Over-education and Italian Ph.D Graduates during the Great Recession.

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Abstract

This paper evaluates the impact of the Great Recession on Ph.D over-education using data drawn from four annual cohorts of Ph.D graduates surveyed by the Italian National Institute of Statistics. Over-education is examined through the definitions of both over-skilling and over-qualification. To assess the effect of the crisis, we adopt several proxies, among which economic resilience. To the best of our knowledge, this is the first time that the nexus over-education-resilience receives attention. The results show that over-skilling is negatively associated with the Great Recession. More generally, working on research-based activities and having study experience abroad are always significant drivers to overcome any kind of job mismatch. Conversely, being self-employed increases the risk of over-education, casting some doubts on the satisfactory additionality of Ph.D employment trajectories beyond academia and research. Finally, in contrast with previous results for graduates, we find that variables related to the family of origins do not exert a significant influence on Ph.D over-education.

Keywords: over-education, over-skilling, over-qualification, Ph.D graduates, Great Recession
JEL Classification: C2, I2, J24.

1 Introduction

Among poor labor market outcomes observed in the Great Recession, over-education has recently received great attention as there is a growing concern over skill mismatch in advanced

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economies (Quintini, 2011). Some studies on cross-country differences in over-education highlighted that structural differences in demand and supply rather than cyclical economic fluctuations affect the mismatch among graduates (Di Pietro, 2002; Groot and Van Den Brink, 2000). Instead, recent contributions stated that the business cycle can affect professional outcomes also in terms of job matching (Verhaest and Omey, 2006; Quintini, 2011; Croce and Ghignoni, 2012; Sattinger et al., 2012; Altonji et al., 2016). Moreover, these effects vary according by status of new labour market entrant or by the level and field of education in a way that accomplish predictions from job competition and job search models (Humburg et al., 2017; Verhaest and Van der Velden, 2013; Dolado et al., 2009; Thurow, 1975). Liu et al. (2016) also find a countercyclical trend of skill mismatch; the correlation is more pronounced among the occupations in the private sector compared to the public one.[1]

Previous literature on the cyclical fluctuation and job mismatch nexus has usually focused on workers with different levels of education, comparing effects on low relatively to high skill workers. An investigation of overeducation among workers with the same high level education has been overlooked.[2] In this paper, we address this topic evaluating the impact of the recent Great Recession on early career's mismatch of Ph.D holders.

Although labour market polarization makes the impact of the Great Recession less dramatic for high-compared to medium-skilled workers (Acemoglu and Autor, 2011; Cockx and Ghirelli, 2016), over-education is likely to emerge also among high-skilled workers because several economic mechanisms operate in the labour market, especially during downturns. On the one hand, modern economies, such as the US, register high rates of under-employment, i.e., workers employed in jobs for which they are over-qualified. Beaudry et al. (2016) even suggest that there is a structural reversal in the demand for cognitive tasks, with high-skilled individuals taking lower skill jobs, pushing lower-skilled workers even further down the occupational ladder. Barnichon and Zylberberg (2014) interpret this evidence by means of a theoretical model. By assuming that hiring is non random, a high-skilled worker moves down the occupational ladder to escape the competition from his/her high-skilled peers, given that the competition to obtain a low-qualification job is less intense. Thus, high-skilled workers end up by working in lower skill requirement occupations.[3] Barnichon and Zylberberg (2014) also demonstrate that under-employment is strongly counter-cyclical, so that, in a slack labour market, over-education - which is very closely related to under-employment - is more likely to occur. On the other hand, this trend toward expanding over-education among high skilled is corroborated by the findings of Modestino et al. (2014, 2016). They observed that during recessions it may well happen that jobs are re-categorized in terms of education level or skill requirement, given that employers adopt a strategic or opportunistic upskilling across occupations during recruitment in response to higher unemployment. Eventually, this behavior by employers changes the return to investment in higher education and also high skill workers may end up being overeducated (Fogg and Harrington, 2011; Di Pietro and Urwin, 2006).

Indeed, recent papers have demonstrated that skill mismatch may be an issue also for Ph.D

[1]As an example, highly-educated workers may accept mismatched jobs, expecially in the begin of their career, while engaging in on-the-job search for better jobs.

[2]As relevant exceptions that focus on graduates, see Caroleo and Pastore (2013), Croce and Ghignoni (2012), Liu et al. (2016).

[3]In this way, high-skilled workers trickle down unemployment to less skilled workers.

workers (Bender and Heywood, 2009, 2011; Gaeta, 2015; Di Paolo and Mañé, 2016; Ermini et al., 2017). The risk of over-education has increased for Ph.D workers over the last decades following the expansion of doctoral education observed in many European countries. The Ph.D courses enlarged their original function of training for careers into academia as Ph.D holders are assumed to be a strategic resource to foster the emergence and consolidation of the so-called knowledge economy and to support the shift toward a learning society. However, shrinking academic positions and job contraction outside the university sector during slack labour market, as in the case of Great Recession, may have not protected Ph.D workers from overeducation, if not unemployment, regardless the contribution of growing technical progress to the search for high-skilled workers. Moreover, Ermini et al. (2017) in their study observe that the impact of certain drivers of over-education changes across the time span of the Great Recessions. These authors, however, do not provide a direct assessment of the impact of the Great Recession on overeducation.

However, it has been suggested that shocks such as the Great Recession lower the opportunity costs and the adjustment costs toward a reallocation of resource to accomplish the technological change. Eventually, skill requirement may change. Hershbein and Kahn (2016), analyzing job vacancy postings, observed a structural shift in the demand for higher skill occurred in those metropolitan areas that suffered larger employment shocks during the Great Recession. In addition, this study detected an increase in general and IT capital investment, a structural shift in line according to a paradigm of routine-biased technological change (RBTC) which however made up-skill more likely as to complement a profitable adoption of such technologically driven changes.[4] The Great Recession accelerated this process and Hershbein and Kahn (2016) interprete these results as evidence that recessions will be times of cleaning in terms of production, as in the tradition of the Schumpeter's creative destruction. More important for the purpose of the present paper, they suggest that routine-cognitive occupations and formerly middle-skill jobs are apparently becoming higher-skilled and, instead of a great reversal in the demand for cognitive skill, it may well be that cognitive workers still retain a substantial advantage over the low-skilled. Thus, Great Recession ends up with higher opportunities for high-skill workers to attain jobs that matched their skills, with a reduction in over-skilling.

Given the above different employment scenarios, the revealed impact of the Great Recession on over-skilling is a matter of empirical investigation, a task which will be fullfilled with the present paper.

