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OVER-EDUCATION AND THE GREAT RECESSION. THE CASE OF ITALIAN PH.D GRADUATES.

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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.The results show that over-skilling is positively associated with the Great Recession, whereas the relationship between the crisis and over-qualification is statistically significant only when the estimated model includes interaction terms for the crisis and jobs within academia or R&D-related sectors. More generally, working on research-based activities and 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 socio-demographic variables do not exert a significant influence on Ph.D over-education.

JEL Class: C2, I2, J24

Keywords: Over-education, Over-skilling, Over-qualification, Ph.D graduates, Great Recession

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1 Introduction

In recent years, a growing international consensus on what a Ph.D program is supposed to encompass has emerged. According to this generally-shared view, Ph.D programs should produce knowledge, not only helping students to develop original research and subject-specific attributes (hard skills), but also promoting more general and transferable soft skills, as well as building up creative and inquisitive mindsets (EUA, 2005). All this should facilitate the entry of Ph.D graduates in the labor market recognizing the multiplicity of employment trajectories in addition to academia. The final goal is to foster the emergence and consolidation of the so-called knowledge economy and to promote the creation of a learning society.

In recognition of this crucial role of highly-educated individuals, and on the basis of the presumption that market failure in learning might be pervasive in the society (Stiglitz and Greenwald, 2014), many countries have taken action to expand and reform their Ph.D programs.

The result has been a widespread increase in the number of Ph.D graduates, well in excess of the availability of academic positions, with Ph.D supply probably outstripping demand, despite the contribution of growing technical progress to the search for high-skilled workers.

A possible consequence of these dynamics is the emergence of widespread over-education at Ph.D level (Leuven et al., 2011; Quintini, 2011; Hartog, 2000). 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. Moreover, 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-occupation match. Moreover, to the best of our knowledge, the effects of the ongoing severe economic crisis on Ph.D over-education have not yet been fully explored. Given the polarization and strategic and opportunistic upskilling and under-employment induced by downturns (Barnichon and Zylberberg, 2014; Acemoglu and Autor, 2011; Di Pietro and Urwin, 2006), the crisis may have affected the professional outcomes of low and high-educated individuals in a different manner (Cockx and Ghirelli, 2016; Modestino et al., 2014; Beaudry et al., 2016).

However, while over-education among samples of graduates has received close attention, there has been scant investigation among Ph.D-holders (Gaeta, 2015; Di Paolo and Mañé, 2016) and there is no clearcut understanding on what the primary causes of Ph.D over-education are.

Within this context, the aim of the current paper is to expand the relevant literature 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 graduate information before and after 2008. Consequently, we are able to evaluate the impact of the Great Recession on the probability of matching skills and educational level to occupational attainment. In so doing, we adopt three different proxies to take the recession effect into account. 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 provide fresh evidence on the situation of Italian Ph.D graduates. To our knowledge, our study is the first to use the recently issued survey of the professional outcomes of all Italian Ph.D graduates carried out by ISTAT (2014).

Our main results confirm that the Great Recession increased the risk of over-skilling while the impact on over-qualification was less robust. Working in R&D based occupations, both within academic or other sectors of the economy, reduces the detrimental effect of the economic crisis on over-education in general. Ph.D recipients that 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 sociodemographic variables do not impact strongly on Ph.D over-education. Remarkably, among Ph.D workers, education and social background seem not to significantly affect 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 reviews the relevant literature on over-education and the effect of economic fluctuations on skill and education job mismatch. Section 3 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 4 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 5.

2 Literature background

Even if today there is a vast literature on over-skilling and over-qualification, a unifying theory on the relevant mechanisms underlying them does not exist. Indeed, the economic literature has proposed a combination of different approaches imported from labor-market theories to interpret these two phenomena.

On the one hand, in line with the human capital theory (Becker, 1964; Mincer, 1974), entering a Ph.D program can be seen as a rational investment which is expected to increase the individual's future returns. In fact, assuming that firms are able rapidly to adapt their production function to the level of human capital available in the economy, over-education may be plausible only over the short run, as long as firms adjust their production processes to fully utilize the individuals' human capital or until workers find the appropriate match through the job search. Similarly, according to the career mobility and search theory (Sicherman, 1991), over-education may be the result of Ph.D-holders' search for the professional experience considered necessary to obtain a job more consistent with their education and skills in the near future. In this case as well, over-education may emerge as a short-term phenomenon at the individual level, even if, in aggregate, it is a constant feature of society today.

On the other hand, the high number of over-educated workers may be related to a variety of labor-market imperfections and to the imbalance between the demand and supply of qualified labor. This is particularly important for Ph.D graduates in view of the widespread and growing saturation of academic positions. By assuming that the labor market is characterized by imperfect information, Spence (1973)'s job-screening model postulates that education is a signal with which employers can identify more able and motivated individuals. In order to acquire more of this signal, individuals will invest more in education. As a result, over-education may emerge because the attained qualification may be higher than the one required. In fact, the larger the number of educated people in the economy, the more imperative it is for them to invest in education. Similarly, the job competition theory developed by Thurow (1975) departs from the neoclassical human capital paradigm by assuming that firms cannot rapidly adapt their production processes to the actual level of individual human capital. In this case, increasing investment in human capital turns out to be a distinguishing feature for job seekers, increasing their likelihood of accessing the available job opportunities. In both the job screening and job competition frameworks, over-education may end up being a persistent phenomenon.

