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RESEARCH PAPER

The Effect of Job–Education Vertical Mismatch on Wages Among Recent PhD Graduates: Evidence From an Instrumental Variable Analysis

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Abstract
Existing studies suggest that recent PhD graduates with a job vertically mismatched with their education tend to earn lower wages than their matched counterparts. However, by being based on cross-sectional ordinary least squares (OLS) estimates, these studies raise endogeneity concerns and can only be considered evidence of a correlation between vertical mismatch and wages. This paper improves this literature by applying a heteroskedasticity-based instrumental variable estimation approach to analyzing Italian PhD holders' cross-sectional micro-data. Our analysis suggests that previous empirical studies have provided slightly upward estimates of the impact of vertical mismatch on wages. Nevertheless, our results show that the effect of overeducation on wages is sizeable. However, no wage effect is found for overskilling. The heterogeneity of these findings by field of study and gender are also inspected.

Keywords Job-education mismatch · Overeducation · Overskilling · Wage penalty · PhD graduates · Heteroskedasticity-based internally generated instruments

JEL Codes C26 · I23 · I26 · J13 · J24 · J2

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1 Introduction

Over recent years, the remarkable proliferation of PhD education (Auriol et al. 2013; OECD 2016) and the subsequent increase of doctorate holders looking for jobs in non-academic sectors have raised significant concerns in most OECD countries regarding doctoral graduates' occupational outcomes (Benito and Romera 2013; The Economist 2016).

Many country-level empirical studies have highlighted that, a few years after graduation, a large proportion of PhD holders report vertical job–education mismatch.[1] Such a vertical mismatch is defined as overeducation, i.e. holding a job not in line with having a PhD, or overskilling, i.e. misalignment between the skills acquired during the PhD and those used at work.

To the best of our knowledge, limited data availability restricts evidence regarding this phenomenon to early-career PhD holders. Among this early-career population, experiencing vertical mismatch seems to have several negative impacts. For example, vertically mismatched PhD holders seem to report lower earnings than their matched counterparts, as recent contributions have demonstrated. Bender and Heywood (2009) revealed that, among US PhD holders, the detrimental effect of overeducation on wages ranges between 7 and 14%, depending on the study field. Examining Spanish data, Canal Domınguez and Rodrıguez Gutierrez (2013) showed that overeducated doctorate holders working in the non-academic sector experience a wage penalty that varies between − 18 and − 25%. Gaeta et al. (2017) suggested that the gap between wages for those overeducated and those earned by their matched counterparts ranges from − 7 to − 11% in Italy.

Empirical studies have suffered from the absence of longitudinal data, with very few exceptions (Carroll and Tani 2013). These empirical studies have all been based on cross-sectional estimates of a Mincer equation whose right side includes one measure of overeducation (and/or overskilling). As noted by the extensive literature focused on university graduates (for a comprehensive review, see McGuinness and Bennett 2007; Hartog 2000), the cross-sectional nature of these studies prevents the identification of any causal effect of overeducation/overskilling on wages (Leuven and Oosterbeek 2011). The reason lies in the potential endogeneity of the overeducation/overskilling variables in relation to the vertical mismatch status. On the one hand, the mismatch is "measured as a difference between two possibly mis-measured schooling levels [and this] leads to exacerbation of measurement error problems" (Leuven and Oosterbeek 2011, p. 306). This is particularly problematic when one relies on self-reported measures of vertical mismatch, as is often the case because most of the existing data do not include any objective mismatch indicators.

On the other hand, the apparent impact of overeducation/overskilling on earnings may be spurious and driven by unobserved ability heterogeneity (Pecoraro 2014; Sloane 2003). In addition, one might suspect that reverse causality is at work when one studies the link between vertical mismatch and wages. Indeed, low wages might

[1] For studies on Italy, see Gaeta (2015) and Ermini et al. (2019); for evidence concerning Spain, see Di Paolo and Mane (2016); for data concerning the US, see Bender and Heywood (2009).

be a source of low job satisfaction, and this might trigger negative evaluation of the usefulness of the educational level achieved and the related skills.

In our view, providing robust evidence regarding the effect that vertical job–education mismatch has on earnings is particularly important. Indeed, the existence of any impact of overeducation (overskilling) on wages would lead to substantial private costs (besides societal ones). The presence and magnitude of these private costs might translate into people's reconsideration of investment in education, i.e. disincentivizing future generations' investment (Tsang and Levin 1985). In this scenario, evidence regarding private costs would require policies to promote job–education vertical matching acting on the demand or the supply side of the job market.

The literature seems to be conscious of the importance of robust and reliable estimates of the wage penalty determined by the vertical mismatch. Indeed, many recent papers investigating the case of university graduates have provided analyses specifically aimed at overcoming the endogeneity issue reported so far (see, for example, Clark et al. 2017; Kleibrink 2016; Nieto and Ramos 2017).

To the best of our knowledge, however, the existing literature on vertical mismatch and associated wage penalties among PhD holders has not tackled the endogeneity issue adequately. Nevertheless, there are reasons to believe that providing robust evidence concerning the impact of job–education mismatch on wages among PhD holders is of tremendous importance. Indeed, while doctoral education and its focus on acquiring R&D skills are considered crucial in current knowledge societies (Shin et al. 2018), overeducation and overskilling seem to be widespread among PhD holders, as noted above. This calls for an investigation of the private costs related to this mismatch that can go beyond the correlational studies, *ceteris paribus*, provided by the literature so far (Bender and Heywood 2009; Canal Domınguez and Rodrıguez Gutierrez 2013; Gaeta et al. 2017). The objective of such an investigation would be to understand whether any detrimental effect of this mismatch on private returns actually exists and, therefore, whether policies are needed to support doctoral studies' expected private benefits.

Our analysis considers the case of PhD holders who have studied in Italy, a country characterized by low investment in R&D[2] where, as a consequence, the non-academic occupational opportunities for PhD holders—who are specialized in R&D—seem to be limited. Not surprisingly, the vertical mismatch between job and education is relatively frequent (Gaeta 2015; Ermini et al. 2019). Our analysis is based on a rich micro-level dataset created by the Italian National Institute of Statistics (ISTAT) that allows observation of PhD holders' occupational outcomes a few years after graduation.

Our investigation of the impact of job–education matching on wages tackles the endogeneity issue by using the instrumental variable (IV) identification strategy proposed by Lewbel (2012, 2018). This strategy has been designed to be "used in applications where other sources of identification such as instrumental variables (…) are not available" (Lewbel 2012, p. 1) and has been widely used (see, for example,

[2] See the data published by the OECD at https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm (accessed May 10, 2021).

Dutta and Roy 2016; Loy et al. 2016; Tiefenbach and Kohlbacher 2015). Such a strategy is based on building a synthetic IV as a function of the available exogenous heteroskedastic covariates (Lewbel 2012).