Within this context, the aim of the current paper is to expand the relevant literature on job mismatch by examining two different definitions of over-education, i.e. over-skilling and over-qualification, using data from four cohorts of Ph.D recipients surveyed from 2004 to 2010 by the Italian National Institute of Statistics (hereafter ISTAT). In particular, our study contributes to the existing literature on the over-education of Ph.D graduates in three main respects. First, focusing on the Italian case, we assess the effect of the recent structural financial and economic crisis on mismatch in the labour market of the most skilled workers. Our dataset includes Ph.D graduates' information just before and after 2008. Consequently, we are able to evaluate the

[4]Actually, Hershbein and Kahn (2016) show that upskilling is relatively concentrated in routine-cognitive occupations. In contrast, routine-manual occupations in harder-hit metropolitan area exhibit a sharp relative decline in employment shares following the Great Recession.

impact of the Great Recession on the probability of matching skills and educational level to occupational attainment. In so doing, we adopt different proxies to take the recession effect into account examining, for the first time to our knowledge, the nexus between over-education and economic resilience of local labor markets (Martin, 2012). Second, we contribute to better understanding of the determinants of over-education by distinguishing over-qualification from over-skilling in order to assess the sensitivity of results to measurement of educational mismatch. Finally, we improve the evidence on the situation of Italian Ph.D graduates. Before the present study, only Gaeta (2015) and Ermini et al. (2017) analyzed overeducation among Italian Ph.D graduates but solely Ermini et al. (2017) adopted both the two surveys of the professional outcomes of all Italian Ph.D graduates carried out issued by ISTAT (2014). Moreover, to the best of our knowledge, none of these studies fully and directly explored the effects of the ongoing severe economic crisis on Ph.D over-education. Focusing on this strand of high skilled workers is important to shed light on the returns to public investment, given that Ph.D education is mostly publicly financed in Italy. Furthermore, it helps to determine the capacity of the economy to keep pace with technological change - and thus avoid the 'low skill, low technology trap' (Snower, 1996; Di Pietro, 2002) - which requires skilled labour to be allocated to the appropriate level. Since over-education represents a source of individual, firm and societal costs especially when it concerns very highly-educated individuals, investigating it may furnish valid suggestions to calibrate policy measures to ensure that Ph.D graduates achieve jobs well-positioned in the labour market in terms of skill match.

Our main results confirm that the Great Recession reduced the risk of over-skilling while the impact on over-qualification is less robust. Ph.D recipients who are self-employed are instead penalized in the labor market when job mismatch is examined. Among other determinants, and in contrast with previous findings for college graduates, it emerges that socio-demographic variables do not impact strongly on Ph.D over-education. Remarkably, among Ph.D workers, social background seems not to affect significantly the likelihood of skill and title mismatch. Among Ph.D-related features, the most striking driver of over-education is completion of study period abroad.

The rest of the paper proceeds as follows. Section 2 presents our data and our econometric approach. It also describes the distinction between the two measures of over-education: over-skilling and over-qualification. Section 3 discusses the results of the empirical analysis, focusing on the impact of the Great Recession and other relevant drivers of over-education. Finally, concluding remarks are made in Section 4.

2 Empirical strategy

2.1 Data and over-education measures

The data for the present study come from two cross-sectional surveys on the professional outcomes of Italian Ph.D graduates carried out by ISTAT in 2009 and 2014.[5] The surveys were based on interviews administered with individuals who had obtained a doctoral degree in Italy

[5] Indagine sull'inserimento professionale dei dottori di ricerca (ISTAT, 2009, 2014). The present analysis uses the ISTAT Microdata for research purposes, available from ISTAT upon request.

in 2004 and 2006 (first survey) and in 2008 and 2010 (second survey), for a total of 41,037 graduates. Among the recipients, the respondents numbered 12,964 (out of 18,568) in 2009 and 16,322 (out of 22,469) in 2014, with an average response rate of approximately 70%.

The surveys reported information on four main issues: personal details and education; job and job search; mobility; family-related characteristics. The employment conditions of Ph.D-holders were assessed some years after graduation (that is, in the years when the surveys were conducted) so that we observe the possible over-education in the short and medium-term.[6] As regards the years investigated, almost 93% of the respondents were employed at the time of the survey and, among them, about 90% worked in the services sector (which includes also academia and other research-based occupations).

For the purpose of this paper, over-education is measured in terms of both skill and qualification mismatch. It should be stressed that we derive over-education by employing a subjective approach based on Ph.D graduates' self-assessment.[7] In particular, the first variable of interest, denoted as *over-skilling*, is defined on the basis of a question of the ISTAT survey asking about the utility of the competences acquired during the doctoral program to carry out the job. More specifically, the question was as follows: "According to you, is possessing a Ph.D necessary to carry out your current job?" and the possible answers were: "Yes, it is"/"No, it isn't".

The question was put to all the respondents employed at the time of the survey. On the basis of the 27,189 collected answers, *over-skilling* has been defined as a dummy variable and used as dependent variable in the present analysis: it is equal to one when respondents reported that the skills and competences acquired during the Ph.D were not useful to perform the job, and zero otherwise.

The second definition of over-education aims to assess the utility of the Ph.D title in obtaining a job. In this case, respondents were asked the following question: "Was the Ph.D title an explicit requirement to get your current job?" and the possible answers were: "explicitly required", "not required but useful", "neither required nor useful". Differently from the question about over-skilling, this one was put only to those individuals who had obtained their job after completion of their Ph.D. The relevant sample comprised 18,564 respondents representing about 68% of the Ph.D graduates employed at the time of the survey. In the analysis that follows, a dummy variable denoted as *over-qualification* has been defined, taking the value of one when respondents declared that the Ph.D title was neither required nor useful to get the current job and zero if the Ph.D was required or at least useful, even if not formally required.

In order to better compare the two definitions of over-education just described, we decided to restrict the sample used in the present analysis only to those doctoral graduates who started

[6] In the first survey the employment conditions of the respondents were assessed 3 and 5 years after Ph.D graduation (for those who were awarded the title in 2006 and 2004 respectively), while in the second survey the professional outcome was examined 4 and 6 years after graduation (for those who were awarded the title in 2010 and 2008 respectively).

[7] Usually, the choice among objective, statistical or subjective approaches for the measurement of over-education is driven by data availability because every method has advantages and drawbacks (Hartog, 2000). For instance, the subjective approach - adopted here - on the one hand is supposed to over-report over-education, but on the other, it makes it possible to obtain updated estimates of the phenomenon (Verhaest and Omey, 2006; Capsada-Munsech, 2015), and it has been widely used in the literature (Capsada-Munsech, 2015; Gaeta, 2015; Di Paolo and Mañé, 2016; Di Pietro and Urwin, 2006).

Table 1: Over-education among Italian Ph.D graduates

	Over-skilling		
Over-qualification	Yes	No	Total
Yes	3,247	237	3,484
No	4,646	8,053	12,699
Total	7,893	8,290	16,183

Source: Authors' elaboration - ISTAT, 2009, 2014

Table 2: Over-education in academia and in other R&D based occupations (%)

	University		R&D	
%	Yes	No	Yes	No
Over-skilled	14.34	85.66	18.15	81.85
Over-qualified	3.35	96.65	4.88	95.12

Source: Authors' elaboration - ISTAT, 2009, 2014

working after Ph.D completion and who worked in Italy at the time of the survey.

The total distribution of over-skilling and over-qualification in our sample is presented in Table 1. About 50% of the respondents in our sample declared that they were over-skilled (7,893 out of 16,183), while slightly more than 20% of them declared that the Ph.D title was neither required nor useful for obtaining their job; they were thus over-qualified (3,484 out of 16,183). Moreover, almost 50% were adequately matched in terms of job entry requirements and required skills (8,053 out of 16,183), while 20% were both over-qualified and over-skilled (3,247 out of 16,183) signaling that in Italy over-education is a crucial concern also for the most educated workers. The incidence of over-skilling and over-qualification is much more limited in academia and for those respondents employed in R&D activities (see Table 2).