An explanation intermediate between human capital theory and job screening/competition theory is provided by the assignment models (Sattinger, 1993; Belman and Heywood, 1997) according to which both the characteristics of workers and those of jobs available in the economy explain the possible labor mismatches.

In fact, all these different approaches share the idea that whatever explanation is provided, over-education is a potential source of considerable costs to the individual, firm and society. At the individual level, overqualified workers undergo salary penalties and experience lower job satisfaction (Verhaest and Omey, 2006; Badillo-Amador and Vila, 2013). Overqualified workers also tend to show higher turnover and absenteeism (Allen and van der Velden, 2001), and lower participation in training (Buchel and Mertens, 2004). On the other hand, these features and behaviors entail costs at the firm level, with repercussions in terms of lower productivity and product quality (Kampelmann and Rycx, 2012) and constraints on technological change (Di Pietro and Urwin, 2006). At the societal level, given the high levels of public funding devoted to Ph.D programs in most countries, over-education is associated with a sub-optimal human resources allocation implying a significant waste of public resources, higher unemployment (Groot and Van Den Brink, 2000), lower tax revenues, and less national income (Mavromaras et al., 2007).

To limit these negative consequences, it becomes important to explore the main causes of labor mismatch and identify effective policy actions to address them. By the same token, the determinants of over-education have been examined by various studies producing mixed empirical evidence. The results are sensitive both to the definition of labor mismatch and also to many supply and demand side heterogeneities (see Leuven et al. (2011); Quintini (2011); Caroleo and Pastore (2013) for recent in-depth reviews). Furthermore, the empirical literature comprises mainly studies applied to first university degree graduates whereas, by contrast, over-education among Ph.D recipients has received limited attention and only few recent empirical studies have investigated the issue.

Indeed, measuring skill mismatch between Ph.D workers and job attributes is a complex task. Detailed information on the competencies and skills possessed by educated workers and those required by their jobs is limited. Even Ph.D recipients' self-assessments of skill mismatch are quite rare. This is why most of the over-education academic literature focuses on qualification mismatch. While the number of years of education is undoubtedly a good proxy for skills, a small body of literature has investigated the difference between qualification and skill mismatch. Only recently has the literature examined the occupational outcomes and labor mismatches of Ph.D graduates. The causes and consequences of over-education at doctoral level have been investigated for the US by Bender and Heywood (2011). For Spain, Di Paolo and Mañé (2016) analyze which factors influence the qualification and skill mismatch among Ph.D holders and the possible impact of the mismatch in terms of wages and job satisfaction. The Italian case has been studied by some recent papers which draw data from partial surveys covering only some subsets of Ph.D graduates and more often by using data coming from a single university. In this respect, the only exception of which we are aware is Gaeta (2015), who, however, uses only the first Ph.D national survey published by ISTAT in 2009.

A growing strand of literature is analyzing the relationship between over-education and cyclical economic fluctuations. However, this literature has not yet focused on Ph.D graduates. Adopting a sample of European overeducated workers with a tertiary degree, Croce and Ghignoni (2012) suggest that cyclical conditions matter with regard to over-education incidence from 1998 to 2006. They find that the percentage of overeducated graduates reacts significantly to cyclical movements in GDP, and when a cyclical downturn hits the economy, an increase in the incidence of over-education can be expected. In a summary report for the OECD, Quintini (2011) states that skill mismatch is procyclical with recession. Using individual data on Norwegian college graduates, Liu et al. (2016) find a countercyclical trend of skill mismatch; the correlation is more pronounced among the occupations in the private sector compared to the public one. They also show that labor-market conditions have a declining but persisting effect on the likelihood of mismatch during the early stages of the working career. The paper by Altonji et al. (2016) documents that recessions affect labor-market outcomes of graduates mainly in the form of earnings losses, with impacts that vary according to the field of study and, to a lesser extent, of worse occupation match quality. Interestingly, these authors report that the recent Great Recession strongly affected workers' perspective compared with that of the past because of higher cyclical sensitivity of the demand for college graduates, in general, and for high-skilled majors relative to the average major.

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.[1] 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 is corroborated by the findings of the paper by Modestino et al. (2014). 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 workers may end up being overeducated (Fogg and Harrington, 2011; Di Pietro and Urwin, 2006).

The current paper attempts to evaluate empirically if these mechanisms mark the early career patterns of the highly educated and skilled Italian Ph.D graduates who entered the labour market before and during the Great Recession.

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

3 Empirical strategy

3.1 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.[2] The surveys were based on interviews administered with individuals who had obtained a doctoral degree in Italy 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.[3] 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.[4] 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 ques-

[2]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.

[3]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).

[4]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).

tion 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.

The total distribution of over-skilling and over-qualification resulting from the two ISTAT surveys is presented in Table 1. About 50% of the respondents who were employed declared that they were over-skilled. As for those who obtained their job after completion of the Ph.D program, about 20% declared that the Ph.D title was neither required nor useful for obtaining their job. They were thus over-qualified. Moreover, among those who responded to both questions, just over 53% were adequately matched in terms of job entry requirements and required skills, while 18% were both over-qualified and over-skilled (3,404 out of 18,564) signaling that in Italy over-education is a crucial concern also for the most educated workers.[5] However, some heterogeneity is observed by fields of study, as shown in Figure 1, and by sectors. In particular, over-skilling and over-qualification are almost negligible in academia and for those respondents employed in R&D activities (see Table 2).

3.2 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.