To the best of our knowledge, this is the first study to apply this empirical strategy in studying the effect of overeducation (overskilling) on wages among PhD holders. The use of this econometric technique is particularly appropriate for our study because of the unavailability of longitudinal data on PhD holders' occupational outcomes and the difficulty in finding variables that can be used as reliable instruments for vertical mismatch, as noted in previous contributions (Gaeta et al. 2017).

Besides addressing the endogeneity issues that have hampered previous analyses of the impact of job–education vertical mismatch on wages, this paper also offers interesting insights into this effect's heterogeneity. We provide evidence that the wage penalty for vertical mismatch varies between 2009 (when a severe economic crisis hit Italy) and 2018, as well as by the field of doctoral study, gender, and place of residence.

The remainder of the paper is organized as follows. Section 2 extensively describes the data used in the analysis. Section 3 presents and discusses the endogeneity issues that need to be addressed when estimating the impact of vertical job–education mismatch on wages and also illustrates Lewbel's IV empirical strategy implemented in our study. Section 4 details our results. Finally, Sect. 5 provides conclusions.

2 Data and Variables

Limited information on PhD holders' occupational outcomes is a significant issue for scholars and policy-makers aiming to study the incidence and effect of vertical mismatch among these workers. Indeed, while many longitudinal datasets allow monitoring the occupational outcomes of university graduates, to date, the only existing data regarding doctorate holders are cross-sectional.

Our elaborations are based on the publicly available repeated cross-sectional survey data collected by ISTAT through surveys of PhD holders. These surveys have been designed to track doctoral graduates' occupational outcomes a few years after completing their studies.

The first ISTAT cross-sectional survey considered by our study was carried out in 2009. Two cohorts of PhD holders were involved: those who completed their doctoral studies in 2004; and those who finished in 2006. Approximately 50% of the entire PhD holder population participated in the survey. A total of 8814 questionnaires were collected: 3928 for the 2004 cohort; and 4886 for the 2006 cohort.

The second ISTAT cross-sectional survey considered by our study was carried out in 2018, involving PhD holders who graduated in 2012 and 2014. Approximately 72% of the PhD holder population in the two selected cohorts that participated in the survey. A total of 16,057 questionnaires were collected: 8172 for the 2012 cohort; and 7885 for the 2014 cohort.

In 2014, ISTAT administered another cross-sectional survey, covering PhD holders who graduated in 2008 and 2010. Unfortunately, this survey was not helpful for our study because of many missing values (approximately 30% of the observations) reported for the wage variable, which is essential for our research.

Focusing on the 2009 and the 2018 survey data allows us to compare our results with previous studies that used the same information. At the same time, it enables us to compare the wage penalty effect of vertical mismatch observed in times of economic crisis,[3] when it is supposed to be higher (Croce and Ghignoni 2012), with the one reported a few years later (in 2018).

Our analysis focuses on PhD graduates who declared that they had a job at the time of the interview, since they are the only ones reporting wages. In the 2009 survey, 93.05% of respondents reported having a job. Data collected in 2018 show a slightly lower percentage of unemployment (6%). Overall, such unemployment figures are lower than those reported in Italy by university graduates a few years after the completion of their studies.[4]

The variables included in the analysis are described in Table 1, while summary statistics are reported in Table 2. Wages are measured by considering the log of the net hourly wage declared by respondents (*LNHWAGE*). In the 2009 survey, the average net monthly salary was approximately €1,541, and the average net hourly wage was approximately €11. In the most recent edition, the average net monthly salary was about € 1,941, and the average net hourly wage was approximately €15.

The main explanatory variables included in our empirical analysis measure respondents' vertical mismatch in terms of overeducation and overskilling.

Question number 2.33 in the 2009 ISTAT survey asked respondents to assess the usefulness of their PhD in obtaining the job they held at the time; specifically, this question asked: "*To get your current job, was your PhD (i) explicitly required, (ii) not required but useful; (iii) it had no relevance*".[5] Respondents were asked to pick one option. Starting from the answers to this question, we built a binary variable that takes the value of 1 if a PhD was neither required nor helpful in obtaining their job (option iii in the survey question) and zero otherwise.

The 2018 ISTAT survey presented a slightly different version of this question. Specifically, question 2.41 asked: *"Was the PhD explicitly required to get your current job?*" Possible answers were: "*(i) Yes it was explicitly required and useful*;" "*(ii) Yes it was explicitly required but turned out to be not useful*; "*(iii) No, it was not explicitly required but it turned out to be useful*;" and "*(iv) No, it was not required and not useful.*"[6] Starting from the replies to this question, we built a binary variable

[3] In 2009, when the first cross-sectional survey was administered, Italy was experiencing particularly turbulent economic conditions. As is well known, the country was affected by a severe economic crisis from 2007 until 2013, with economic recession reported from the second quarter (Q2) of 2008 until Q2 2009, from Q3 2011 until Q3 2013, and from Q1 2014 until Q4 2014.

[4] See, for example, the university graduates' unemployment figures collected by ISTAT in 2011 examining those who completed their studies in 2007. Data are available at https://www.istat.it/it/files//2012/06/Statistica_report_laureati.pdf (accessed on May 10, 2021).

[5] The exact Italian wording of this question is: "*Per accedere al suo attuale lavoro, il titolo di dottore di ricerca era espressamente richiesto, non era richiesto ma è stato utile o non ha avuto alcuna rilevanza?*".

[6] The exact Italian wording of the question is: "*Il dottorato era espressamente richiesto per accedere alla sua attuale attività lavorativa?*" The exact Italian wording of possible replies is: "*(i) sì, era espressamente richiesto ed è stato utile*;" "*(ii) sì, era espressamente richiesto ma non è stato utile*;" "*(iii) no, non era richiesto ma è stato utile*;" and "*(iv) no, non era richiesto e non è stato utile.*".

Table 1 Description of variables

Variable group	Variable label	Variable description
DEP. VARIABLE	LNWAGE	Natural logarithm of hourly net income
MAIN	OVEREDUCATION	1 = PhD was not required nor useful to obtain the current job
	OVERSKILLING	1 = Are you satisfied of your job 0 otherwise
SOCIO- DEMOGRAPHIC	AGE: LESS THAN 30§	1 = Ph.D. achieved at less than 30
	AGE: 30 YEARS	1 = Ph.D. achieved at 30
	AGE: 31 YEARS	1 = Ph.D. achieved at 31
	AGE: 32 YEARS	1 = Ph.D. achieved at: 32
	AGE: 33 AND MORE	1 = Ph.D. achieved at 33 or more
	FEMALE	1 = Female
	MARRIED	1 = Married
	CHILDREN	1 = has at least one child
STUDY FIELD		
Physics and Engineering + Life Science	MATH and STATISTICS	1 = Math or Statistics was the Ph.D. field of study
	PHYSICS and ASTRONOMY	1 = Physics and Astronomy
	EARTH and ENVIR. SC	1 = Earth and environmental sciences
	CHEMISTRY	1 = Chemistry
	BIOLOGICAL SCIENCE	1 = Biological Science
	MEDICAL SCIENCE	1 = Medical Science
	AGRIC. and VETERINARY	1 = Agriculture and Veterinary
	ARCHITECTURE	1 = Architecture
	ENGINEERING SCIENCE	1 = Engineering