2.2 Econometric approach

To investigate the relationship between over-education (OE) and the Great Recession (GR), we estimated the following model:

$$OE_i = \alpha + \beta GR_i + X\gamma + \epsilon_i \tag{1}$$

where $OE = OS, OQ$ for each respondent i and OS is over-skilling and OQ is over-qualification. GR is a proxy for the Great Recession computed for each respondent i. X is the matrix of our potential determinants of OE and ϵ is the individual error term.

Our dependent variable has a binary outcome, $OE \in (0, 1)$. It assumed value one when workers are over-educated; it is zero otherwise. Therefore, equation (1) can be estimated by a probit model.

Table 3: Over-education before and after the crisis (%)

		Before the crisis	After the crisis
Over-skilling	Yes	49.01	48.55
	No	50.99	51.45
	Total	100.00	100.00
Over-qualification	Yes	20.47	22.51
	No	79.53	77.49
	Total	100.0	100.0

Source: Authors' elaboration ISTAT 2009, 2014

In addition, our sample was a non-random selection of potential observations, since the probability of being over-educated was assessed only for those respondents employed at the time of the survey; it was unobserved otherwise. To correct for possible sample selection bias, we estimated a probit model with sample selection (Heckman, 1979; Van de Ven and Van Praag, 1981) to ascertain if unobservable factors affecting the propensity to obtain a job also impacted on over-education.[8] This approach yielded consistent, asymptotically efficient estimates for all parameters in the model when the correlation through the error terms of the main probit equation of determinants of over-education and the probit selection equation of the probability of being employed was other than zero. Differently, ignoring the selection into the labour market by using a simple probit model would have produced biased estimates of the determinants of the risk of over-education.

2.3 Great Recession measures and other regressors

The main purpose of our analysis was to assess the impact of the Great Recession on the risk of over-education among Ph.D recipients.

As to measurement issues, as a main proxy for the Great Recession we generated *crisis*, a dummy variable that assumed value one if Ph.D graduates were awarded their degree during the economic crisis, i.e. from 2008 onwards, and zero otherwise. This variable captured global discontinuity in the economic system due to adverse fluctuations and the related economic contraction. According to our sample, this cut-off distinguishes respondents to the first ISTAT survey (graduated in 2004 and 2006) from respondents to the second one (graduated in 2008 and 2010).

Moreover, under the assumption that the crisis resulted in a general slowdown of growth and a decline in the values of the main economic indicators, we elaborated two further indicators to depict the behavior of a worsening local labour market that, before and after the economic crisis, operated in significantly different economic conditions and with different opportunities for the newcomer Ph.D holders.[9]

[8] For example, if no matched jobs are available, unemployment is an option to avoid over-education. Thus, most likely to be overeducated are those least likely to enter employment (Büchel and Van Ham, 2003).

[9] The mean values of the two variables computed before and after the crisis signal a deterioration of the labor market's performance post-recession. Indeed, tests of the difference between the two periods' means returned to

Accordingly, as a second indicator of the Great Recession, we approximated the crisis of labour market prospects by computing the variation of the value added (*varVA*) registered in the provincial job area of a worker who entered the labour market as a Ph.D holder before and after the crisis, as follows:

$$varVA_{k,p} = \frac{VA^p_{k,t(k)} - VA^p_{k,t(k)-1}}{VA^p_{k,t(k)-1}}$$

with $k = 2004, 2006, 2008, 2010$, i.e. the cohort of graduates, $p = 1, 2...110$, i.e. the Italian province where the job is located and $t(k)$ the relevant year to compute the variation across two points of time as a function of k such that $t(k) = \begin{cases} \text{2007 if k=2004, 2006} \\ \text{2011 if k=2008, 2010} \end{cases}$. Higher values of *varVA* denote a lower exposure to the economic crisis pointing out the growth of value added across the two points of time.

Finally, according to Martin (2012), differences in the region's sensitivity to an economic fluctuation can be observed because of its economic resilience. We built on the concept of resilience to elaborate a measure of regional difference in employment opportunities. We basically compared percentage growth in employment in a region relative to the national one, before and after the crisis. By so doing, we were able to assess if the crisis had worsened the capacity of the labour market to give workers an occupation. For the post-recession, this measure corresponds to the economic resilience described by Martin (2012). In fact, the impact of the crisis depends on the real exposure of the local labor market to the fluctuation and on its capacity to restructure economically in response to a crisis. To our knowledge, the nexus between territorial economic resilience in the broad sense and over-education has not yet received attention. We think that investigation of this relationship is of interest, given that more resilient labour markets can offer more opportunities for skill-job matching because they are better able to drive regional transformation, to retain manufacturing, and to innovate a high-tech economy - that is, to offer more abstract and non-routine occupations to high skilled workers. Accordingly, we used *resilience* as an additional proxy to evaluate the impact of the crisis on the risk of over-education among Ph.Ds. Thus, we computed:

$$resilience_{k,p} = \frac{\frac{\Delta E^p}{E^p} - \frac{\Delta E^N}{E^N}}{|\frac{\Delta E^N}{E^N}|}$$

with: $\frac{\Delta E}{E}$=employment variation; $\frac{\Delta E^p}{E^p} = \frac{E^p_{k,t(k)} - E^p_{k,t(k)-2}}{E^p_{k,t(k)-2}}$; k = 2004, 2006, 2008, 2010; $t(k)$ = $\begin{cases} \text{2007 if k=2004, 2006} \\ \text{2010 if k=2008, 2010} \end{cases}$; $p = 1, 2...110$ is the province of jobs and N=Italy.[10] Values of $resilience$ above zero indicate the greater resistance of the province to economic shocks compared to the nation. In contrast, values less than zero indicate a decreased ability to cope with a recessionary period compared to the national average.

being statistically significant. Results are available on request.

[10]When using employment as a measure to evaluate the state of the local labour market, we adopted a temporal lag larger than the one assumed to evaluate changes in value added, given that the employment level reacts slowly to variations in local economic conditions: that is, employment effects are more persistent.

We completed our analysis of the drivers of over-education by including three different categories of covariates ($\mathbf{x}_i$) in the main equation: socio-demographic information, Ph.D features and job attributes.

In the first group we included dummy variables to control if the respondent was female (*female*) and an Italian citizen (*IT_citizenship*). To investigate the impact of social mobility on labour market outcomes, the social background of the graduates' family of origin was proxied by parents' social class (*parclass*).[11]

Features and performance related to the Ph.D course were examined by including in the regressions the scientific field of study (*studyfield*), a dummy denoting whether the Ph.D was obtained in due course (*PhD_end*), a dummy indicating if the Ph.D graduate was granted a scholarship during the doctoral program (*scholarship*) and a dummy to signal if individuals spent a study period abroad (*visiting_abroad*). Finally, because of data limitations, we were able to capture effects related to institutional characteristics at university level, and mainly the Ph.D program quality effect, only by including the province where the university awarding the Ph.D title was located (*PhD_province*).

