0089	0.0034***	0.0087	0.0033***	0.0095	0.0033***
Undereducation	−0.0275	0.0032***	−0.0185	0.0030***	−0.0184	0.0029***	−0.0176	0.0029***
Experience	0.0223	0.0017***	0.0146	0.0016***	0.0140	0.0016***	0.0145	0.0016***
Experience^2	−0.0003	0.0000***	−0.0002	0.0000***	−0.0002	0.0000***	−0.0002	0.0000***
Empl_training			0.0289	0.0099***	0.0114	0.0050**	0.0186	0.0099*
Vert_scope					0.0236	0.0100***		
Hor_scope					0.0301	0.0052**		
Proactivity							0.0421	0.0054***
Reliability							−0.0065	0.0047
Consulting							0.0195	0.0055***
Teamwork							0.0018	0.0048
Physical skills							−0.0084	0.0054
Autonomy							0.0059	0.0048
Gender			−0.0862	0.0114***	−0.0788	0.0115***	−0.0740	0.0115***
Part_time			0.1294	0.0288***	0.1300	0.0286***	0.1358	0.0284***
Gender × Part_time			−0.0472	0.0331	−0.0478	0.0329	−0.0500	0.0326
Temp			−0.0922	0.0198***	−0.0888	0.0197***	−0.0794	0.0197***
LnSize			0.0102	0.0021***	0.0119	0.0021***	0.0129	0.0021***
North_East[a]			0.0239	0.0126**	0.0208	0.0125*	0.0230	0.0125*
Centre[a]			−0.0030	0.0135	−0.0018	0.0135	−0.0024	0.0134
South[a]			−0.0515	0.0134***	−0.0472	0.0134***	−0.0536	0.0134***
Managers[b]			0.3567	0.0214***	0.3374	0.0216***	0.3153	0.0219***
Professionals[b]			0.2294	0.0335***	0.2131	0.0335***	0.2192	0.0333***
Associate professor[b]			0.1815	0.0239***	0.1677	0.0239***	0.1580	0.0242***
Skilled_trades[b]			0.0176	0.0203	0.0153	0.0203	0.0275	0.0205
Administrative[b]			0.0652	0.0193***	0.0579	0.0193***	0.0592	0.0196***
Personal services[b]			0.0062	0.0595	−0.0026	0.0592	−0.0230	0.0605
Sales[b]			0.0107	0.0248*	0.0101	0.0247	−0.0109	0.0256
Plant&Machine[b]			0.0378	0.0200	0.0465	0.0199**	0.0524	0.0200***
Industry dummies	No		Yes		Yes		Yes	
Adjusted R^2	0.377		0.519		0.524		0.530	
F-test	366.162***		103.876***		99.633***		89.696***	

Notes: Dependent variable: Ln w; OLS regressions; [a]Baseline: Northwest Italy; [b]Baseline: elementary jobs; 2,835 observations; $***p<1\%$, $**p<5\%$, $*p<10\%$

Table VI. Wage determinants for private sector employees in Italy

more prudent behaviour by Italian employers in acknowledging the value of human capital. This evidence extends to ORU models the results of past studies of the Italian case that did not discriminate between required and supplied educational qualifications (Brunello and Miniaci, 1999; Flabbi, 1999).

The addition of employee-specific, firm-specific and job-specific explanatory variables to the basic model proved useful for increasing the explanatory power of the econometric estimate: the adjusted R^2 increases from 0.377 in Model 1 to 0.519 in Model 2. The additional explanatory variables partly capture the heterogeneity of observed individuals, as evidenced by the sizeable reductions in the coefficients of human capital variables (McGuinness, 2006). Controls for gender, occupation, firm size and employer location reflect expectations based on the existing literature. The positive, albeit declining, return to labour market experience supports the hypothesis of substitutability between on-the-job experience and formal education. Formal training with the current employer has a positive and significant impact on earnings. However, when training after entry in the labour market substitutes for training with the current employer, the regressor coefficient is no longer statistically significant. In line with the recent results by Brunello *et al.* (2010), this finding suggests that employers are willing to reward training efforts only when they target firm-specific needs.