Table 1 (continued)

Variable group	Variable label	Variable description
Social Sciences and Humanities	HUMAN SCIENCE	1 = Human Sciences
	HISTORY and PHILOSOPHY	1 = History and Philosophy
	LAW	1 = Law
	ECONOMICS and STATISTICS	1 = Economics and Statistics
	POLITICAL SCIENCE§	1 = Political Science
	OTHERFINIMP	1 = Financial aid other than grant was used in order to complete the Ph.D
	TAUGHT	1 = taught courses during Ph.D
	GRANT	1 = Grant received during Ph.D
	EXTENSION	1 = time extension needed to conclude Ph.D
	2004§	1 = Ph.D. earned in 2004
	2006	1 = Ph.D. earned n 2006
EDUCATIONAL	FROMDTOPHD	Number of years between MA degree and Ph.D
	DEGREESCORE	= 1 if degree score from 66 to 90
PERFORMANCES		= 2 if degree score from 91 to 100
BEFORE PHD		= 3 if degree score from 101 to 105
		= 4 if degree score from 106 to 109
		= 5 if degree score from 110

Table 1 (continued)

Variable group	Variable label	Variable description
JOB FEATURES	SELFEMPLOYED	1 = Self-employed
	PRODUCTS	Number of products (publications, patent) after Ph.D. completion
	PERMANENT	1 = current job is permanent
	ACADEMY	1 = current employer is University
	AGRICULTURE	1 = Agriculture is job sector: is current job sector
	MANUFACTURE	1 = Manufacture is current job sector
	MIGRANT	1 = moved to a different province from Ph.D
	PARTTIME	1 = part time job
	TEACHING	1 = teaches university courses
	WKEXPYR	Number of years of work experience after Ph.D
	RD = Partially RD	1 = current job is partially focused on R&D
	RD = NOT AT ALL§	1 = current job is does not include R&D at all
	RD = ONLY RD	1 = current job is entirely focused on R&D
	PhDnetwork	1 = Someone met during your Ph.D. support you to find out current job
	OTHERNETWORK	1 = Someone (do you not meet during your Ph.D.) support you to find out current job
MACRO-REGION	NORTHWEST	1 = lives in the NW
OF RESIDENCE	NORTEAST	1 = lives in the NE
	CENTER	1 = lives in the Center
	SOUTH	1 = lives in the South
	ABROAD§	1 = lives in abroad

§Indicates reference categories in regression analyses excluded to avoid perfect collinearity

Table 2 Descriptive statistics

Variable	Survey 2004–2006					Survey 2012–2014				
	Obs	Mean	Std.Dev	Min	Max	Obs	Mean	Std.Dev	Min	Max
LNHWAGE	5778	3.687	.431	2.12	6.215	10,364	2.477	.608	− .519	7.131
Monthly Wage	5778	1541.59	710.213	500	7000	10,364	1941.65	1023.01	200	7000
Hourly Wage	5778	10.544	6.045	1.984	119.048	10,364	14.795	18.48	.595	1250
OVEREDUCATION	5778	.187	.39	0	1	10,364	.184	.388	0	1
OVERSKILLING	5778	.457	.498	0	1	10,364	.499	.5	0	1
PhDnetwork	5778	.506	.5	0	1	10,364	.031	.175	0	1
OTHERN	5778	.462	.499	0	1	10,364	.046	.209	0	1
DEGREESCORE	5778	4.496	.892	1	5	10,364	4.253	1.186	1	5
EXTENSION	5778	.087	.281	0	1	10,364	.158	.365	0	1
OTHERFINIMP	5778	.092	.289	0	1	10,364	.158	.364	0	1
TAUGHT	5778	.332	.471	0	1	10,364	.71	.454	0	1
FROMDTOPHD	5778	2.271	2.123	0	25	10,364	5.648	2.923	3	36
AGES1	5778	.323	.468	0	1	10,364	.193	.395	0	1
AGES2	5778	.165	.371	0	1	10,364	.34	.474	0	1
AGES3	5778	.145	.352	0	1	10,364	.308	.462	0	1
AGES4	5778	.111	.314	0	1	10,364	.159	.366	0	1
FEMALE	5778	.536	.499	0	1	10,364	.532	.499	0	1
MARRIED	5778	.589	.492	0	1	10,364	.465	.499	0	1
CHILDREN	5778	.334	.472	0	1	10,364	.33	.47	0	1
PRODUCTS	5778	3.351	1.818	0	10	10,364	2.88	1.798	0	9
SELF	5778	.085	.278	0	1	10,364	.081	.273	0	1
PERMANENT	5778	.41	.492	0	1	10,364	.361	.48	0	1
ACADEMY	5778	.511	.5	0	1	10,364	.28	.449	0	1
RD2	5778	.536	.499	0	1	10,364	.4	.49	0	1

Table 2 (continued)

Variable	Survey 2004–2006					Survey 2012–2014				
	Obs	Mean	Std.Dev	Min	Max	Obs	Mean	Std.Dev	Min	Max
RD3	5778	.224	.417	0	1	10,364	.307	.461	0	1
AGRICULTURE	5778	.016	.127	0	1	10,364	.009	.096	0	1
MANUFACTURE	5778	.083	.276	0	1	10,364	.094	.292	0	1
MIGRANT	5778	.433	.496	0	1	10,364	.428	.495	0	1
PARTTIME	5778	.096	.295	0	1	10,364	.075	.263	0	1
TEACHING	5778	.572	.495	0	1	10,364	.532	.499	0	1
WKEXPYR	5778	2.959	1.483	1	6	10,364	2.64	1.689	0	6
First year wave	5778	.468	.499	0	1	10,364	.557	.497	0	1
Second year wave	5778	.532	.499	0	1	10,364	.443	.497	0	1
NORTH WEST	5778	.22	.414	0	1	10,364	.221	.415	0	1
NORTH EAST	5778	.172	.377	0	1	10,364	.16	.367	0	1
CENTER	5778	.233	.423	0	1	10,364	.229	.42	0	1
SOUTH	5778	.295	.456	0	1	10,364	.322	.348	0	1
ABROAD	5778	.081	.273	0	1	10,364	.065	.247	0	1
MATH & PROGR	5778	.039	.195	0	1	10,364	.041	.199	0	1
PHYSICS	5778	.065	.246	0	1	10,364	.053	.223	0	1
EARTH	5778	.073	.26	0	1	10,364	.058	.233	0	1
CHEMISTRY	5778	.035	.183	0	1	10,364	.023	.15	0	1
BIOLOGICAL SCIENCE	5778	.141	.348	0	1	10,364	.108	.31	0	1
MEDICAL SCIENCE	5778	.08	.272	0	1	10,364	.143	.35	0	1
AGRIC & VETERINARY	5778	.08	.272	0	1	10,364	.058	.235	0	1
ARCHITECTURE	5778	.075	.263	0	1	10,364	.077	.266	0	1
ENGINEERING	5778	.063	.242	0	1	10,364	.131	.337	0	1