As regards the professional profile of Ph.D graduates, we included the variable (*sector*) to identify if the Ph.D worker was active in agriculture, industry or service sector. We also added a dummy taking value one if the respondent worked in the academic sector, and zero otherwise (*academic*). Similarly, the dummy *R&D* signalled if the Ph.D worker had a job mainly based on research and development activities. Furthermore, we took into account if Ph.D recipients worked as employed or self-employed workers (*selfemployed*), and we included the number of hours worked per week (*week_hours*). The variable *jobexp* registered the number of professional experiences between the year of Ph.D completion and the year of the survey, while the dummy *mobility_PhDjob* controlled for regional mobility occurring between the region where the Ph.D university was located and the job region. We completed the set of job features by considering whether family networks or other informal channels helped in obtaining the job (*informal_access*).

As regards the selection equation adopted to correct for potential sample selection, the estimation procedure required inclusion in the selection equation of regressors that could be legitimately excluded from our explanatory variable set of the main model of the risk of over-education.[12] In other words, we needed to select at least one instrument variable influencing the probability of being employed at the time of the survey, but not the probability of being over-educated. Following the relevant literature, we used two variables pertaining to the graduate's own family as exclusion restrictions for the employment equation: marital status (*married*) and children (*children*). More specifically, studies on the reliance of wage premium for married men have confirmed that married men are, or are perceived to be, more valuable employees because they are more stable and committed workers (see de Linde Leonard and Stanley (2015) for a recent survey). This prejudice may help married men to outperform in employment selection. Additionally, well documented is the inertia of sociological models such as the "male bread

[11] For the definition of the variable *parclass* we followed ISTAT (2003).

[12] Actually, the model was basically identified by functional form because the bivariate probit model is non-linear. However, adopting a proper set of instruments allowed us to avoid multicollinearity problems and ensure a better identification of the model (Büchel and Van Ham, 2003).

winner", which assign more financial responsibility to men within Italian families (Naldini and Jurado, 2013). Besides the marital status, also having children may have some bearing on the motivation of the Ph.D graduate towards paid employment, as pointed out in Dolton and Vignoles (2000) and Di Pietro and Cutillo (2006) and, also in this case, the influence of childcare may be different between men and women. In light of the arguments just illustrated, the variables chosen as exclusion restrictions were included in the selection equation both directly and interacted with the variable *female*. Additionally, socio-demographic information, Ph.D-related features and the variable on the area of residence were included among the regressors of the employment status in the selection equation.

All the dependent and independent variables outlined above are briefly defined in Table 4, which also reports the relevant summary statistics.

3 Results and discussion

This section presents the empirical results of our econometric analysis. First, we present the results of the empirical model of over-skilling. We then analyze the drivers of over-qualification. As a general approach, we start by estimating a baseline model which includes the entire set of assumed drivers of over-skilling and over-qualification excluding proxies for the Great Recession. Second, we examine the impact of the Great Recession by adding our adopted proxies for the crisis (*crisis*, *varVA* and *resilience*).

3.1 Overskilling

Table 5 reports the estimates of the probability of being over-skilled. When the coefficients of the selection term are statistically different from zero, we rely on the estimates of the probit model with sample selection. Actually, the sample selection is relevant for all the models we estimated. The variables chosen as instruments in the selection equation are significant and show the expected sign: having children and being married increase the probability of getting a job, denoting a relatively higher urgency to provide family sustenance. However, when also the gender variable is taken into account, a disadvantage for women emerges: being a woman with children or being a married woman reduces the probability of being employed, confirming our theoretical predictions. Notably, the coefficient of the dummy *crisis* shows a negative and significant sign confirming our expectation that during a recession opportunities to find a job are relatively scarce and being unemployed is more likely. Overall, the results of the whole selection model appear to be fairly stable across all the estimated specifications.

Columns (1)-(3) of Table 5 report estimates of the baseline equation, whereas columns (4)-(12) present the estimates of the impact of the Great Recession on over-skilling using the three key regressors discussed above: *crisis*, *varVA* and *resilience*.

Before discussing the impact of the Great Recession, we briefly comment on the estimates reported in column (2) to investigate the drivers of over-skilling among Ph.D graduates.

As for the socio-demographic characteristics, we detect a significantly higher probability of being over-skilled for Italian Ph.D recipients compared to foreign peers. This result echoes that of Lindley (2009), who finds some positive returns to occupational skills for some minority ethnic and immigrant groups. It may also suggest that foreign workers are characterized by a high propensity to mobility across countries, so that, if they are unable to obtain a matched job in a given place, they may decide to move elsewhere to find a more suitable job (for example, by returning to the country of origin). Furthermore, being a female workers turns out to generally increase the likelyhood of the mismatch. Differently, social background, as proxied by parents' class, appears not significant in predicting over-skilling. This finding diverges from previous empirical evidence of a positive correlation between higher socio-economic family endowment and job-education matching (Di Pietro and Cutillo, 2006). However, contrary to the general belief that intergenerational social mobility is persistently low in Italy (Checchi, 2010; Causa and Johansson, 2011) and more in line with our results, Capsada-Munsech (2015) highlights that parental background is pervasive for over-education exclusively for Italian graduates from fields of study that do not lead to a specific occupation, while socio-economic origins do not influence the outcome of those who choose more occupationally targeted fields of study. We suspect that this effect is even stronger within our sample as Ph.D programs provide further professional specialization.[13]

On looking at the Ph.D-related features, results suggest that finishing the Ph.D in due course reduces the probability of being mismatched. When significant, the coefficient of the variable PhD_end is in fact negative. A similar result holds for those who have been granted a scholarship. Furthermore, Ph.D graduates who have spent study periods abroad are found to be at a lower risk of mismatch relatively to their non-mobile peers. Even if we cannot rule out that this difference may depend on unobserved individual features, nevertheless experience abroad may integrate the educational training, thereby signaling a better-quality educational pattern. Among the scientific fields of study, Economics and Statistics (the reference category) proves to be the discipline associated with the lowest probability of over-skilling in tandem with Hard Sciences and Technical Sciences, whose coefficients are not statistically different from the reference field of study.

As for the job-related variables, doctoral courses are confirmed to be a forge of qualified human capital particularly tailored to research activity. Those who are employed in the academic sector or conduct R&D activity within other institutions or firms report a lower risk of being over-skilled because they can entirely take advantage of the knowledge acquired during their doctoral studies. As in Bender and Roche (2013), self-employed workers are characterized by a higher risk of mismatch compared to those working as employees. Similarly, to rely on family connections or other informal channels to get the job does not ensure a proper skill-job match. In addition, working in industry compared to other sectors turns out to be associated with a higher likelihood of mismatch. Moreover, having had only one professional experience after the completion of the Ph.D (instead of more than one) is associated with a worse match. Finally, the higher the number of hours worked weekly, the lower risk of over-skilling.