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.[6] 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

[5]While these features resemble those emerged with reference to Spanish Ph.D holders (Di Paolo and Mañé, 2016), Croce and Ghignoni (2012) show that the average level of over-education among tertiary graduates in Italy over the period 1998-2006 is about 40%.

[6]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).

the labour market by using a simple probit model would have produced biased estimates of the determinants of the risk of over-education.

3.3 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.

Within our definitions of over-education, we expected to observe a stronger effect of the economic crisis on over-skilling compared to over-qualification. Over-skilling was defined by a comparison between the skills acquired during the Ph.D course and the actual knowledge and abilities required to carry out the occupation held. It is a well-documented phenomenon that downturns have a more painful impact on middle-skilled workers, who also suffer from the competition of those high-skilled workers who take middle- and low-skilled jobs. In other words, during recessions we observe so-called 'upskilling', i.e. a larger share of high-skilled workers in middle-and low-skill occupations. In turn, this upskilling may reflect both a changing behavior of employers demanding higher levels of education and more years of experience when skilled workers are plentiful (Modestino et al., 2014), and/or changing search behavior of high-skill workers, who become also willing to accept jobs for which they appear to be over-skilled (Barnichon and Zylberberg, 2014). Thus, given this scenario, over-skilling among high-skilled workers may easily emerge in a slack (polarized) labour market. On the contrary, we do not necessarily observe over-qualification. In this latter case, the match makes reference to a correspondence between the attained education title and the one required to apply for the job. Consequently, if the above-mentioned upskilling, which emerges during recessions, is the result of a ranking mechanism by employers who formally envisage higher qualifications, we may end up in a hypothetical situation where over-qualification does not emerge even if jobs could be carried out by less skilled and less educated workers. Moreover, Ph.D courses mould individuals with a strong "taste for science" who, vocationally, are oriented to careers in academic or research units (Roach and Sauermann, 2010). Usually, for these positions the Ph.D title is a substantial, if not mandatory, prerequisite to access the job; thus, we observe a match between title and job requirement. Overall, this setting gives rise to the expectation that cyclical fluctuations - and even more so during severe crises as in the case of Italy - affect over-qualification less severely than over-skilling. Indeed, as shown in Table 3, our data indicate that the incidence of over-skilling has increased substantially during the crisis, while the proportion of over-qualified workers appears to be more stable across the two periods.

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.[7]

[7] The mean values of the two variables computed before and after the crisis signal a de-

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 $t(k) = \begin{cases} 2007 \text{ if k=2004, 2006} \\ 2011 \text{ if k=2008, 2010} \end{cases}$. 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; $t(k) = \begin{cases} 2007 \text{ if k=2004, 2006} \\ 2010 \text{ if k=2008, 2010} \end{cases}$; $p = 1, 2...110$ is the province of jobs and N=Italy.[8] 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.

terioration of the labor market's performance post-recession. Indeed, tests of the difference between the two periods' means returned to being statistically significant. Results are available on request.

[8]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 (*ita 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' educational level (*parents edu*) and social class (*parents class*).[9] The categorical variable (*province*) controlled for the geographical origin of graduates and possible unobserved heterogeneities.

Features and performance related to the Ph.D course were examined by including in the regressions the scientific field of study (*study field*), the age at Ph.D award (*Ph.D age*)[10] and a dummy to signal if individuals spent a study period abroad (*visiting abroad*). By means of the variable *recent cohort*, related to the distance between the year of the survey and the year of Ph.D title awarded, we identified the newcomer cohort of Ph.D graduates that had entered the labour market. Specifically, *recent cohort* was equal to one for individuals who were awarded the title in 2006 and in 2010, and zero for the others. 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 (*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 a variable describing whether the job was full or part-time (*part time*), also distinguishing if the part time was voluntary or compulsory. The variable (*jobexp*) registered the number of professional experiences between the year of Ph.D completion and the year of the survey, taking into account also if the actual job was already held before the Ph.D was acquired. 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.[11] 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

[9] For the definition of the variable *parents class* we followed ISTAT (2003).

[10] The format of microdata used in this analysis does not report the exact age of respondents; it reports age by class at the time of Ph.D completion. Because of different codings of age classes across surveys, we were only able to build a dummy variable taking value one if the title had been obtained at the age of 29 or earlier, and zero otherwise.

[11] 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).

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 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.

4 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.

4.1 Overskilling

Table 5 reports the estimates of the probability of being over-skilled for all Ph.D recipients. As the coefficients of the selection term were statistically different from zero, we relied on the estimates of the probit models with sample selection.[12] Table 5 shows these estimates, distinguishing the results of the main model of determinants of over-skilling (columns 1, 3, 5 and 7) and the results of the employment selection equation (columns 2, 4, 6 and 8). 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) and (2) of Table 5 report estimates of the baseline equation, whereas columns (3)-(8) present the estimates of the impact of the Great Recession on over-skilling using the three key regressors discussed above: *crisis*, *varVA* and *resilience*.

[12] Nevertheless, the probit models and the probit models with sample selection returned similar estimated coefficients in terms of sign and significance of regressors. Results of the probit models are available upon request.

Before discussing the impact of the Great Recession, we briefly comment on the estimates reported in column (1) to investigate the drivers of over-skilling among Ph.D graduates. Our results show a weak impact of the socio-demographic characteristics of Ph.D holders, a piece of evidence already found in previous studies (Gaeta, 2015; Di Paolo and Mañé, 2016). As an exception, 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).