Table 2 (continued)

Variable	Survey 2004–2006					Survey 2012–2014				
	Obs	Mean	Std.Dev	Min	Max	Obs	Mean	Std.Dev	Min	Max
HUMAN SCIENCE	5778	.097	.296	0	1	10,364	.094	.292	0	1
HISTORY & PHIL	5778	.089	.285	0	1	10,364	.08	.271	0	1
LAW	5778	.063	.243	0	1	10,364	.053	.225	0	1
ECONOMICS & STAT	5778	.068	.252	0	1	10,364	.05	.217	0	1
POLITICA SCIENCE	5778	.032	.175	0	1	10,364	.032	.177	0	1
PE	5778	.349	.477	0	1	10,364	.382	.486	0	1
LS	5778	.301	.459	0	1	10,364	.309	.462	0	1
SH	5778	.349	.477	0	1	10,364	.309	.462	0	1

that takes the value of 1 if the PhD was neither required nor helpful in obtaining the job (option iv in the survey question) and zero otherwise.

In line with the existing literature, we consider the variable from these questions a self-reported measure of overeducation (Dolton and Silles 2008). In both editions of the ISTAT survey, these overeducation questions were asked only to those who had obtained their current work after completing their PhD (67.2% of the sample interviewed in 2009 and 66.47% of the sample interviewed in 2018). As a consequence, to investigate overeducation, our analysis was restricted to 5,778 respondents in the 2009 survey and 10,673 in the 2018 survey.

In both the editions of the survey, one question asked: "*To carry out your job, is it necessary to have a PhD?*,"[7] with responses limited to "*yes*" or "*no*." We interpreted this question as asking about the usefulness of skills acquired during PhD studies in carrying out the job. We built a dummy variable taking the value of one for those respondents who replied yes and zero otherwise, and considered self-reported answers to this question as a measure of overskilling. The entire sample of employed respondents replied to this question.

The use of overeducation and overskilling self-assessed measures similar to those illustrated above is widespread in the empirical literature on job–education mismatch even though it has been noted that these measures might be a source of measurement error bias in empirical analyses (Leuven and Oosterbeek 2011; McGuinnes 2006). However, no other measures of overeducation and overskilling are available in the ISTAT database, nor could they be built otherwise because of the lack of further details about jobs held by PhD graduates.

Table 2 shows that, in both the editions of the survey considered in our study, approximately 18% of respondents declared themselves to be overeducated (18.7% in the 2009 survey and 18.1% in the 2018 survey). A total of 45.7% in the 2009 survey and 49.9% in 2018 reported being overskilled.

Comparisons with data collected by studies focusing on other countries are difficult because these studies adopted overeducation measures different from ours and considered different years. However, our data are consistent with those provided by Auriol (2010), who reported that, in European countries, the percentage of 1990–2006 doctorate holders in a job not related to a doctoral degree varied between 1.2% (Portugal) and 29.6% (Belgium).

Alongside the measures of overeducation and overskilling, regressors used in the analysis included a broad set of controls chosen by examining previous contributions on PhD holders' wage determinants (Gaeta et al. 2017). We selected the regressors by considering those variables that were included in both the editions of the ISTAT survey considered in our study. These control variables are grouped as detailed in the following sub-sections.

[7] The exact Italian wording of the question is: "*Per svolgere questa attività (lavorativa o relativa alla borsa/assegno di ricerca), secondo lei, possedere un titolo di dottore di ricerca è necessario?*".

2.1 Socio-economic and Demographic Variables

The first variable included in this group was the respondents' age on completion of a PhD. The ISTAT survey only provides this information in various categories (younger than 30 years old, 30 years old, 31 years old, 32 years old, 33 years old, and so on), and this variable was labeled *AGE*. Age is usually included in Mincer-type regressions since it is presumed to be a proxy for work experience. Given that doctoral studies have an institutional duration of three years, with only one extra year usually allowed, older respondents presumably started their doctoral studies later. This may be due to work experience acquired before PhD enrolment or to a delay in completing university graduate studies. Therefore, the effect of age is a priori undefined. The potential existence of a gender gap in wages (Alfano et al. 2019a, b) was controlled through the *FEMALE* dummy. Several covariates controlled for the family situation of respondents, which in some cases may contribute to determining penalties in the labor market [Pacelli et al. (2013), for example, focused on labor market penalties for mothers in Italy]. More specifically, our set of regressors included one variable controlling for respondents' marital status (*MARRIED*) and another controlling for whether they have children (*CHILDREN*).

2.2 Variables Related to the Respondent's Educational Performance Before the PhD and Their PhD Enrolment

The first variable in this group was the respondent's final degree grade (*DEGREESCORE*), which included five categories [between 66 (the minimum possible grade) and 110 (the maximum)]. Several scholars (McGuinnes and Bennet 2006; Sloane 2003) have criticized the overeducation literature by claiming that equally educated workers are heterogeneous in ability. According to these scholars, ability positively correlates with earnings, with "overeducated" workers corresponding to those who are less able. The final university grade should reflect individual ability, and therefore the inclusion of *DEGREESCORE* among covariates should help identify the effect of overeducation on wages.

The second variable measured the number of years between completing a master's degree and beginning a PhD (*FROMDTOPHD*). We believe that this variable should be positively related to wages since respondents whose PhD program matriculation was postponed presumably acquired some professional experience before starting their PhD studies. This is consistent with the idea that post-schooling work experience included in a Mincer-type wage equation is positively related to wages (Lemieux 2006). However, Di Paolo and Mañé (2016) found a negative effect of this variable on wages among Spanish doctoral graduates.

2.3 Variables Related to Respondents' PhD Studies

The field of study has been found to be a strong determinant in explaining wage heterogeneity among Italian university graduates (Caroleo and Pastore 2018;

Cutillo and Di Pietro 2006) as well as among PhD holders in other countries (Canal Domínguez and Rodríguez Gutiérrez 2013; Di Paolo and Mañé 2016). Thus, a respondent's field of doctoral studies was considered in our regression through a set of 14 dummies corresponding to the Italian university research areas (we used political science as a reference category). Given the studies undertaken, it seems reasonable to assume that hard science sectors are associated with higher wages than humanities and social sciences.

We also included some variables more specifically related to respondents' experience with their PhD program. One dummy identified those who completed their PhD in three years (i.e. the ideal institutional length; *EXTENSION*). *Ceteris paribus*, the completion of doctoral studies within the institutional time limit may be interpreted as a proxy of individual ability. Another dummy recorded whether respondents had taught a course, or part of a course, while they were PhD candidates (*TAUGHT*). There is no literature on the effects of these variables on wages to the best of our knowledge. However, all these experiences may be positively correlated with wages for two primary reasons. On the one hand, they are frequently accessible only through selection (i.e. only the best students are generally asked to teach); from this perspective, these experiences may also be considered as proxies for ability. On the other hand, these experiences enable PhD candidates to acquire skills and competencies that may later be remunerated in the labor market.

