Skill mismatch, routine bias technical change and unemployment: evidence from Italy

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Abstract

In this article we assess the role of skill mismatch and routine bias technical change (RBTC) on unemployment risk. We use the panel component of the INAPP- *Survey on Labour Participation and Unemployment* (PLUS) for the years 2014-2016-2018 to construct different measures of skill mismatch and we merge it with the INAPP *Survey on Italian Occupations* (ICP) an *O*NET-type survey* from which we build a Routine Task Index (RTI). In terms of education, we use revealed match measures of vertical and horizontal mismatch and a self-reported measure of educational mismatch. In addition, we introduce a self-reported measure of general skill mismatch as well as a measure of the sheepskin effect assessing whether or not the educational level of a worker is required to get a given job. The econometric strategy consists in estimating transition probabilities from employment to unemployment between 2014 and 2016 and between 2016 and 2018. Problems of selection are addressed by using a *Heckmann* two-stage mode. Results indicate that i) the effect of overeducation depends on the age cohort, with young overeducated workers experiencing unemployment risk 4 percentage points higher than average ii) the horizontal mismatch is positively related to unemployment risk in all age cohorts iii) these effects are stronger in the private sector and the sheepskin effect is particularly important for manufacturing employment iv) all results about mismatch are robust to the sample selection v) as to the RTI index, after controlling for mismatch, it remains positive and significant for adult workers, while becomes negative and significant for youngers. Moreover, after also controlling for sample selection, RTI becomes insignificant for all age cohort. All in all our findings indicate that that technological unemployment affects mostly overeducated workers as they tend to be employed in more routine intensive occupations. In other words, the technology driven unemployment risk seems to be less robust than the skill-mismatch one.

Keywords: overeducation, educational mismatch, skill mismatch, routine bias technical change, unemployment, occupation, task, Italy, Heckman model.

JEL codes: D91, J24, J64, J82

1. Introduction

Technological progress in the last decades induced substantial changes in the employment structure and wage distribution of advanced and emerging economies. *Routine biased technological change* (RBTC) implied a substitution between labour and capital for occupations characterized by routine intensive tasks while increasing the demand for cognitive and abstract tasks. This led to job polarization in employment and wage structures, with increasing demand and wages of high and low skilled workers occupied in non-routine intensive tasks, and falling employment and relative wages of medium skill workers specialized in routine intensive tasks (Autor et al., 2003, 2006, 2013, Autor and Dorn 2013, Goos and Manning, 2007). It emerges that technological change, in determining a growing obsolescence of skills, tends to exacerbate the mismatch between skills and tasks (Zago, 2018). Moreover, the effects of technological trend appear age-biased, causing a decreasing in the relative demand for older workers (Aubert et al., 2006; Behaghel et al., 2014). Consequently, one of the most important challenges for policy makers in the current digital age is to understand the skill mismatch and adopt tailored policies. In this article, we investigate the effect of skill mismatch and RBTC on unemployment risk in Italy. Three questions are relevant here: i) Is the technology driven unemployment risk more relevant than the mismatch one? ii) Does the effect of mismatch depend on the measure we adopt? iii) Are the effects age-biased?

Skills demand and supply became of central importance in understanding technology driven changes in the employment composition and in unemployment levels. The interaction between technological upgrading and skill upgrading might result in sub-optimal outcomes in terms of productivity and unemployment when skill mismatches between demand and supply of labour exist. If firms struggle to find workers with skills complementing new technologies, entrepreneurs might be less willing to upgrade their capital stock with R&D investments (Redding 1996, Scicchitano 2010). In addition, skill mismatches have negative effects on productivity due to the incomplete exploitation of workers' potential. This is particularly the case when mismatches are due to overeducation as overeducated workers might experience cognitive decline (De Grip et al., 2008) and be less inclined to participate in training activities (Verhaest and Omey, 2006). Overeducation also reduces job satisfaction and this increases job mobility (Verhaest and Omey, 2006) leading to a reduction in ability of firms to accumulate human capital.