Social background, as proxied by parents' education and class, appears not significant in predicting over-skilling for the whole sample. 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, it emerges that more recent cohorts of graduates have a higher probability of obtaining a matched job. The labour market seems to reward those who are endowed with more updated skills. This result is at odds with those theories predicting over-education as a temporary state (Rubb, 2003). Moreover, 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 Socio-political Sciences and Humanities, 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. In addition, working in industry compared to other sectors is detrimental for a successful skill-job match. Participation in the labour market as a part-time worker, both if it is voluntary or due to the

[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 is highly 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 (Brunello and Checchi, 2007; Caroleo and Pastore, 2013).

lack of full-time opportunities, is characterized by a higher risk of over-skilling compared to being a full-time worker. Moreover, to start working after completion of the Ph.D seems to increase the probability of over-skilling compared to starting before the attainment of the doctoral title. The lack of statistical significance of the variable *informal access* adds robustness to the result that social networks do not impact on Ph.D over-skilling.

Moving to possible differences in skill-job matching before and after the financial crisis, we examine the econometric results set out in columns (3)-(8). The coefficient of *crisis*, which is the main proxy for the Great Recession, is positive and significant. This result suggests that the Great Recession has reduced the probability of Ph.D-holders finding the job most appropriate for their skills. The risk of over-skilling is more likely during a downturn. In column (5) we report the estimated coefficient of *varVA*. The correlation between this variable and over-skilling is negative, suggesting that as the index grows - signaling that the area is less hit by the crisis - over-skilling is less likely. This reinforces the belief that recessions do not offer opportunities for adequate job matching. We then assess the predictive power of the variable *resilience* in column (7). As the coefficient is negative and statistically, even if weakly, significant, we can conclude that Ph.D-holders working in areas with a higher level of market potential were at less risk of over-skilling. Overall, the above evidence validates the hypothesis that the Great Recession brought about a deterioration of professional outcomes also in terms of over-skilling determining a waste of human capital as a possible outcome.

In an attempt to account for the heterogeneous impact of the crisis across job characteristics of our sample of Ph.D-holders, we extended the empirical model reported in columns (3)-(4). Hence, we interacted the *crisis* dummy with *academic* and *R&D*: that is, those variables that best capture the worker's taste for science, which corresponds to the primary vocational attitude of academically-trained Ph.D students. We expected that being occupied in such sectors could protect the workers from the negative effect of the economic fluctuation because these high-skilled jobs are at less risk of downskilling. Moreover, the highly qualified human capital holding such jobs can be a key factor in relieving an economic crisis. Indeed, economic resilience of a region hinges on the capacity to maintain and to booster the territorial competitiveness by branching into related or entirely new paths of development (Martin and Sunley, 2015). It entails restructuring and reorienting human and capital resources, a task that high human capital employed in knowledge and technology-led sectors can more easily perform. We report the estimates of interest in Table 6. The results for over-skilling, set out in column (1), are in line with our expectations of negative coefficients of the interaction terms. Actually, for those who worked in academia or in R&D based occupations, which can be intended as vocation jobs of Ph.D training courses, the Ph.D proves to be worthy to avoid over-skilling also in risky economic conditions such those related to downturns. This result deserves attention when the efficiency of public investment in PhD is examined.

4.2 Over-qualification

Table 7 presents estimates of the predictors, including the impact of the Great Recession, of over-qualification as an alternative definition of over-education. In the survey's design, this variable was defined only for those Ph.D graduates who had found jobs after obtaining their doctorates.

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 7 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 (1)-(2), 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 exceptions, female Ph.D graduates are more likely to be over-qualified than males. 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. Moreover, the variable *recent cohort* now appears to be positively correlated with over-education. This shows that the mismatch regarding the title required to perform a job is less penalizing for less recent graduates, suggesting that over-qualification is a temporary phenomenon.

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 *age at graduation*, revealing that younger Ph.D holders are less likely to suffer from over-qualification. Conversely, this variable didn't affect over-skilling.

Inspection of columns (3)-(8) of Table 7 to assess the impact of the recent downturn on over-qualification does not find any correlation between the entire set of proxies for the Great Recession and title requirement 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.

However, on augmenting the model in columns (3)-(4) with interaction terms for the crisis and job characteristics, in order to control for sector and job peculiar responses to the Great Recession, the variable *crisis* significantly increases the risk of over-qualification. At the same time, it is confirmed that working in academia or having a job in R&D moderates the dampening effect of a recession on over-education.

5 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. We found that these percentages increased during downturns. In particular, our estimates revealed a striking 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, and the local labour market's resilience. As expected, our findings show that the impact of the crisis is less pronounced when labour markets are more resilient. Moreover, the effect of downturns on over-skilling is less marked among Ph.Ds working in academia or R&D activities. The protective effect of these factors against the downturn disruptions appears to be at work also when over-qualification is examined. Conversely, the direct impact of the Great Recession on over-qualification is less robust. In fact, in our model of over-qualification, the adopted proxies for the crisis returned significant coefficients only when crisis variables were considered within an interaction term which captured the peculiarities of research-oriented occupations. This result can be explained by the behavior of employers, who, during downturns when skilled workers are plentiful, formally envisage higher qualifications even for less skill-demanding jobs.