To control for respondents' financial condition during the PhD, we included the following covariates: *GRANT* (a dummy that takes the value of one for those PhD graduates who received a scholarship during their doctoral studies) and *OTHERFINIMP* (identifies those who received financial support from other sources to complete their doctoral studies). These variables may also serve as ability proxies, since grants and financial supports are generally assigned competitively. Finally, the variable *2006* captured the year of completion of the PhD. The inclusion of this variable allowed us to check whether those who completed their PhD studies more recently had, *ceteris paribus*, lower wages. This is consistent with the idea that work experience plays a role in determining wages. Furthermore, the inclusion of this variable was essential because overeducation is often described as a temporary phenomenon (Rubb 2003). Therefore, its incidence should be more evident among those who graduated more recently.

2.4 Job-related Variables

Job characteristics are usually included on the right side of Mincer-type regressions (Di Pietro and Urwin 2006). We considered one regressor reflecting the employment sector, which could be manufacturing (labeled as *MANUFACTURE*), agriculture (*AGRICULTURE*), research and development services (*RDSERVICES*, used as reference category), or strictly academic (*ACADEMY*). Two more variables were added to reflect the specific activities carried out by respondents. One was a dummy identifying those whose job implied carrying out teaching (*TEACHING*) and the other reflected how much each respondent's job was based on R&D activities (*RD*), distinguishing between "mostly," "partially," and "not at all." The number of innovations (patents, organizational and procedural innovations) and publications produced by respondents after completing their PhD was recorded by the *PRODUCTS* variable. Unfortunately, it was not possible to measure the prestige of these innovations and publications. Furthermore, we added dummies identifying respondents' contractual position (Da Silva and Turrini 2015): *SELF* for those who were self-employed; *PERMANENT* for those with an open-ended (permanent) contract; and *PARTTIME* for those with a part-time position. The *MIGRANT* dummy took the value of 1 in the case of doctoral recipients who worked in a different region from that in which they undertook their PhD (expected to have a positive impact on wages). To account for respondents' job experience, we introduced *WKEXPYR*, which measures years of work experience. Finally, the dummy variables *PHDNETWORK* and *OTHERNETWORK* reflected whether respondents' current job had been obtained through the support of a known member of the university (met during the PhD) or someone else who was not met during the PhD.

Alongside these covariates, to reflect respondents' place of residence at the time of the interview, we used *NORTHWEST*, *NORTHEAST*, *CENTER*, and *SOUTH* variables. This allowed us to account for unobserved heterogeneity among contexts (in terms of economic development, unemployment, features of the economy, etc.), which is highly relevant among Italian macro-regions whose disparities have been widely studied (Ercolano 2012).

3 Methodology

To estimate the impact of vertical mismatch on wages, one can use the following cross-sectional wage equation:

$$LNHWAGE_i = OVER_i' \gamma + X_i' \beta + \varepsilon_i \tag{1}$$

where, on the left-hand side, *LNHWAGE* indicates the natural logarithm of the net hourly wage reported by the i-th PhD holder, while, on the right side, *OVER* is a vector of variables including both overeducation and overskilling, X is a vector that includes the control variables presented in Sect. 2, γ and β are vectors of parameters to be estimated, and ε is the error term. According to the reasoning presented in Sect. 1, *OVER* can be considered endogenous because of measurement error, omitted variable(s), and reverse causality.

To address all these issues, one can use an IV estimation (Becker 2016; Stock 2015). The IV approach implies estimating the following two-step equations:

$$OVER_i = \delta IV_i + X_i \mu + \varepsilon_{2i} \tag{2}$$

$$LNHWAGE_i = \gamma \widehat{OVER}_i + X_i \beta + \varepsilon_{1i} \tag{3}$$

where Eq. (2) predicts *OVER* ($\widehat{OVER}$) as a function of a vector of exogenous variables and an IV, while Eq. (3) predicts wage as a function of the predicted overeducation status resulting from the first stage.

An adequate IV has to show two characteristics. First, it has to be strongly correlated with the *OVER* variable (relevance condition). This hypothesis is testable if the coefficient δ in Eq. (2) is large and statistically significant, which means that there is a higher correlation between the instrument(s) and endogenous variables. Usually, an F test for δ is implemented for confirmation. Second, its relation with the dependent variable has to be uniquely through *OVER* variables ($\mathrm{E}(\varepsilon_{1i}|IV_i)=0$) (exclusion restriction or orthogonality condition). This is testable by relying on a t-test on the residual of Eq. (2) added to Eq. (3). If the residual is statistically significant, the IV is not valid because the IV explains wages, at least partially, without passing through *OVER*.

As already reported, the existing literature has highlighted that finding an adequate IV for the overeducation/overskilling variable is difficult. Therefore, the existing contributions on the effect of overeducation/overskilling on wages rely simply on ordinary least squares (OLS) cross-sectional estimates of Eq. (1), which are exposed to the risk of providing biased estimates.

In our case, a possible solution to the seemingly inextricable problem of finding a valid IV (respecting both relevance and orthogonal conditions) is the procedure developed by Lewbel (2012, 2018). The main aim is to generate a synthetic IV from the estimation of the following triangular model:

$$LNHWAGE_i = \gamma OVER_i + X_i\beta_1 + \varepsilon_{1i} \tag{4}$$

$$OVER_i = X_i\beta_2 + \varepsilon_{2i} \tag{5}$$

To identify this system, it is necessary either to impose an equality constraint on β_1 or, if ε_{1i} and ε_{2i} are not correlated, a valid instrument $\left(Z - \underline{Z}\right)\varepsilon_{2i}$ for *OVER*. Lewbel builds a valid instrument for *OVER* starting from the heteroskedasticity of ε_{2i}. We estimate β_2 from Eq. (5) and calculate the estimated residuals $\hat{\varepsilon}_{2i}$. We then impose $Z=X$ (from the constant) and finally obtain the IV as $(X_i–\underline{X})\hat{\varepsilon}_{2i}$. This procedure allows identification when the available instruments are weak or do not meet the exclusion restrictions.

Of course, being based on a "synthetic" IV, this method does not allow interpretation and discussion of the theoretical implication of the IV choice, as is usual in the case of IV analyses.

To be applied, this approach requires the following assumptions: $Cov\left(Z, \varepsilon_1\varepsilon_2\right) = 0$ and $Cov\left(Z, \varepsilon_2^2\right) \neq 0$, where $Z=\mathrm{X}$ or a subset of X. Baum and Lewbel (2019) suggested three conditions that are sufficient to make these assumptions hold. These conditions are sufficient but they are not necessary, i.e. even if they are not satisfied, the Lewbel method can still hold.