Skill mismatches have additional negative consequences on labour markets. Lower productivity gains reduce wage and economic growth, leading to higher structural unemployment and lower job creation rates (Skott and Auerbach, 2005; Olitsky, 2008). From a microeconomic point of view, these dynamics increase unemployment risk as well unemployment duration as the low job creation rate will reduce the probability to find a job.

The Italian case is peculiar with respect to both technological change and skill mismatch. If we look at the latest 2018 data about the Digital Economy and Society Index (DESI) - a composite indicator dealing with Europe's digital performance – Italy, after Bulgaria, Romania and Greece evidences the lowest scores. Italy reveals unsatisfactory results in all the 5 areas included in DESI (connectivity, human capital, use of internet, integration of digital technology and digital public services) but the area of human capital shows the greatest suffering. With regard to the RBTC, Italy is the only country in the G7 where most graduates are involved in routine tasks (Marcolin et al.

2016). Existing studies have shown that the process of job polarization took place at lower pace in the country with respect to the other advanced economies (Biagi et al. 2018). Furthermore, younger workers seem to be relatively more engaged into routinary jobs (Gualtieri et al 2018). These outcomes are closely related to the problem of skill mismatch. The PIAAC Survey carried out by the OECD has shown that Italy is one of the countries with the higher rate of mismatch. This is due to both supply and demand factors as the low level of qualifications of the labour force couples with a sectoral specialization in low tech and low skill intensive sectors (Franzini and Raitano, 2012; Adda et al., 2017). OECD (2017) highlights that skill mismatch is so pervasive as to prevent Italy from leaving its "low-skills low-quality trap". It negatively affects Italy's capacity to develop a high sustainable growth. Thus, *Promoting skills assessment and anticipation to reduce skills mismatch* is reported as one of the main challenges for Italy. These findings suggest that skill mismatches in Italy can be one of the main determinants low productivity growth, affecting by consequence both potential output growth and unemployment dynamics. With respect to the latter, the country shows unemployment rates above the EU average and in spite of the recent labour market reforms, the negative consequences of crisis on unemployment levels in Italy seem to be still in place (Izquierdo et al. 2017).

The aim of the paper is to provide micro-level evidence on the effect of qualification mismatch and RBTC on unemployment risk in Italy. This is done by using a uniquely detailed professional dataset on tasks, skills, work attitudes, recently built merging two surveys. The first one is the last wave of the Survey on Labour Participation and Unemployment (PLUS), a sample survey on the Italian labour market. We use the panel component which provides information for more about 16,000 individuals, for the years 2014-2016-2018. PLUS contains information on several characteristics of the labour force and allows us to build several both empirical and self-reported measures of skill mismatch. The second data-set is the Italian Survey of Professions (ICP), which provides detailed information of the task-content of occupations at the 4-digit occupation level. The ICP is the Italian equivalent of the US Model based on the O*NET repertoire (Author and Dorn 2013, Autor et al. 2013, Gualtieri et al. 2018). Notably, Italy is one of the few European countries to have such a dictionary of occupations similar to the US O*NET. It allows us to build the well-known Routine Task Index (RTI) for the 2012, which is the most relevant and robust indicator to evaluate the effects of RBTC on the labour market. Thus, we merge the RTI to the PLUS data set in order to show how and to what extend the RBTC can exacerbate the effects of skill mismatch on the risk of unemployment.

Extensive research has been carried out on the way to measure skill mismatch and the results of empirical analysis have been strongly influenced by the type of measure used, making it complicate to generalize the results. Most studies focus on empirical or statistics-based measures, given by the comparison between an individual's educational level with the one that is considered to be specific for a given occupation. Occupation-specific educational requirements are most commonly calculated using median values, due to the scarcity of information on more objective measures of skill demand. Alternative to empirical measures, educational mismatches can be calculated using self-reported measures based on individuals' questionnaires. Self-reported measured have the advantage of capturing the perception of owns labour market condition. Self-perceptions can be more informative as they include aspects related to job satisfaction and to other contingent elements which hardly captured by data. These measures, however, can suffer from self-reporting bias as individuals might tend to overestimate their skill level and increase by consequences mismatches due to overskilling.