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. Moreover, the risk of over-education is not equally distributed across fields of study since Ph.D graduates in Humanities are more likely to be mismatched than peers graduated in Economics or Science and Technology. 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 a phenomenon which, although it is becoming increasingly widespread, costly, and persistent - and even more so during downturns â is still overlooked. Second, indicators of the state of the labour market should also include the important dimension of over-education in order to avoid underestimating its real costs, especially during recessions. Third, over-education is not only a problem for individuals (dissatisfied workers) and firms (declining productivity); it should also be a concern 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. Fourth, the sensitivity of over-education to economic fluctuations calls for economic policies designed not only to promote employment but also to favor job matching and to ensure proper returns to education for very high-skilled workers. Policies should aim at creating job opportunities so as to integrate Ph.D-holders into the process of producing and distributing goods and services. Indeed, human capital is a key factor in developing regional resilience, which is itself an effective strategy to deal with economic fluctuations and to cope with cyclical variations. Finally, 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. The current economic crisis makes this need even more urgent. 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.

The above findings and observations should not be interpreted as suggesting that investment in PhD training is today less rewarding. Indeed, the right match still applies to the majority of PhD graduates, and it is largely ensured in research-oriented jobs. On the other hand, it is important to investigate the job placement of these high-skilled workers in order to pursue the highest returns to Ph.D education from an individual and societal perspective. Thus, the investigation of returns to education adopting indicators other than over-qualification is an important goal for future research. Moreover, there is also a need to monitor and analyze the dynamics of over-education once the Great Recession has finished - a task that unfortunately, at least for Italy, cannot yet be carried out.

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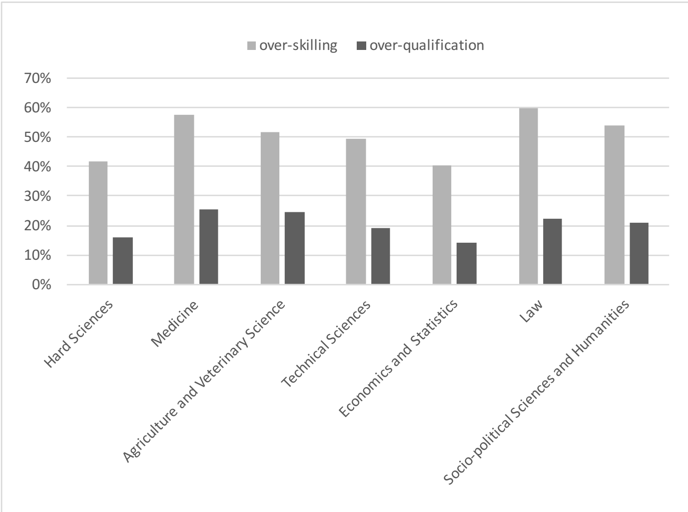
Figure 1: Over-education by study field



Source: Authors' elaboration - ISTAT, 2009, 2014

Legend: *Hard Sciences*: Mathematics and Computer Science, Physics, Chemistry, Earth Sciences, Biology; *Technical Sciences*: Civil Engineering and Architecture, Industrial and IT Engineering; *Socio-political Science and Humanities*: Philology and Literature, History Philosophy and Psychology, Political and Social Sciences. Remaining fields of study are self-explanatory.

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

	Over-skilling		
Over-qualification	Yes	No	Total (N)
Yes	3,404	248	3,652
No	4,977	9,935	14,912
*Not applicable**	5,175	3450	8,625
Total (N)	13,556	13,633	27,189

*Not entitled to answer about over-qualification because already employed before Ph.D attainment.

Source: Authors' elaboration - ISTAT, 2009, 2014

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

	University		R&D		Total (N)
	yes	no	yes	no	
Over-skilled	10.0	90.0	15.7	84.3	13556
Over-qualified	6.2	93.8	10.7	89.3	3652

Source: Authors' elaboration - ISTAT, 2009, 2014

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

		Before the crisis	After the crisis	Total
Over-skilling	No	54.7	46.5	50.1
	Yes	45.3	53.5	49.9
	Total	100.0	100.0	100.0
Over-qualification	No	80.8	79.9	80.3
	Yes	19.2	20.1	19.7
	Total	100.0	100.0	100.0