Moving to possible differences in skill-job matching before and after the financial crisis, we

[13]Nevertheless, we cannot exclude that socio-economic background influences labor-market outcomes in a more indirect way. For example, it influences the probability of getting a job because, according to our estimates, parents' social class turns out to be more significant in the selection equation. In addition, the indirect impact of socio-economic background emerges already from high school when the educational pattern is chosen, for example by influencing the educational pattern and thus conditioning the future professional path (Brunello and Checchi, 2007; Caroleo and Pastore, 2013).

examine the econometric results set out in columns (4)-(12). The coefficient of *crisis*, which is our main proxy for the Great Recession, is negative and significant. This result suggests that the Great Recession has increased the probability of Ph.D-holders finding the job most appropriate for their skills. In other words, for this group of highly educated workers, the risk of over-skilling seems to be less likely during a downturn. In column (7) we report the estimated coefficient of *varVA*. The correlation between this variable and over-skilling is positive, suggesting that as the index grows - signaling that the area is less hit by the crisis - over-skilling is more likely, in line with the evidence emerged by using the dummy *crisis*. We then assess the predictive power of the variable *resilience* in column (11) which is in line with the previous one (*varVA*). Also in this case, in fact, the estimated coefficient is positive and significant, referring that Ph.D-holders working in areas with a lower level of market potential faced a lower risk of mismatch. Overall, the above evidence supports the hypothesis according to which the investment in qualified and skilled human capital turned out to be one possible way to face a downturn.

3.2 Over-qualification

Table 6 presents estimates of the predictors, including the impact of the Great Recession, of over-qualification as an alternative definition of over-education.

Given the results of the selection mechanism, we chose for our econometric approach the probit model with sample selection. For any of the empirical specifications, Table 6 reports our estimates of the main model of over-qualification and of the employment selection equation. To be noted is that the excluded instruments performed as expected in predicting the probability of being employed: being married and having children prompt individuals to work, but they can be obstacles if the worker is a woman. Moreover, bad economic conditions reduce the probability of being employed.

Considering first the baseline equation shown in columns (2)-(3), the estimates replicate the findings when over-skilling was examined: over-qualification is mainly driven by job attributes, and a minor role is played by socio-demographic characteristics of individuals. As in the estimates for over-skilling, female Ph.D graduates are more likely to be over-qualified than males. Differently, citizenship turns out to be not significant in explaining the mismatch in terms of qualification: native Ph.D-holders were more prone to be over-skilled, whereas they do not differ from foreign Ph.D-holders as regards over-qualification.

Furthermore, since the definition of over-qualification focuses on the title as a yardstick of educational attainment and human capital accumulation, we expect that those variables proxying for the ease and the ability to successfully complete the doctoral path show a negative coefficient. This is in fact the case for *PhD_end* and *scholarship*, whose coefficients are negative when significant.

Concerning the impact of the recent downturn on over-qualification, inspection of columns (4)-(12) of Table 6 does not find any correlation between the entire set of proxies for the Great Recession and the title mismatch. This result is not completely unexpected. We foresaw a reduced effect of the Great Recession on over-qualification compared to over-skilling. In fact, sectors where the title requirement was relevant or mandatory probably performed poorly in terms of jobs offered because of the crisis - as also revealed by the coefficient of *crisis* in the selection equation - but it is more unlikely that they underperformed in terms of over-qualification.

Moreover, outside these sectors qualification-job match may be produced by mechanisms like those leading to under-employment or up-skilling in the labour market.

4 Final remarks

In this paper we have sought to shed light on the impact of the Great Recession on Ph.D graduates' over-education. We have focused on Italian Ph.D-holders, graduated from 2004 to 2010, using two very informative surveys carried out by ISTAT (2009, 2014). Based on ISTAT data, skill and qualification mismatches appear to be widespread phenomena. Almost 50% of the respondents declared that they were over-skilled, whereas about 20% were over-qualified. Our estimates revealed a considerable impact of the Great Recession, especially on over-skilling. This effect emerged when the incidence of the crisis was measured both using a crude dummy and when we adopted more refined indicators that explicitly took account of economic performance at provincial level, such as value added growth or resilience. The direct impact of the Great Recession on over-qualification is less robust.

As regards other drivers of over-education, socio-demographic variables do not seem to affect significantly the probability of being over-educated - at least, not as much as they do in the case of college graduates. Surprisingly, the family of origin of doctoral graduates does not influence over-education. International exposure emerges as a key aspect of a Ph.D course, because spending a study period abroad proves to be the characteristic that most affects a successful job matching. Overall, a strong result of this paper, in line with the assignment model approach, is that job characteristics are the main drivers of the risk of mismatch among Ph.D-holders; they exert a similar impact on over-skilling and over-qualification. Besides a prominent protective effect induced by working in a university or R&D-based center, we stress that self-employers or workers in the manufacturing sector are at a greater risk of over-education.

These findings prompt several considerations. First, closer attention should be paid by economic studies to the education-job mismatch concerning the most high-qualified workers, a phenomenon which is still relatively overlooked. Second, over-education is not only a concern for individuals (dissatisfied workers) and firms (declining productivity); it should be an important issue also for policy makers. In fact, governments devote growing amounts of financial resources to Ph.D initiatives; consequently, they should monitor the return on public investment in doctorate programs, contemplating over-education as well. Moreover, policy makers can affect over-education by influencing both the demand for and the supply of Ph.D graduates. Especially during downturns, demand policies might provide tax incentives for hiring skilled workers, whereas, on the other hand, governments could affect the supply of Ph.Ds by considering the distributional heterogeneity of over-education among different scientific subjects. If so, governments should address the issue of how to shift the Ph.D system away from those areas in which over-education is higher. Third, our findings concerning doctoral education provide support for the hypothesis that investment in human capital turns out to be an effective strategy to deal with economic fluctuations and to cope with cyclical variations. Fourth, our evidence seems to confirm that the Italian Ph.D is still based on a research-oriented educational pattern, since working in academia or in research-based sectors provides the most successful matching. In this regard, if there is consensus that Ph.D programs should also favor the transfer of knowledge outside academia, our evidence highlights the need for more incisive policies to achieve that purpose. Indeed, our findings call for policy actions promoting a more applicable type of knowledge which might be more valuable outside the pure research sectors. Hopefully, this should produce successful outcomes also among self-employed workers, who, according to our results, appear to be at a disadvantage. Finally, there is also a need to monitor and analyze the dynamics of over-education once the effects of the Great Recession will be overcome.