In this paper, we use different measures of educational and skill mismatch. In terms of education, we use empirical measures of vertical and horizontal mismatch and a self-reported measure of educational mismatch. In addition, we introduce a self-reported measure of general skill mismatch as well as a measure of the sheepskin effect. The latter represents the effect of mandatory educational attainments. Mismatched workers are those declaring that their level/field of education is not mandatory for their job. Hence, it is a measure of educational mismatch but encompasses elements of both vertical and horizontal mismatch.

The paper contributes to the existing literature from three points of view. First, we provide evidence on the relation between unemployment risk and skill mismatch in Italy for the most recent years (2014-2018). To our knowledge, this is the first study investigating the issue. Second, we use different measures of skill mismatch and compare the significance and contribution of empirical and self-reported measures. Third, we control for the effect of RBTC by using routine intensive indexes based on Italian data. Most existing studies use the O*NET classification based on US data.

The remaining of the paper is structured as follows. In Section 2, we review the main literature on the measurement of skill mismatch and its relation with technological change and labour market outcomes. In Section 3, we provide descriptive evidence on unemployment dynamics and on the characteristics of mismatched workers. Section 4 describes the econometric strategy and discusses main results. Section 5 and 6 reports robustness checks in terms of sectorial differences and sample selection respectively. Section 6 draws summary conclusions and policy implications.

2. Survey of the literature

2.1 Causes and consequences of skill mismatch

There are several reasons that lead to the existence of skills and educational mismatches. From a theoretical point of view, skill mismatch is considered a loss of human capital and its effects depend on the underlying theoretical model. The standard human capital theory considers mismatch to be a short-run phenomenon due to the adaptation of firms to the supply of skill. The signalling theory (Spence, 1973) and the job competition theory (Berg, 1970) consider mismatch to be a persistent phenomenon caused by the reduction in training and education costs. The standard augment for the analysis of mismatch is the assignment model where overqualification and skill mismatch arise due to difference in the share of complex jobs between skilled and unskilled workers. Overqualified workers cannot fully exploit their productivity while underqualified workers have limited room for productivity increases.

Beyond these general intuitions, substantial literature investigated the causes of skill mismatch at micro and macro level. In this respect, we can distinguish between causes related to the economic performance and those related to specific characteristics of workers and their work place. Macroeconomic dynamics might affect skill mismatch due to short-run and long-run factors. Short-run factors are related to the business cycle (Liu et al. 2012) and to the fact that mismatch tend to be pro-cyclical. This is because during recessions, unemployment risk is higher for low-productivity individuals and overeducated individuals cannot fully exploit their productivity potential. Considering structural factors, a mismatch can arise because of technology-driven structural changes in the economy requiring new skills and different fields of study (Mendes de Oliveira et al. 2000) compared to the existing supply. Both demand and supply factors are more relevant in high and low technology countries respectively (Ghignoni and Verashchagina, 2014). The ability of labour markets to adapt to these changes depends on several factors such as firm size, union density, employment protection, and expenditure on education and training (Marsden et al. 2002). There could be also a signalling effect of individual and institutional quality of study on individual horizontal mismatch (Domadenik et al. 2013). If we look specifically at over qualification, it tends to be more concentrated in small firms operating in the retail sector (Dolton and Silles, 2002) and among workers with unstable contracts (Green and McIntosh, 2007). In addition, mismatch is more likely in firms which rely heavily on shifts (Belfield, 2019) or less integrated geographical areas (Ramos and Sanroma, 2011). Moreover, empirical evidence shows that geographical mobility helps to reduce overeducation (Hensen et al., 2009).