Source: Authors' elaboration ISTAT 2009, 2014

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	27189	0.499	0.500	0	1
Over-qualification *(overqual)*	dummy=1 if over-qualified	18564	0.197	0.398	0	1
Employment *(employm)*	dummy=1 if employed	29286	0.928	0.258	0	1
Great Recession *(crisis)*	dummy=1 if awarded during Great Recession	29286	0.557	0.497	0	1
Value Added variation *(varVA)*	Provincial variation of Value Added	24446	0.029	0.022	-0.050	0.135
Provincial Economic Resilience *(resilience)*	Provincial labour market economic resilience	24264	-0.341	2.669	-18.810	7.721
SOCIO-DEMOGRAPHIC VARIABLES						
Gender *(female)*	dummy=1 if female	29286	0.521	0.500	0	1
Citizenship *(ita citizenship)*	dummy=1 if Italian	29286	0.984	0.126	0	1
Marital status *(married)*	dummy=1 if married or living together	29286	0.523	0.499	0	1
Children *(children)*	dummy=1 if having at least one child	29286	0.377	0.485	0	1
Parents education *(parents edu_i)*	Parents' highest educational level:					
	_1: junior high school diploma or lower*	29286	0.253	0.435	0	1
	_2: high school or post-high school diploma	29286	0.378	0.485	0	1
	_3: degree or post-graduate	29286	0.369	0.483	0	1
Parents class *(parents class_i)*	Parents' highest social class:					
	_1: bourgeoisie*	29286	0.301	0.459	0	1
	_2: middle class	29286	0.400	0.490	0	1
	_3: petite bourgeoisie	29286	0.170	0.376	0	1
	_4: working class	29286	0.101	0.301	0	1
	_5: other	29286	0.027	0.164	0	1
Province of residence before University	categorical variable, province of residence	29286			0	1
Ph.D-RELATED VARIABLES						
Recent cohort(s) *(recent cohort)*	dummy=1 if most recent cohort of graduates	29286	0.536	0.499	0	1
Age at graduation *(Ph.D age)*	dummy=1 if 29 (or younger)	29286	0.284	0.451	0	1
Visiting abroad *(visiting abroad)*	dummy=1 if visiting abroad for at least 1 month	29286	0.350	0.477	0	1
Study field *(study field)*	Ph.D scientific field of study:					
	- Hard Sciences	29286	0.257	0.437	0	1
	- Medicine	29286	0.143	0.350	0	1
	- Agriculture and Veterinary Sciences	29286	0.067	0.250	0	1
	- Technical Sciences	29286	0.191	0.393	0	1
	- Economics and Statistics*	29286	0.059	0.236	0	1
	- Law	29286	0.072	0.259	0	1
	- Socio-political Sciences and Humanities	29286	0.210	0.407	0	1
Province of Ph.D University	categorical variable, province of Ph.D University	29286			0	1
JOB-RELATED VARIABLES						
Self-employment *(selfemployed)*	dummy=1 if self-employed	27189	0.138	0.345	0	1
Informal access *(informal access)*	dummy=1 if informal channels to find job	27189	0.078	0.267	0	1
Academic *(academic)*	dummy=1 if academic sector	27189	0.342	0.474	0	1
R&D *(R&D)*	dummy=1 if R&D prevalent in job	27189	0.431	0.495	0	1
Part time *(part time_i)*	Part-/Full-time contract:					
	_0: Full-time*	27189	0.895	0.306	0	1
	_1: Part-time, no full-time opportunities	27189	0.063	0.244	0	1
	_2: Part-time, voluntary	27189	0.041	0.199	0	1
Job experience *(jobexp_i)*	Number of jobs:					
	_0: One job (current) started before Ph.D completion*	27189	0.317	0.465	0	1
	_1: One job (current) started after Ph.D completion	27189	0.299	0.458	0	1
	_2: More than one job after Ph.D completion	27189	0.384	0.486	0	1
Sector *(sector_i)*	Sector:					
	_1: Industry*	27189	0.084	0.278	0	1
	_2: Service	27189	0.897	0.303	0	1
	_3: Agriculture	27189	0.018	0.134	0	1

* denotes the reference category in the estimation.

Table 5: Over-skilling, the Great Recession and other determinants.