Table 4: Variables and summary statistics

Variable *(label)*	Description	Obs	Mean	Std. Dev.	Min	Max
DEPENDENT VARIABLES						
Over-skilling *(oversk)*	dummy=1 if over-skilled	16,183	0.488	0.500	0	1
Over-qualification *(overqual)*	dummy=1 if over-qualified	16,183	0.215	0.411	0	1
Employment *(employm)*	dummy=1 if employed	18,280	0.885	0.319	0	1
GREAT RECESSION VARIABLES						
Great recession *(crisis)*	dummy=1 if Ph.D awarded during the Great Recession	18,280	0.526	0.499	0	1
Value Added variation *(varVA)*	Provincial variation of Value Added	16,183	0.030	0.022	-0.050	0.135
Provincial Economic Resilience *(resilience)*	Provincial labour market economic resilience	16,058	-0.341	2.691	-18.810	7.721
SOCIO-DEMOGRAPHIC VARIABLES						
Gender *(female)*	dummy=1 if female	18,280	0.549	0.498	0	1
Citizenship *(IT_citizenship)*	dummy=1 if Italian	18,280	0.989	0.104	0	1
Marital status *(married)*	dummy=1 if married or living together	18,280	0.510	0.500	0	1
Children *(children)*	dummy=1 if having at least one child	18,280	0.351	0.477	0	1
Parents class	Parents' highest social class:					
(parclass_bourge)	bourgeoisie*	18,280	0.284	0.451	0	1
(parclass_middle)	middle class	18,280	0.409	0.492	0	1
(parclass_petitebourge)	petite bourgeoisie	18,280	0.177	0.382	0	1
(parclass_working)	working class	18,280	0.104	0 .306	0	1
(parclass_other)	other	18,280	0.026	0.159	0	1
Ph.D-RELATED VARIABLES						
Ph.D end *(PhD_end)*	dummy=1 if Ph.D in due course	18,280	0.887	0.316	0	1
Scholarship *(scholarship)*	dummy=1 if granted a scholarship during the Ph.D	18,280	0.814	0.389	0	1
Visiting abroad *(visiting abroad)*	dummy=1 if visiting abroad for at least 1 month	18,280	0.358	0.479	0	1
Study field	Ph.D scientific field of study:					
(studyfield_hardsc)	Hard sciences	18,280	0.283	0.450	0	1
(studyfield_medicine)	Medicine	18,280	0.133	0.339	0	1

continue to the next page

Table 4: continued from the previous page

Variable *(label)*	Description	Obs	Mean	Std. Dev.	Min	Max
(studyfield_agrivet)	Agriculture and Veterinary sciences	18,280	0.075	0.263	0	1
(studyfield_tech)	Technical Sciences	18,280	0.185	0.388	0	1
(studyfield_ecostat)	Economics and Statistics*	18,280	0.056	0.230	0	1
(studyfield_law)	Law	18,280	0.059	0.236	0	1
(studyfield_socpolhum)	Socio-political sciences and humanities	18,280	0.210	0.408	0	1
JOB-RELATED VARIABLES						
Self-employment *(selfemployed)*	dummy=1 if self-employed	16,183	0.100	0.300	0	1
Informal access *(informal_access)*	dummy=1 if informal channels to find job	16,183	0.077	0.267	0	1
Academic *(academic)*	dummy=1 if academic sector	16,183	0.393	0.488	0	1
R&D *(R&D)*	dummy=1 if R&D prevalent in job	16,183	0.464	0.499	0	1
Week hours *(week_hours)*	Number of hours worked per week (logarithm)	16,180	3.536	0.481	0	4.511
Sector *(sector)*	Employment sector:					
(sector_ind)	Industry*	16,183	0.091	0.288	0	1
(sector_serv)	Service	16,183	0.891	0.312	0	1
(sector_agric)	Agriculture	16,183	0.018	0.133	0	1
Job experience	Number of jobs:					
(jobexp_one)	One job (current) started after Ph.D completion	16,183	0.446	0.497	0	1
(jobexp_more)	More than one job after Ph.D completion*	16,183	0.554	0.497	0	1
Mobility *(mobility_PhDjob)*	dummy=1 if the PhD region is different from the job region	16,183	0.290	0.454	0	1

* denotes the reference category in the estimation.

Table 5: Great Recession and over-skilling

	Probit	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	oversk	oversk	employm	oversk	oversk	employm	oversk	oversk	employm	oversk	oversk	employm
crisis			-0.170***	-0.192***	-0.203***	-0.159***			-0.156***			-0.171***
			(0.027)	(0.025)	(0.023)	(0.026)			(0.027)			(0.027)
varVA							3.356***	3.055***				
							(0.589)	(0.590)				
resilience										0.010**	0.008*	
										(0.005)	(0.005)	
children			0.174***			0.127**			0.173***			0.173***
			(0.059)			(0.057)			(0.059)			(0.059)
children × female			-0.360***			-0.324***			-0.363***			-0.360***
			(0.071)			(0.068)			(0.071)			(0.071)
married			0.280***			0.266***			0.283***			0.279***
			(0.051)			(0.050)			(0.052)			(0.052)
married × female			-0.281***			-0.255***			-0.283***			-0.281***
			(0.064)			(0.062)			(0.065)			(0.064)
female	0.059**	0.083***	0.035	0.059**	0.001	0.017	0.061**	0.081***	0.037	0.056**	0.080***	0.034
	(0.025)	(0.025)	(0.036)	(0.025)	(0.023)	(0.035)	(0.025)	(0.025)	(0.036)	(0.025)	(0.025)	(0.036)
IT_citizenship	0.425***	0.354***	0.357***	0.396***	0.447***	0.346***	0.420***	0.363***	0.360***	0.418***	0.348***	0.355***
	(0.119)	(0.117)	(0.106)	(0.119)	(0.108)	(0.105)	(0.119)	(0.119)	(0.106)	(0.119)	(0.117)	(0.106)
parclass_middle	-0.004	0.005	-0.066**	0.001	-0.017	-0.070**	-0.005	0.003	-0.066**	-0.004	0.006	-0.067**
	(0.029)	(0.029)	(0.032)	(0.029)	(0.027)	(0.031)	(0.029)	(0.029)	(0.032)	(0.029)	(0.029)	(0.032)
parclass_petitebourge	0.090**	0.107***	-0.147***	0.088**	0.035	-0.144***	0.086**	0.101***	-0.147***	0.085**	0.102***	-0.148***
	(0.037)	(0.036)	(0.038)	(0.037)	(0.034)	(0.038)	(0.037)	(0.036)	(0.038)	(0.037)	(0.036)	(0.038)
parclass_working	-0.024	-0.012	-0.073	-0.016	-0.035	-0.081*	-0.021	-0.011	-0.075	-0.032	-0.019	-0.075
	(0.043)	(0.043)	(0.046)	(0.044)	(0.040)	(0.046)	(0.044)	(0.043)	(0.046)	(0.044)	(0.043)	(0.046)
parclass_other	-0.062	-0.017	-0.279***	-0.013	-0.099	-0.261***	-0.041	-0.005	-0.281***	-0.062	-0.016	-0.279***
	(0.080)	(0.079)	(0.074)	(0.081)	(0.073)	(0.073)	(0.081)	(0.080)	(0.074)	(0.081)	(0.079)	(0.074)
PhD_end	-0.069*	-0.094**	0.173***	-0.080**	-0.010	0.168***	-0.073*	-0.094**	0.174***	-0.068*	-0.093**	0.174***
	(0.040)	(0.039)	(0.038)	(0.040)	(0.037)	(0.038)	(0.040)	(0.040)	(0.038)	(0.040)	(0.039)	(0.038)
scholarship	-0.056*	-0.063**	0.057*	-0.066**	-0.041	0.050	-0.058*	-0.065**	0.059*	-0.056*	-0.064**	0.057*
	(0.031)	(0.031)	(0.032)	(0.031)	(0.029)	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)	(0.032)
visiting_abroad	-0.192***	-0.203***	0.145***	-0.166***	-0.105***	0.127***	-0.183***	-0.194***	0.144***	-0.191***	-0.203***	0.145***
	(0.026)	(0.025)	(0.028)	(0.026)	(0.025)	(0.028)	(0.026)	(0.025)	(0.028)	(0.026)	(0.025)	(0.028)
studyfield_hardsc	0.076	0.090	-0.090	0.092	0.055	-0.074	0.079	0.091	-0.092	0.074	0.088	-0.093
	(0.059)	(0.057)	(0.063)	(0.059)	(0.054)	(0.063)	(0.059)	(0.058)	(0.063)	(0.059)	(0.058)	(0.063)
studyfield_medicine	0.261***	0.260***	0.005	0.287***	0.247***	0.049	0.272***	0.271***	0.002	0.262***	0.262***	-0.002
	(0.063)	(0.062)	(0.069)	(0.063)	(0.059)	(0.069)	(0.063)	(0.062)	(0.069)	(0.063)	(0.062)	(0.070)
studyfield_agrivet	0.149**	0.170**	-0.163**	0.161**	0.088	-0.124*	0.154**	0.172**	-0.166**	0.155**	0.176**	-0.166**
	(0.072)	(0.071)	(0.075)	(0.072)	(0.067)	(0.074)	(0.072)	(0.071)	(0.075)	(0.072)	(0.071)	(0.075)
studyfield_tech	0.076	0.067	0.117*	0.095	0.102*	0.145**	0.081	0.073	0.115*	0.075	0.066	0.116*
	(0.061)	(0.059)	(0.068)	(0.061)	(0.056)	(0.067)	(0.061)	(0.060)	(0.068)	(0.061)	(0.060)	(0.068)
studyfield_law	0.242***	0.268***	-0.234***	0.250***	0.158**	-0.220***	0.244***	0.267***	-0.235***	0.235***	0.261***	-0.234***
	(0.075)	(0.073)	(0.076)	(0.075)	(0.069)	(0.075)	(0.075)	(0.074)	(0.076)	(0.075)	(0.073)	(0.076)
studyfield_socpolhum	0.092	0.147**	-0.379***	0.097	-0.022	-0.363***	0.094	0.140**	-0.380***	0.091	0.146**	-0.382***
	(0.060)	(0.060)	(0.063)	(0.060)	(0.056)	(0.062)	(0.060)	(0.061)	(0.063)	(0.060)	(0.060)	(0.063)
mobility_PhDjob	-0.060**	-0.058**		-0.062**	-0.051**		-0.063**	-0.062**		-0.059**	-0.057**	
	(0.027)	(0.026)		(0.027)	(0.024)		(0.027)	(0.027)		(0.027)	(0.026)	