Academic achievement and the field of study are also crucial in determining a potential mismatch. Overeducation tends to be concentrated in specific fields of study (Ortiz and Kucel, 2008), with higher intensities in Social Sciences and Humanities (Chevalier, 2003; Büchel and Pollmann-Schult, 2004; and Frenette, 2004). In these fields, the skill assessment by employer is more complicate as it cannot rely on specific definition of competencies implied in these fields. Therefore, students tend to obtain additional qualification to improve the signal about their skills on the labour market (Meliciani and Radicchia 2016). The length of study may be a significant determinant of vertical overeducation, particularly in Italy (Caroleo and Pastore, 2018, Aina and Pastore, 2012). In addition, personality traits might be an important determinant of overeducation (Blasquez and Budria, 2012; Engelhardt, 2017) as they affect both educational (Koch et al. 2015) and employment choices. In terms of duration of overeducation, typically young workers have a higher tendency to be overeducated but overtime, vertical mobility allows moving to job more in line with the skills owned. This pattern is confirmed by Frei and Pouza-Souza (2012) whereas Verhaest et al. (2015) find a substantial persistence of overeducation among Belgian graduates.

Educational and skill mismatch have consequences on several aspects of the economy. From a macroeconomic point of view, mismatch, and overeducation in specific, can have macroeconomic consequences on GDP growth (Mavromaras et al., 2007; Ramos et al, 2012; Kampelmann and Rycx, 2012). Effects on GDP are likely to be mediated by effects on productivity. In this respect, lower productivity of overeducated workers can be due to cognitive decline (De Grip et al., 2007) and to the lower tendency to participate in training activities (Büchel and Mertens, 2002; Verhaest and Omey, 2006). Recent studies using the OECD-PIAAC Survey found a link between mismatch and productivity (McGowan and Andrews, 2015; McGowan and Andrews, 2017).

The theory of endogenous growth identifies the skill mismatch as one of the main factors that determine the persistence over time of *low-skills low-quality traps*, i.e. paths characterized by low rates of economic growth and low accumulation of human capital (Redding 1996, Scicchitano 2010). Since the seminal paper by Nelson and Phelps (1966), this line of research is based on the complementarity between human capital and technological innovations, a true engine of economic growth. In these models education is seen above all as an essential factor for the introduction and dissemination of innovations and mismatch prevents workers' skills from turning into productivity through technological innovations. In this regard, Italy is the right country to investigate the skill mismatch, because it is seen as one of the determining factors in trapping Italy into a “low development equilibrium” (OECD 2017).

Substantial research have been carried out to assess the impact of overeducation on wages. In this respect, theoretical models indicate that overeducated workers incur in wage penalty compered to individuals with similar educational levels but well matched. Evidence of wage penalty is found in several works (McGuinness and Poulikas, 2016; Levels et al. 2014; Sloane, 2014; Sanchez-Sanchez and McGuinness, 2015, Caroleo and Pastore, 2018, Gaeta et al. 2017, Kracke et al. 2017, Romero et al. 2018 among the most recent). Some studies found that the wage penalty due to overeducation is larger for female workers (Mavromaras, 2012; Sanchez-Sanchez and McGuinness, 2015). Scicchitano et al. (2019) show that skills mismatch is significant in terms of wage penalty only for insecure workers on average and that the effect is only relevant at the bottom of the wage distribution. Other studies investigated the relation between mismatch and job satisfaction (Verhofstadt and Omey, 2007; McGuinness and Sloane, 2011; Fleming and Kler, 2014; McGuinness and Byrne, 2015; Congregado et al. 2016, Mateos-Romero and Salinas-Jimenez 2018). Overqualification affects job mobility (Verhaest and Omey, 2006) both among different job of within th same job (Büchel, 2002). It has been demonstrated that skill mismatch has a negative effect on work–life conflict and that this association is fully mediated through job satisfaction (Shevchuk et al. 2019).