First, the *OVER* variables have to be endogenous because an unobserved error term component is common to Eqs. (4) and (5). This point has been discussed in Sect. 1, where we recalled that there are reasons to suspect that our vertical mismatch variables suffer from measurement error and/or that omitted ability or reverse causality can bias the OLS estimate of Eq. (1). In our case, unobserved ability can affect wage but not *OVER* variables.

Second, Eq. (4) is a structural model and, as a consequence: the unobserved error term component is homoscedastic; and Eq. (4) does not contain any relevant omitted variables. The former can be tested following Pagan and Hall (1983), as suggested by Baum and Lewbel (2019). Even if homoskedasticity is rarely found in our estimations, this does not systematically mean that the second hypothesis is rejected. Concerning the latter, since we have used as independent variables the entire set of socio-economic, family-related, curricula-related, and job experience variables used by the existing literature on PhD holders' occupational outcomes, it can be presumed that there are no relevant omitted variables.

Third, ε_2^2 is correlated with Z, corresponding to the test of the heteroskedasticity in Eq. (5), which can be obtained testing the Breush–Pagan test (Breush and Pagan 1979). This test's results always show the presence of strong heteroskedasticity and always support the use of the Lewbel methodology. These conditions are sufficient but they are not necessary; therefore, even if they are not satisfied, the Lewbel method can still hold.

In the application of the Lewbel heteroskedasticity-based instrumental variables, we have a similar hypotheses to a standard IV estimate. After applying the Lewbel method to our wage equation, we built synthetic instruments that solve the orthogonality condition problem in the IV estimate, but the two other conditions have to be tested. First, we have to test if instruments are correlated to the endogenous variables; this is simple to test and results are illustrated in the regression table on the *FSTAGE* line that are always significant. Second, we have to test if the endogeneity problem has been solved after using the IV. This implies testing for over-identification by using the Hansen J statistic. The higher the Hansen J p-values are, the higher the precision in the estimation will be, and the more the smearing effect will be minimized (Baum and Schaffer 2020).

Two further points of this estimation method also have to be addressed. First, the *OVER* vector in Eq. (1) includes dummies measuring overeducation and overskilling. This means that, in the first stage, we have to deal with a non-linear estimation. Lewbel (2018) showed that it is possible to obtain consistent results by estimating a liner probability regression in the case of binary endogenous regressors. Second, the system estimation may require either a double-stage estimate or a general method of moments in a unique step. Lewbel (2012) suggested using the latter to increase the efficiency of the estimator.

4 Results

4.1 Main Findings

The regression analyses carried out on data from the 2009 survey are reported in Table 3, while Table 4 illustrates the estimates calculated by considering the data collected in 2018.

All the specifications displayed in these tables (and in the following tables) include the entire set of regressors illustrated in Sect. 2 [the tables only show the coefficients estimated for the variables we are mainly interested in (i.e. overeducation

Table 3 Overeducation and overskilling effects on wages among PhD holders (2009 ISTAT survey data)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Lewbel IV	OLS	Lewbel IV	OLS	Lewbel IV
	Full sample	Full sample	Physics and Engineering + Life Science	Physics and Engineering + Life Science	Social Sciences and Humanities	Social Sciences and Humanities
Overeducation	− 0.121***	− 0.089***	− 0.101***	− 0.076***	− 0.157***	− 0.126***
	(0.016)	(0.019)	(0.018)	(0.022)	(0.032)	(0.035)
Overskilling	0.005	− 0.018	− 0.003	− 0.043	0.022	0.071
	(0.014)	(0.048)	(0.016)	(0.048)	(0.030)	(0.074)
obs	5778	5778	3760	3760	2018	2018
R-squared	0.256	0.255	0.291	0.289	0.217	0.211
Adj R-squared	0.250	0.249	0.283	0.281	0.202	0.196
Pagan and Hall test		625.40***		443.48***		250.37***
Breush-Pagan test		1863.45***		1105.51***		757.81***
FSTAGE		196.42***		151.334***		110.928**
Hansen J Test		101.942 [0.116]		101.465** [0.027]		77.185 [0.209]

OLS estimates and estimates based on the Lewbel (2012) IV methodology

All the covariates presented in Sect. 2 are included among regressors in the models

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4 Overeducation and overskilling effects on wages among PhD holders (2018 ISTAT survey data)

	(1)	(2)	(3)	(4) =	(5)	(6)
	OLS	Lewbel IV	OLS	Lewbel IV	OLS	Lewbel IV
	Full sample	Full sample	Physics and Engineering + Life Science	Physics and Engineering + Life Science	Social Sciences and Humanities	Social Sciences and Humanities
Overeducation	− 0.120*** (0.017)	− 0.105*** (0.018)	− 0.116*** (0.021)	− 0.118*** (0.021)	− 0.137*** (0.032)	− 0.085*** (0.030)
Overskilling	− 0.004 (0.017)	0.008 (0.035)	− 0.022 (0.019)	0.012 (0.043)	0.027 (0.033)	0.036 (0.051)
obs	10,364	10,364	7163	7163	3201	3201
R-squared	0.097	0.097	0.103	0.103	0.088	0.087
Adj R-squared	0.093	0.093	0.098	0.098	0.078	0.076
Pagan and Hall test		722.79***		489.58***		276.08***
Breush-Pagan test		3451.00***		2589.10***		883.53***
FSTAGE		629.35***		401.57***		362.38***
Hansen J Test		105.20 [0.059]		76.74 [0.412]		83.85 [0.068]

OLS estimates and estimates based on the Lewbel (2012) IV methodology

All the covariates presented in Sect. 2 are included among regressors in the models

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

and overskilling) to save space]. Coefficients calculated for the other covariates are available upon request.

Columns 1 and 2 in Tables 3 and 4 report the findings by considering the entire sample. In model 1, a baseline OLS regression was carried out. Its results suggest that the overeducated respondents earn approximately 12% less than their matched counterparts. Such a finding turns out to be highly significant from a statistical point of view ($p<0.01$). On the other hand, no statistically significant correlation was found between overskilling and wages.

In model 2, the robustness of these findings was tested by using the heteroskedasticity-based instrumental variable estimation approach. The results from this analysis qualitatively support the OLS findings. Indeed, we found a negative and highly statistically significant coefficient for overeducation and a non-statistically significant coefficient for the overskilling variable.

On the one hand, these findings provide further empirical support for the idea that, among Italian PhD holders, wages are based on the recognition of qualifications, while skills are not taken into account (Gaeta et al. 2017). On the other hand, this finding might imply that wages are negotiated based on skills different from those considered by the PhD holders when replying to the survey question regarding overskilling. These results are similar to those found by some cross-national studies focused on university graduates (Kankaraš et al. 2016) but different from those found in Spain, where overskilling seems to play a critical role in wages (Di Paolo and Mañé 2016).