Table 5: continued from the previous page

	Probit	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	oversk	oversk	employm	oversk	oversk	employm	oversk	oversk	employm	oversk	oversk	employm
jobexp_one	0.074***	0.070***		0.053**	0.046**		0.064***	0.062***		0.074***	0.070***	
	(0.024)	(0.024)		(0.024)	(0.021)		(0.024)	(0.024)		(0.024)	(0.024)	
sector_serv	-0.331***	-0.325***		-0.318***	-0.277***		-0.326***	-0.322***		-0.332***	-0.327***	
	(0.044)	(0.043)		(0.044)	(0.038)		(0.044)	(0.043)		(0.044)	(0.043)	
sector_agric	-0.350***	-0.346***		-0.326***	-0.271***		-0.338***	-0.336***		-0.357***	-0.352***	
	(0.097)	(0.094)		(0.097)	(0.083)		(0.097)	(0.095)		(0.097)	(0.095)	
week_hours	-0.166***	-0.163***		-0.176***	-0.142***		-0.170***	-0.169***		-0.166***	-0.164***	
	(0.026)	(0.026)		(0.026)	(0.023)		(0.026)	(0.026)		(0.026)	(0.026)	
selfemployed	0.259***	0.255***		0.257***	0.199***		0.260***	0.257***		0.264***	0.259***	
	(0.043)	(0.041)		(0.043)	(0.036)		(0.043)	(0.042)		(0.043)	(0.042)	
informal_access	0.128***	0.126***		0.132***	0.111***		0.128***	0.127***		0.125***	0.122***	
	(0.044)	(0.043)		(0.044)	(0.038)		(0.044)	(0.043)		(0.045)	(0.043)	
academic	-1.101***	-1.062***		-1.109***	-1.026***		-1.109***	-1.081***		-1.098***	-1.060***	
	(0.029)	(0.033)		(0.029)	(0.027)		(0.029)	(0.033)		(0.029)	(0.033)	
R&D	-1.175***	-1.141***		-1.194***	-1.083***		-1.181***	-1.157***		-1.177***	-1.143***	
	(0.026)	(0.030)		(0.026)	(0.026)		(0.026)	(0.030)		(0.026)	(0.030)	
Constant	1.393***	1.494***	1.009***	1.560***	1.136***	1.017***	1.317***	1.415***	0.996***	1.409***	1.507***	1.012***
	(0.182)	(0.177)	(0.143)	(0.184)	(0.167)	(0.141)	(0.182)	(0.180)	(0.143)	(0.182)	(0.178)	(0.144)
Observations	16,180	18,277	18,277	16,180	18,277	18,277	16,180	18,277	18,277	16,055	18,152	18,152
LR test of indep. eqns. $\rho = 0$ (p-value)			9.62 (0.002)			30.84 (0.000)			4.65 (0.031)			9.09 (0.003)

Legend: Significance is indicated as follows: *** denoting the 1%, ** the 5% and * the 10% level.