VARIABLES	(1) oversk	(2) employm	(3) oversk	(4) employm	(5) oversk	(6) employm	(7) oversk	(8) employm
crisis		-0.166***	0.113***	-0.118***		-0.168***		-0.183***
		[0.026]	[0.018]	[0.026]		[0.024]		[0.024]
varVA					-1.410***			
					[0.414]			
resilience							-0.006*	
							[0.003]	
female	0.013	-0.012	0.014	-0.010	0.001	-0.006	-0.001	-0.012
	[0.018]	[0.033]	[0.018]	[0.033]	[0.019]	[0.034]	[0.019]	[0.034]
ita citizenship	0.237***	0.228**	0.238***	0.227**	0.312**	0.199	0.306**	0.203
	[0.091]	[0.115]	[0.091]	[0.115]	[0.124]	[0.145]	[0.124]	[0.145]
parents edu_2	-0.035	-0.049	-0.036	-0.049	-0.034	-0.049	-0.032	-0.047
	[0.026]	[0.035]	[0.026]	[0.035]	[0.027]	[0.035]	[0.027]	[0.035]
parents edu_3	0.007	0.013	0.005	0.012	-0.000	0.017	0.003	0.019
	[0.030]	[0.041]	[0.030]	[0.041]	[0.031]	[0.041]	[0.031]	[0.041]
parents class_2	0.020	-0.084***	0.018	-0.085***	0.007	-0.079***	0.005	-0.079***
	[0.022]	[0.030]	[0.022]	[0.030]	[0.023]	[0.031]	[0.023]	[0.031]
parents class_3	0.005	-0.160***	0.008	-0.161***	-0.009	-0.153***	-0.013	-0.152***
	[0.032]	[0.043]	[0.032]	[0.043]	[0.033]	[0.043]	[0.033]	[0.043]
parents class_4	-0.010	-0.107**	-0.014	-0.108**	-0.016	-0.096*	-0.017	-0.095*
	[0.038]	[0.051]	[0.039]	[0.051]	[0.039]	[0.051]	[0.039]	[0.051]
parents class_5	-0.036	-0.199***	-0.056	-0.212***	-0.058	-0.182**	-0.059	-0.173**
	[0.058]	[0.071]	[0.059]	[0.071]	[0.060]	[0.073]	[0.060]	[0.073]
Ph.D age	-0.021	0.070**	-0.027	0.070**	-0.005	0.042	-0.005	0.041
	[0.020]	[0.028]	[0.020]	[0.028]	[0.021]	[0.028]	[0.021]	[0.028]
recent cohort	-0.055***	-0.113***	-0.049***	-0.111***	-0.045**	-0.116***	-0.046**	-0.116***
	[0.018]	[0.024]	[0.018]	[0.024]	[0.018]	[0.024]	[0.018]	[0.024]
visiting abroad	-0.136***	0.084***	-0.151***	0.080***	-0.120***	0.035	-0.118***	0.037
	[0.019]	[0.026]	[0.019]	[0.026]	[0.020]	[0.026]	[0.020]	[0.026]
jobexp_1	0.104***		0.114***		0.127***		0.124***	
	[0.021]		[0.022]		[0.022]		[0.022]	
jobexp_2	0.019		0.019		0.047**		0.047**	
	[0.021]		[0.021]		[0.021]		[0.021]	
Hard Sc.	0.032	-0.165***	0.030	-0.167***	0.028	-0.173***	0.028	-0.175***
	[0.041]	[0.055]	[0.041]	[0.055]	[0.043]	[0.057]	[0.043]	[0.057]
Medicine	0.203***	0.043	0.198***	0.037	0.192***	0.051	0.192***	0.050
	[0.044]	[0.061]	[0.044]	[0.061]	[0.045]	[0.063]	[0.046]	[0.063]
Agric. Veter. Sc.	0.120**	-0.190***	0.120**	-0.194***	0.085	-0.167**	0.091*	-0.166**
	[0.053]	[0.068]	[0.053]	[0.068]	[0.054]	[0.070]	[0.054]	[0.070]
Technical Sc.	0.106**	0.093	0.104**	0.090	0.084*	0.101*	0.086*	0.100
	[0.042]	[0.059]	[0.042]	[0.059]	[0.044]	[0.061]	[0.044]	[0.061]
Law	0.220***	-0.135**	0.219***	-0.142**	0.196***	-0.124*	0.195***	-0.125*
	[0.049]	[0.066]	[0.050]	[0.066]	[0.051]	[0.067]	[0.050]	[0.067]
Soc.-Pol. Sc. Human.	0.048	-0.334***	0.051	-0.339***	0.004	-0.325***	0.005	-0.328***
	[0.042]	[0.055]	[0.042]	[0.055]	[0.043]	[0.057]	[0.043]	[0.057]
sector_2	-0.242***		-0.251***		-0.229***		-0.225***	
	[0.032]		[0.032]		[0.033]		[0.033]	
sector_3	-0.241***		-0.261***		-0.228***		-0.218***	
	[0.066]		[0.067]		[0.067]		[0.067]	
parttime_1	0.229***		0.224***		0.201***		0.202***	
	[0.033]		[0.033]		[0.031]		[0.030]	
parttime_2	0.218***		0.235***		0.205***		0.196***	
	[0.043]		[0.043]		[0.042]		[0.041]	
selfemployed	0.105***		0.110***		0.087***		0.089***	
	[0.025]		[0.025]		[0.025]		[0.024]	
informal access	0.028		0.030		0.029		0.023	
	[0.031]		[0.031]		[0.032]		[0.032]	
academic	-1.000***		-0.996***		-1.005***		-1.004***	
	[0.022]		[0.022]		[0.023]		[0.023]	
R&D	-1.092***		-1.084***		-1.040***		-1.041***	
	[0.019]		[0.020]		[0.020]		[0.020]	
children		0.200***		0.202***		0.219***		0.218***
		[0.052]		[0.052]		[0.053]		[0.053]
female*children		-0.371***		-0.373***		-0.375***		-0.373***
		[0.061]		[0.061]		[0.062]		[0.061]
married		0.280***		0.281***		0.276***		0.273***
		[0.045]		[0.045]		[0.046]		[0.046]
female*married		-0.257***		-0.260***		-0.237***		-0.229***
		[0.056]		[0.056]		[0.056]		[0.056]
Observations	29,286	29,286	29,286	29,286	26,543	26,543	26,361	26,361
Wald test of $\rho = 0$ (p-value)		32.33 (0.000)		43.35 (0.000)		26.42 (0.000)		18.23 (0.000)

Rob. std. errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ All estimates include: constant, prov. of Ph.D Univ., prov. of residence before Univ.

Table 6: Over-skilling, over-qualification and the Great Recession in R&D-based occupations

	Over-skilling (1)	Over-qualification (2)
crisis	0.323***	0.094***
	[0.026]	[0.032]
academic	-0.852***	-0.707***
	[0.031]	[0.061]
crisis*academic	-0.324***	-0.268***
	[0.043]	[0.074]
R&D	-0.930***	-0.857***
	[0.028]	[0.051]
crisis*R&D	-0.342***	-0.175***
	[0.038]	[0.061]
Baseline controls	yes	yes
Observations	29,286	20,661

Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Over-qualification, the Great Recession and other determinants.