The estimates in column 2 suggest that the OLS estimates for the detrimental effect of overeducation on wages have a slight upwards bias. The IV results suggest that such an effect is − 9% for the 2009 survey (it was − 12% in the OLS) and moderately higher in the 2018 survey (− 10.5%). Such an upward bias is possible, for example, if one assumes that the OLS estimates incorporate the effect of unobserved low ability (Caroleo and Pastore 2018). While the coefficients estimated through the IV approach have a magnitude lower than the OLS ones, they strongly suggest that the detrimental effect of overeducation on wages is still sizeable. Such a finding supports the idea that overeducation is a severe issue for PhD holders since it compromises private returns from their education.

At the bottom of Tables 3 and 4, we report three tests that support the adequateness of our IV analysis. First, the Pagan–Hall heteroskedasticity test (PH test, Pagan and Hall 1983) suggests that our data reveal a considerable presence of heteroskedasticity, which is crucial to applying the Lewbel IV strategy. Second, the first stage (*FSTAGE*) shows the significance of the relationship between overeducation and overskilling with the instruments, in all cases. Finally, Hansen's (1982) J statistic and the corresponding high p-values support the validity of the IV over-identifying restrictions.

We are aware that these main findings might be biased by selection for employment (recall that the unemployed respondents could not report any wage and vertical mismatch). To take this potential bias into account, we re-ran our analyses by including in the Mincer equation the inverse Mills ratio resulting from a first stage probit that explains employment. Our main findings were confirmed by this additional analysis.

Furthermore, we are aware that selection for a job different from the one held before the doctoral studies might bias our main findings (recall that the overeducation variable was collected only for those who obtained their position after completing their PhD). To take this potential bias into account, we re-ran our analyses by including in the Mincer equation the inverse Mills ratio resulting from a first stage probit that explains holding a job different from any position held before the PhD. Our main findings here were also confirmed by this additional analysis. The results of these robustness check exercises are available upon request.

4.2 Findings by Study Field

Previous studies focusing on Italy report that PhD holders' probability of experiencing vertical mismatch and their monthly wages vary dramatically according to the field of study (Gaeta 2015; Gaeta et al. 2017). We therefore decided to split our total sample by separately considering those doctoral graduates who specialized in hard sciences and those who specialized in social sciences and humanities. More specifically, following the European Research Council (ERC), we classified respondents into two study fields: the hard sciences study field, including physics and engineering (PE) and life sciences and medicine (LS); and social sciences and humanities (SH).[8] Such a sub-sample analysis seems appropriate to provide further insights into the detrimental effect of overeducation on private returns from doctoral studies.

In Tables 3 and 4, the results obtained by considering the hard sciences study field are reported in columns 3 and 4, while the social sciences and humanities are analyzed in columns 5 and 6. In both cases, the OLS and the IV estimates are reported. The adequateness of our IV heteroskedasticity-based instrumental variable estimation is not fully confirmed for the 2009 data analysis focused on hard sciences since the Hansen *J* test fails to support the validity of over-identifying restrictions of our instruments. Therefore, the IV results for this study field have to be taken with caution.

Overall, the sub-sample analysis suggests four main findings.

First, whatever the field of study and survey edition considered, overeducation seems to be linked with wages, while no statistically significant effect is found for overskilling.

Second, all the estimated OLS coefficients turn out to be upwardly biased. This confirms the idea that our IV analysis is able to correct, at least partially, the endogeneity issues illustrated in Sect. 2.

Third, while in the 2009 survey overeducation seems to affect social sciences and humanities more severely than hard sciences (− 12% vs − 7% for the IV estimates), the 2018 data seem to suggest the opposite (− 8% vs − 11%). This finding might

[8] We recoded the 14 study areas recorded by the ISTAT survey as follows. Physics and engineering (PE) includes: math, physics, and astronomy; earth and environmental science; chemistry; engineering; and architecture. Life sciences and medicine (LS) includes: biological science; medical science; and agriculture and veterinary science. Social sciences and humanities (SH) includes: human science; history and philosophy; law; economics and statistics; and political and social sciences.

indicate that social sciences and humanities graduates suffered much more than their hard science colleagues from the economic crisis experienced by Italy in 2009.

Fourth, while for hard sciences the detrimental effect of overeducation on wages was largely similar in the 2009 and 2018 data (ranging from − 10% in the 2009 data and − 11.6%/− 11.8% in the 2018 data), the social sciences and humanities field reveals much higher variability (the IV estimates ranged from − 12% in the 2009 data and − 8% in the 2018 data).

4.3 Findings by Gender

Table 5 reports the results of additional analyses inspecting the heterogeneity of our main findings by PhD holders' gender. Table 5 considers the 2009 and the 2018 survey data separately and reports the results when the analysis was restricted to the men and women sub-samples.

Examining the tests at the bottom of Table 5, most of the IV estimates have to be taken with caution because the Hansen *J* test fails to support the adequateness of our IV.

If we rely on the OLS findings, we find evidence that overeducation affected women slightly more than men, both in 2009 and in 2018. This finding suggests that further inquiry is required into the role that overeducation might play in explaining the gender pay gap among PhD holders that has been found by previous analyses (Alfano et al. 2019a, b).

4.4 Findings by Place of Residence

Widespread national and international literature has studied the persistent economic dualism between the less developed Italian Southern regions and the richer Center–North of the country (Ercolano 2012; Fratianni 2012). The economic divide between these two areas of the country is reflected and reinforced by a remarkable regional heterogeneity in R&D expenditure and performance in research and innovation (Nascia and Pianta 2018). As a consequence, the R&D working opportunities, i.e. those opportunities that are presumably in line with PhD holders' education and skills, are unevenly distributed in the country and more widespread in the Center–North. In addition, the wider literature has asserted that, compared with other countries, the Italian economy is characterized by low R&D intensity (Nascia et al. 2018), which suggests that finding a job that allows PhD holders to exploit their background is easier abroad than in Italy.

In our view, such heterogeneity in the PhD holders' labor market opportunities can exert a significant impact on the overeducation wage penalty. Indeed, in places where R&D activities are more widespread and developed, the economy fully recognizes the importance of a PhD. In these places, matched doctoral graduates can earn a sizeable wage premium compared with their mismatched counterparts. In contrast, in those places where R&D activities are less developed, the importance of the PhD is less recognized, which means that the wage premium gained by matched

Table 5 Overeducation and overskilling effects on wages among PhD holders: gender differences

	Survey 2004–2006				Survey 2012–2014			
	Male		Female		Male		Female	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	OLS	Lewbel	OLS	Lewbel	OLS	Lewbel	OLS	Lewbel
Overeducation	− 0.110*** (0.024)	− 0.075*** (0.025)	− 0.127*** (0.021)	− 0.105*** (0.026)	− 0.102*** (0.027)	− 0.122*** (0.024)	− 0.133*** (0.023)	− 0.104*** (0.024)
Overskilling	− 0.008 (0.021)	− 0.052 (0.055)	0.011 (0.019)	0.071 (0.058)	− 0.022 (0.025)	− 0.046 (0.046)	0.012 (0.022)	0.039 (0.048)
Obs	2679	2679	3099	3099	4847	4847	5517	5517
R-squared	0.253	0.249	0.276	0.271	0.115	0.113	0.085	0.082
Adj R-squared	0.241	0.236	0.265	0.260	0.106	0.105	0.077	0.074
Pagan and Hall test		373.79***		373.29***		451.53***		430.04***
Breush-Pagan test		1061.91***		826.85***		2112.12***		1439.47***
FSTAGE		156.53***		131.73***		361.39***		357.87***
H J TestÂ§		106.41** [0.050]		103.18* [0.076]		81.62 [0.491]		129.89*** [0.000]

OLS estimates and estimates based on the Lewbel (2012) IV methodology

Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1

doctoral graduates compared with their mismatched counterparts tends to have a lower magnitude.