Whereas part-time contracts are beneficial for employees' hourly wage, a large penalty (over 9 per cent in Model 2) is associated with being on a temporary contract. This finding suggests that temporary work not only limits the time span of individual projects but also involves a real earnings penalty.

The estimates of Models 3 and 4 show that individual heterogeneous ability, as captured by individual skills, is a significant determinant of individual wages, yet its quantitative impact is negligible. This result is supported by the small value of the significant coefficients of skill proxies and by the tiny increase in the adjusted R^2 compared to Model 2. In particular, Model 3 shows that after controlling for occupation, gender, industry and employer size and location, individuals whose vertical scope is one standard deviation above the average enjoy a small wage premium of 2.4 per cent, while the corresponding return for horizontal scope amounts to a (less significant) 3 per cent. When individual heterogeneity is proxied for by the effectiveness of provided skills (Model 4), our results show similarly small impacts of proactivity and consulting capabilities, whereas the remaining competence areas have no significant impact on earnings.

The overall picture sketched by Models 3 and 4 outlines a conservative approach taken by Italian employers in valuing the skills of their employees. Given the higher values taken on average by the empirical measures of required education and experience compared to the measures of employee ability (Table V), the former variables overcome by large the impact of individual skills, measured as either job requirements (Model 3) or effectiveness in task performance (Model 4). In addition, the comparability between the coefficients of *Undereducation* and *Experience* suggests that, especially in the presence of qualification inflation or grade drift, learning on the job can compensate for entry into the labour market with lower than required educational attainment and provides older employees with capabilities comparable to those of more educated new entrants into the labour market.

The comparison between Model 2 and Models 3 and 4 shows that the addition of measures for individual skills leaves the coefficients of control variables substantially unchanged, with the noticeable exceptions of *Empl_training*, *Gender* and *Temp*. When accounting for individual skills, the impact of training with the current employer halves in size and decreases in significance. This piece of evidence highlights a significant correlation between skills and training. The higher wage of employees targeted by training efforts is largely explained by their better skills, which arguably increased thanks to focused employer-specific training. At the same time, the lower penalties suffered by female and temporary workers when accounting for their skill levels suggests that a sizeable share of their disadvantage depends on the poorer skills of these "weaker" categories of workers. From this point of view, training policies focused on better-endowed employees may risk segregating less skilled individuals to lower career profiles.

5. Concluding remarks

The OAC archive allowed assessment of the incidence of educational mismatch in the Italian private sector and appreciation of the economic returns to educational and skill mismatch. The Italian case presents some peculiarities compared to other industrialised countries. Contrary to most of the international evidence based on self-assessment, the OAC database shows a higher incidence of undereducation compared to overeducation. Nevertheless, matching levels are sensibly higher than those reported in the international literature. Italy displays lower returns to required education and overeducation, suggesting that social, contractual and institutional factors constrain wage bargaining in Italy to a larger extent than they do in other countries. The direct measures of individual ability allowed for by the OAC data show a significant correlation between individual ability and wage. Responsibility and task variety are associated with higher wages after controlling for individual, job and employer characteristics. Individual effectiveness has a positive impact on earnings, although it is significant only when better performance involves proactive behaviour or consulting capabilities. However, the economic returns to both required and provided skills are quite small. The addition of proxies for individual ability does not change the significances or the signs of human capital determinants and causes only a minor reduction in their coefficients. This result suggests that the OLS estimates of traditional ORU models are surely biased due to the omission of controls for the heterogeneous ability of employees. However, the bias may be small enough to make simple OLS estimates on available cross-sectional data an acceptable compromise to provide policy makers with reasonably accurate and up-to-date information.

Our empirical analysis outlines some potential weaknesses of the Italian private industry. The large share of undereducated employees who compensate for their lack of education with experience and a parsimonious resort to training highlight the risk of the obsolescence of available skills, especially if the evolution of the competitive environment forces a move away from an incremental approach to innovation and workplace change. The penalisation of temporary and female employment also stresses the risk that Italian employers may disregard the potential contributions of all participants in the labour market. In addition, the comparably low returns to investment in education and skills provide low incentives for the development of a polyvalent workforce apt at learning and coping with change.