Table 6: Great Recession and over-qualification

	Probit	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	overqual	overqual	employm	overqual	overqual	employm	overqual	overqual	employm	overqual	overqual	employm
crisis			-0.140***	-0.010	0.020	-0.144***			-0.138***			-0.142***
			(0.026)	(0.026)	(0.026)	(0.027)			(0.026)			(0.026)
varVA							0.823	0.459				
							(0.610)	(0.597)				
resilience										0.005	0.003	
										(0.005)	(0.005)	
children			0.155***			0.154***			0.156***			0.153***
			(0.058)			(0.058)			(0.059)			(0.058)
children × female			-0.350***			-0.347***			-0.352***			-0.347***
			(0.070)			(0.070)			(0.071)			(0.071)
married			0.296***			0.295***			0.297***			0.295***
			(0.051)			(0.051)			(0.051)			(0.051)
married × female			-0.293***			-0.292***			-0.294***			-0.293***
			(0.064)			(0.064)			(0.064)			(0.064)
female	0.047*	0.082***	0.039	0.047*	0.085***	0.037	0.047*	0.081***	0.039	0.048*	0.084***	0.037
	(0.027)	(0.028)	(0.036)	(0.027)	(0.027)	(0.036)	(0.027)	(0.028)	(0.036)	(0.027)	(0.028)	(0.036)
IT_citizenship	0.121	0.035	0.371***	0.119	0.032	0.371***	0.119	0.039	0.372***	0.116	0.030	0.369***
	(0.133)	(0.130)	(0.106)	(0.133)	(0.128)	(0.106)	(0.133)	(0.131)	(0.106)	(0.133)	(0.129)	(0.106)
parclass_middle	0.001	0.014	-0.068**	0.001	0.014	-0.067**	0.001	0.013	-0.068**	0.000	0.014	-0.069**
	(0.032)	(0.031)	(0.032)	(0.032)	(0.030)	(0.032)	(0.032)	(0.031)	(0.032)	(0.032)	(0.031)	(0.032)
parclass_petitebourge	0.027	0.054	-0.146***	0.026	0.056	-0.146***	0.026	0.052	-0.146***	0.025	0.053	-0.146***
	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)	(0.038)
parclass_working	0.065	0.078*	-0.077*	0.066	0.077*	-0.076	0.067	0.078*	-0.077*	0.061	0.074*	-0.078*
	(0.046)	(0.044)	(0.046)	(0.046)	(0.044)	(0.046)	(0.046)	(0.044)	(0.046)	(0.046)	(0.045)	(0.046)
parclass_other	-0.005	0.058	-0.280***	-0.003	0.058	-0.278***	0.001	0.059	-0.280***	0.006	0.070	-0.280***
	(0.084)	(0.083)	(0.074)	(0.084)	(0.082)	(0.074)	(0.084)	(0.083)	(0.074)	(0.084)	(0.083)	(0.074)
PhD_end	-0.029	-0.066	0.177***	-0.029	-0.068*	0.176***	-0.030	-0.065	0.177***	-0.027	-0.066	0.178***
	(0.041)	(0.041)	(0.038)	(0.041)	(0.040)	(0.038)	(0.041)	(0.041)	(0.038)	(0.041)	(0.041)	(0.038)
scholarship	-0.081**	-0.090***	0.058*	-0.082**	-0.089***	0.058*	-0.082**	-0.090***	0.059*	-0.083**	-0.092***	0.058*
	(0.032)	(0.031)	(0.032)	(0.032)	(0.031)	(0.032)	(0.032)	(0.031)	(0.032)	(0.033)	(0.031)	(0.032)
visiting_abroad	-0.101***	-0.120***	0.144***	-0.100***	-0.124***	0.145***	-0.099***	-0.118***	0.144***	-0.102***	-0.121***	0.145***
	(0.028)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)
studyfield_hardsc	0.032	0.050	-0.100	0.033	0.051	-0.100	0.032	0.050	-0.100	0.030	0.050	-0.103
	(0.066)	(0.064)	(0.063)	(0.066)	(0.063)	(0.063)	(0.066)	(0.064)	(0.063)	(0.067)	(0.064)	(0.063)
studyfield_medicine	0.241***	0.234***	-0.002	0.242***	0.231***	-0.002	0.243***	0.236***	-0.003	0.246***	0.239***	-0.009
	(0.069)	(0.067)	(0.069)	(0.069)	(0.067)	(0.069)	(0.069)	(0.067)	(0.069)	(0.070)	(0.067)	(0.069)
studyfield_agrivet	0.098	0.127*	-0.165**	0.098	0.129*	-0.164**	0.099	0.127	-0.166**	0.111	0.141*	-0.167**
	(0.080)	(0.077)	(0.075)	(0.080)	(0.076)	(0.075)	(0.080)	(0.077)	(0.075)	(0.080)	(0.077)	(0.075)
studyfield_tech	0.011	-0.001	0.116*	0.012	-0.004	0.116*	0.012	-0.001	0.115*	0.010	-0.003	0.114*
	(0.068)	(0.066)	(0.068)	(0.068)	(0.065)	(0.068)	(0.068)	(0.066)	(0.068)	(0.068)	(0.066)	(0.068)
studyfield_law	0.120	0.161**	-0.241***	0.120	0.163**	-0.241***	0.120	0.159**	-0.241***	0.116	0.159**	-0.242***
	(0.081)	(0.079)	(0.076)	(0.081)	(0.078)	(0.076)	(0.081)	(0.079)	(0.076)	(0.082)	(0.079)	(0.076)
studyfield_socpolhum	0.149**	0.221***	-0.385***	0.150**	0.225***	-0.385***	0.149**	0.218***	-0.386***	0.160**	0.233***	-0.389***
	(0.067)	(0.067)	(0.063)	(0.067)	(0.067)	(0.063)	(0.067)	(0.068)	(0.063)	(0.067)	(0.067)	(0.063)
mobility_PhDjob	-0.067**	-0.064**		-0.067**	-0.063**		-0.069**	-0.065**		-0.069**	-0.065**	
	(0.029)	(0.027)		(0.029)	(0.027)		(0.029)	(0.027)		(0.029)	(0.027)	

Table 6: continued from the previous page

	Probit	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*		*Probit*	*Probit with sample sel.*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	overqual	overqual	employm	overqual	overqual	employm	overqual	overqual	employm	overqual	overqual	employm
jobexp_one	0.041	0.035		0.040	0.036		0.039	0.034		0.045*	0.038	
	(0.026)	(0.024)		(0.026)	(0.024)		(0.026)	(0.025)		(0.026)	(0.025)	
sector_serv	-0.369***	-0.354***		-0.368***	-0.353***		-0.369***	-0.355***		-0.378***	-0.362***	
	(0.041)	(0.040)		(0.041)	(0.040)		(0.041)	(0.040)		(0.041)	(0.040)	
sector_agric	0.010	0.003		0.011	-0.000		0.012	0.005		0.003	-0.003	
	(0.092)	(0.088)		(0.092)	(0.087)		(0.092)	(0.088)		(0.092)	(0.088)	
week_hours	0.060**	0.053**		0.060**	0.052**		0.059**	0.053**		0.059**	0.051**	
	(0.027)	(0.026)		(0.027)	(0.025)		(0.027)	(0.026)		(0.027)	(0.026)	
selfemployed	0.514***	0.492***		0.514***	0.489***		0.515***	0.494***		0.514***	0.490***	
	(0.037)	(0.037)		(0.037)	(0.037)		(0.037)	(0.038)		(0.037)	(0.037)	
informal_access	0.193***	0.187***		0.193***	0.185***		0.193***	0.188***		0.182***	0.177***	
	(0.042)	(0.040)		(0.042)	(0.040)		(0.042)	(0.041)		(0.043)	(0.041)	
academic	-0.888***	-0.826***		-0.888***	-0.815***		-0.889***	-0.833***		-0.885***	-0.821***	
	(0.039)	(0.054)		(0.039)	(0.056)		(0.039)	(0.055)		(0.039)	(0.055)	
R&D	-0.942***	-0.888***		-0.943***	-0.878***		-0.943***	-0.894***		-0.940***	-0.884***	
	(0.033)	(0.047)		(0.033)	(0.048)		(0.033)	(0.047)		(0.033)	(0.047)	
Constant	-0.531***	-0.328*	0.979***	-0.522***	-0.330*	0.983***	-0.550***	-0.348*	0.977***	-0.511**	-0.307	0.984***
	(0.198)	(0.197)	(0.143)	(0.199)	(0.194)	(0.143)	(0.199)	(0.201)	(0.143)	(0.199)	(0.197)	(0.143)
Observations	16,180	18,277	18,277	16,180	18,277	18,277	16,180	18,277	18,277	16,055	18,152	18,152
LR test of indep. eqns. $\rho = 0$ (p-value)			6.22 (0.013)			6.64 (0.010)			5.00 (0.025)			6.28 (0.012)

Legend: Significance is indicated as follows: *** denoting the 1%, ** the 5% and * the 10% level.

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