Bearing this in mind, we re-ran our regression analyses by splitting our sample into three sub-samples. The first includes only those doctoral graduates that are resident in the Center–North of Italy, the second has only residents in the Southern regions, and the third only includes those who live abroad. Table 6 summarizes the results obtained when focusing on these sub-samples using the 2009 data, while Table 7 reports the results when considering the 2018 data.

On the whole, the findings seem to support our predictions. Indeed, the IV-estimated coefficients in Tables 6 and 7 suggest that the overeducation wage penalty is not statistically significant in the Southern Italian regions, while it is statistically significant and sizeable in the Center–North of Italy (where it ranges from − 8.7 to –10.3%) and especially abroad (where it ranges from –14.7% to –15.6%). In addition, the analysis returns a statistically significant, positive, and sizeable effect of overskilling among those employed abroad in 2009, in times of severe economic crisis. Such a finding suggests that, in times of crisis, using non-doctoral skills guaranteed higher private returns than holding a position focused on PhD skills.

Of course, we are aware that these findings might be biased by self-selection regarding migration. Indeed, the literature on PhD holders suggests that spatial mobility triggers job-education matching (Alfano et al. 2019a, b) and that labor mobility is associated with higher wages (Di Cintio and Grassi 2017). This would imply that migrants report a higher incidence of matching and higher salaries, which might affect our findings. From this perspective, these findings should be interpreted with caution and their robustness requires a more detailed examination, which is beyond this paper's scope.

5 Conclusions

This paper adds to the existing literature on the occupational outcome of PhD holders by inspecting the effect that education–job vertical mismatch exerts on wages. We have proposed an empirical analysis whose main contribution to the literature is applying Lewbel's IV methodology (Lewbel 2012), which allows us to address the endogeneity issues that might have biased previous studies on this topic.

The results achieved through our estimates support the idea that being in a condition of overeducation, i.e. holding a job that is not in line with one's PhD, has a detrimental effect on wages. Our findings suggest that previous OLS estimates have upward biases. Nevertheless, the negative impact of overeducation on wages found by our IV estimates is still sizeable, ranging between − 9 and − 10%.

At the same time, our findings suggest that being in an overskilled condition does not imply any detrimental effect on wages. This would mean that wages are set consistently with the formal qualification required to access jobs more than they are for skills, or that more detailed measures of overskilling are needed to gauge the effect of the misuse of skills on wages.

In a time of great economic crisis (2009), we found that the impact of overeducation on wages was much higher among PhD holders specializing in the social

Table 6 Overeducation and overskilling effects on wages among PhD holders (2009 ISTAT survey data)

	(1)	(2)	(3)	(4)	(5)	(6)
	Italy Center-North		Italian Southern regions		Abroad	
	OLS	Lewbel IV	OLS	OLS	Lewbel IV	OLS
Overeducation	− 0.144*** (0.019)	− 0.103*** (0.021)	− 0.050* (0.029)	− 0.012 (0.035)	− 0.184 (0.114)	− 0.147** (0.060)
Overskilling	0.015 (0.017)	0.006 (0.051)	− 0.017 (0.026)	− 0.084 (0.072)	0.051 (0.066)	0.113** (0.049)
obs	3609	3609	1702	1702	467	467
R-squared	0.210	0.208	0.285	0.280	0.253	0.229
Adj R-squared	0.201	0.198	0.267	0.262	0.179	0.153
Pagan and Hall test		332.04***		174.35***		65.164**
Breush-Pagan test		1108.52***		429.22***		697.89***
FSTAGE		148.872***		96.703***		128.992***
Hansen J Test		101.59 [0.038]		82.05 [0.355]		85.183 [0.271]

OLS estimates and estimates based on the Lewbel (2012) IV methodology

All the covariates presented in Sect. 2 are included among regressors in the models

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7 Overeducation and overskilling effects on wages among PhD holders (2018 ISTAT survey data)

	(1)	(2)	(3)	(4)	(5)	(6)
	Italy Center-North		Italian Southern regions		Abroad	
	OLS	Lewbel IV	OLS	Lewbel IV	OLS	Lewbel IV
Overeducation	− 0.110*** (0.020)	− 0.087*** (0.021)	− 0.111*** (0.042)	− 0.057 (0.041)	− 0.134** (0.060)	− 0.156*** (0.053)
Overskilling	0.014 (0.020)	0.018 (0.041)	− 0.036 (0.039)	0.068 (0.072)	0.032 (0.046)	− 0.069 (0.060)
obs	6330	6330	2136	2136	1898	1898
R-squared	0.065	0.064	0.084	0.077	0.101	0.095
Adj R-squared	0.059	0.058	0.066	0.059	0.082	0.075
Pagan and Hall test		430.55***		238.25***		94.40
Breush-Pagan test		1587.80***		455.64***		2637.84***
FSTAGE		389.01***		96.703***		259.50***
Hansen J Test		79.30 [0.375]		90.89 [0.117]		76.155 [0.409]

OLS estimates and estimates based on the Lewbel (2012) IV methodology

All the covariates presented in Sect. 2 are included among regressors in the models

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

sciences and humanities. In contrast, in 2018, doctoral graduates specializing in hard sciences reported an overeducation wage penalty slightly higher than their social sciences and humanities colleagues. On the whole, our analysis suggests that overeducation affects women more than men and that such a wage penalty is more visible in places where the economy is more developed and R&D activities are more widespread.

On the one hand, these findings suggest that the consequences of overeducation on wages affect doctoral graduates, and not only university graduates, whose case has been extensively studied by the existing literature. This finding calls for a more detailed analysis of the links between the level of education and the consequences of overeducation.

These findings also provide valuable insights into the private returns that come with possession of a doctoral degree in times of economic crisis, such as those when the survey data analyzed were collected. From this perspective, they inform policy decisions concerning the design of incentives that might trigger PhD holders' matched employability. Such incentives are essential in current societies, where doctoral graduates are expected to play a critical role in promoting new knowledge and in triggering innovation-oriented economic development.

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