The picture presented by the OAC data fits with the results proposed by Naticchione and Ricci (2008), who argue that the decreasing wage inequality recently observed in the Italian labour market is due to the slower rate of adoption of new technologies by Italian firms, which has resulted in declining educational wage premia and increasing segregation of educated employees to low value-added jobs. This interpretation reduces the emphasis on the increase in the number of highly educated employees that has often been stressed by EU policy makers since the Bologna Declaration on the European space for higher education and highlights the need for coordinated intervention on both sides of the labour market. Educational and skill mismatches can be solved by further investment in the education and training of citizens, by increasing the selectivity of access to higher education, by channelling students towards educational paths that meet employers' expectations, by encouraging firms to invest in skill-intensive innovation, or, more sensibly, by a careful balance of the above tools.

Notes

1. OAC is the acronym for *Organizzazione*, *Apprendimento*, *Competenze* (Organisation, Learning, Competences).
2. It must be noted that required education can be specified either for new entrants (skill requirements "to get" the job) or for incumbent employees (skill utilisation "to do" the job).

3. Despite the comparatively low correlation between overeducation and undereducation levels measured according to different criteria, the literature reports no systematic biases in the estimates of their economic returns (Groot and Maassen van den Brink, 2000; McGuinness, 2006).

4. According to Sloane *et al.* (1999), 10 per cent of employees with less than two years of experience are undereducated, whereas the same figure is 24 per cent among employees with over 20 years of experience. In contrast, overeducation affects 43 per cent of employees with less than two years of seniority in the labour market and drops to 25 per cent for employees with over 20 years of experience.

5. The survey did not include employees in mining, agriculture and personal services.

6. Possible answers included: primary school certificate; compulsory education certificate; compulsory education plus one-year vocational school certificate; compulsory education plus two-year vocational school certificate; compulsory education plus three-year vocational school certificate; secondary school diploma from a technical high school; secondary school diploma from a lyceum; bachelor's or master's degree; bachelor's or master's degree plus one-year specialisation; bachelor's or master's degree plus two-year specialisation; PhD degree.

7. Following the international literature, the five educational levels considered in this analysis are as follows: compulsory school certificate, vocational school certificate, high school diploma, university graduate diploma and university post-graduate diploma.

8. This result contrasts with the evidence reported by Istat (2005) based on an objective criterion that crosses the Isco-88 classification of jobs with the Isced-97 classification of educational qualifications. According to this approach, Istat reports 16.5 per cent overeducation and 9 per cent undereducation among Italian employees (entrepreneurs, managers and military professionals excluded).

9. In most cases, only a subset of listed tasks was reported to be relevant for the jobs performed by interviewed employees. Because factor analysis excludes observations with missing values, the value 0 was assigned to non-rated skills.

10. The reliability of the data were increased by deleting the 33 observations with null variance in the score given to all relevant skills. Null variance was interpreted as a signal of low accuracy and commitment by questionnaire respondents.

11. Positive self-evaluation may also stem from satisfaction with working conditions or personal relationships in the workplace. However, the inclusion of a control for employee commitment based on agreement with the statement "I'm proud of my job" does not appreciably change the coefficients of the other regressors in the estimated wage equations.

12. The employee's age at the time of the interview was excluded from the empirical analysis due to the very high correlation with the overall working experience ($\rho = 0.858$, $p < 0.001$).

13. Despite the selective nature of the OAC sample, which does not fully reflect the characteristics of the observed population, the estimated regressions use unweighted observations. A set of Hausman tests, as suggested by Pfeffermann (1993), proved the consistency of unweighted compared to weighted coefficients for the models estimated in Table VI (for Model 1, $\chi^2_6 = 1.673$; for Model 2, $\chi^2_{31} = 1.804$; for Model 3, $\chi^2_{33} = 4.024$; and for Model 4, $\chi^2_{37} = 2.596$).

14. Groot and Maassen van den Brink (2000) estimate the return to an additional year of required education in the 1990s to be 12 per cent, compared to the smaller value of 7.9 per cent for the 1970s and the 1980s. Their estimate of the return to undereducation also changes in time, from -4.9 per cent before the 1990s to -3 per cent in the following ten years.

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