VARIABLES	(1) overqual	(2) employm	(3) overqual	(4) employm	(5) overqual	(6) employm	(7) overqual	(8) employm
crisis		-0.150***	0.014	-0.152***		-0.174***		-0.177***
		[0.027]	[0.028]	[0.028]		[0.027]		[0.027]
varVA					0.267			
					[0.648]			
resilyy							0.000	
							[0.005]	
female	0.080***	0.009	0.083***	0.008	0.060*	0.041	0.065**	0.039
	[0.030]	[0.036]	[0.030]	[0.036]	[0.032]	[0.037]	[0.031]	[0.037]
ita citizenship	-0.007	0.213*	-0.008	0.214*	-0.022	0.117	-0.025	0.120
	[0.134]	[0.124]	[0.133]	[0.124]	[0.171]	[0.157]	[0.171]	[0.157]
parents edu_2	0.001	-0.040	0.001	-0.040	0.002	-0.042	0.008	-0.042
	[0.038]	[0.038]	[0.038]	[0.038]	[0.039]	[0.039]	[0.039]	[0.039]
parents edu_3	0.009	0.011	0.008	0.011	-0.014	0.017	-0.011	0.018
	[0.044]	[0.045]	[0.043]	[0.045]	[0.045]	[0.046]	[0.045]	[0.046]
parents class_2	0.018	-0.077**	0.019	-0.077**	0.005	-0.068**	0.005	-0.070**
	[0.032]	[0.034]	[0.032]	[0.034]	[0.034]	[0.034]	[0.034]	[0.034]
parents class_3	0.066	-0.157***	0.067	-0.157***	0.032	-0.144***	0.038	-0.143***
	[0.046]	[0.047]	[0.046]	[0.047]	[0.048]	[0.048]	[0.048]	[0.048]
parents class_4	0.086	-0.094*	0.086	-0.093*	0.058	-0.076	0.059	-0.076
	[0.054]	[0.056]	[0.054]	[0.056]	[0.056]	[0.057]	[0.056]	[0.058]
parents class_5	0.024	-0.269***	0.024	-0.269***	0.007	-0.256***	0.024	-0.257***
	[0.084]	[0.079]	[0.083]	[0.079]	[0.088]	[0.082]	[0.087]	[0.082]
PhD age	-0.094***	0.204***	-0.097***	0.204***	-0.077**	0.180***	-0.081***	0.180***
	[0.030]	[0.030]	[0.030]	[0.030]	[0.031]	[0.030]	[0.031]	[0.030]
recent cohort	0.058**	-0.165***	0.061**	-0.165***	0.069**	-0.179***	0.075***	-0.179***
	[0.027]	[0.027]	[0.027]	[0.027]	[0.029]	[0.027]	[0.029]	[0.027]
visiting abroad	-0.151***	0.200***	-0.154***	0.200***	-0.112***	0.146***	-0.117***	0.146***
	[0.028]	[0.028]	[0.028]	[0.028]	[0.029]	[0.029]	[0.029]	[0.029]
jobexp_1	0.039		0.040		0.034		0.038	
	[0.025]		[0.025]		[0.026]		[0.026]	
Hard Sc.	0.013	-0.081	0.013	-0.081	0.040	-0.083	0.040	-0.086
	[0.060]	[0.061]	[0.060]	[0.061]	[0.063]	[0.063]	[0.063]	[0.063]
Medicine	0.217***	0.015	0.215***	0.015	0.233***	0.035	0.237***	0.029
	[0.064]	[0.068]	[0.064]	[0.068]	[0.068]	[0.069]	[0.068]	[0.070]
Agr. Veter. Sc.	0.102	-0.166**	0.103	-0.166**	0.088	-0.134*	0.103	-0.135*
	[0.075]	[0.075]	[0.075]	[0.075]	[0.078]	[0.076]	[0.078]	[0.076]
Technical Sc.	-0.018	0.108*	-0.019	0.108*	-0.000	0.134**	-0.002	0.135**
	[0.062]	[0.066]	[0.062]	[0.066]	[0.066]	[0.067]	[0.066]	[0.067]
Law	0.146*	-0.281***	0.148*	-0.281***	0.174**	-0.253***	0.179**	-0.254***
	[0.077]	[0.075]	[0.077]	[0.075]	[0.080]	[0.077]	[0.079]	[0.077]
Soc.-Pol. Sc. Human.	0.171***	-0.385***	0.175***	-0.385***	0.155**	-0.365***	0.174**	-0.368***
	[0.066]	[0.061]	[0.065]	[0.061]	[0.070]	[0.063]	[0.069]	[0.063]
sector_2	-0.379***		-0.378***		-0.383***		-0.389***	
	[0.040]		[0.040]		[0.043]		[0.043]	
sector_3	0.007		0.005		0.015		0.015	
	[0.087]		[0.087]		[0.091]		[0.090]	
parttime_1	0.202***		0.200***		0.188***		0.181***	
	[0.042]		[0.042]		[0.043]		[0.043]	
parttime_2	0.297***		0.298***		0.278***		0.279***	
	[0.056]		[0.056]		[0.058]		[0.057]	
selfemployed	0.478***		0.476***		0.470***		0.466***	
	[0.038]		[0.038]		[0.039]		[0.039]	
informal access	0.155***		0.155***		0.163***		0.150***	
	[0.041]		[0.041]		[0.043]		[0.043]	
academic	-0.830***		-0.824***		-0.829***		-0.814***	
	[0.052]		[0.054]		[0.060]		[0.063]	
ReD	-0.931***		-0.924***		-0.894***		-0.881***	
	[0.044]		[0.046]		[0.051]		[0.053]	
children		0.140**		0.139**		0.169***		0.166***
		[0.059]		[0.058]		[0.060]		[0.060]
female*children		-0.368***		-0.367***		-0.386***		-0.382***
		[0.070]		[0.070]		[0.072]		[0.072]
married		0.284***		0.284***		0.295***		0.294***
		[0.050]		[0.050]		[0.051]		[0.051]
female*married		-0.289***		-0.287***		-0.286***		-0.286***
		[0.064]		[0.064]		[0.065]		[0.065]
Observations	20,661	20,661	20,661	20,661	18,280	18,280	18,155	18,155
Wald test of $\rho = 0$ (p-value)		5.51 (0.019)		6.09 (0.014)		3.89 (0.049)		5.19 (0.023)

Rob. std. errors in brackets. *** p<0.01, ** p<0.05, * p<0.1 All estimates include: constant, prov. of Ph.D Univ., prov. of residence before Univ.