Looking at the relation between mismatch and unemployment, several works have proved the existence of a causal link from mismatch to size and duration of unemployment (Jackman et al., 1991; Sneessens, 1995; Manacorda and Petrongolo, 1999; Thissé and Zebou, 2000; Marsden et al., 2002; Skott and Auerbach, 2005; and Olitsky, 2008). The main reasons for over qualification to affect unemployment is job satisfaction (Verhaest and Omey, 2006; Verhofstadt and Omey, 2007): overqualified workers tend to have a lower job satisfaction and hence are more likely to leave their current job and move into unemployment. The duration of the unemployment spell depends on the structure of labour demand and on the development of labour market institutions. On the other hand, mismatches affect firm productivity as well as wage and economic growth, leading to a higher structural unemployment and a lower job creation rate. This happens in particular for overqualified workers as their job would not allow to fully exploit their potential productivity. On the same token, the low job satisfaction usually results in higher mobility (Verhaest and Omey, 2006), reducing the rate of accumulation of the skills specific to a given occupation and hence the accumulation of human capital by firms.

In this paper, we focus on the relation between skill mismatch and unemployment risk. Research aimed at estimating the direct contribution of mismatch on unemployment is scarce; most evidence is indirect and existing studies refer to the period before the global financial crisis We selected Italy, being among the European countries that has suffered the most from the crisis in terms of GDP and employment (Izquierdo et al. 2017). Our analysis is linked to the literature on technology driven unemployment risk (Autor and Dorn, 2013; Autor et al. 2013, Centra et al., 2019). In specific, we innovate with respect to the previous studies by linking educational mismatches to the adoption of

Routine Biased technologies, hence shaping the pace at which RBTC affect technological unemployment. Our analysis covers the period 2014-2018 and focuses on a phase during which the country experienced a marked recovery after the recessions of the years 2008-2009 and 2011-2013.

2.2 The measurement of skill mismatch

The skill mismatch problem is multidimensional but the measures used to assess the phenomenon usually refer to single aspect of the problem. A large amount of papers focuses on the educational mismatch based on the assumption that educational levels are a good indicator of the actual skill level. However, a large body of literature has shown that educational and skill mismatch measures two different phenomena. In the context of educational mismatch, there are two dimensions to be considered: vertical and horizontal mismatch. The vertical dimension refers to the comparison between actual years of schooling and those required to perform a specific job. The resulting outcomes are well matched, overeducated and undereducated. Horizontal mismatch refers to the choice of the field of study whereby an individual is mismatched if its field of education does not match the field required to perform a specific job (Nordin et al, 2010; Verhaest et al., 2017; Reis, 2018; Somers et al., 2019). In the context of education mismatch, measures and analyses focussed mostly on vertical mismatch due to the difficulties to calculate indicators of horizontal mismatch.

Educational and skill mismatch have been measured in different ways in the literature[1]. Following Munoz de Bustillo-Lorente et al. (2018), we can classify mismatch measures into three categories: Job Assessment measures (JA); realized match measures (RM); and Self-assessment measures (SA). Job Assessment and Realized Match measures are calculated by comparing the actual educational attainment of an individual with the proper educational level for a specific occupation. In JA measures, the proper educational level is derived by analysing the skill and educational requirements of each profession at very disaggregated level. Hence, it is the result of an assessment provided by experts. The RM measure uses the median or mean educational attainment for each profession calculated on disaggregated ISCO categories. Self-Assessment measures are obtained by asking directly to workers whether own educational levels are in line with those required to get a job (educational requirement) or to perform a job (skill requirement). In this respect, we distinguish between measures of educational mismatch and measures of skill mismatch. All measures can be used to calculate both vertical and horizontal mismatch indicators.

In terms of performance of the different measures, the literature is not univocal and a dominant measure has not been identified. JA measures have the advantage to assess precisely what is the required educational or skill level for a given occupation but it relies on information that is rarely available for a large number of countries and time periods. Recent studies attemted to calculate detailed measures of skill shortages using a multidimensional approach based on the OECD Survey of Adult Skills (Flisi et al., 2017; Pellizzari and Fichen, 2017) or the European Skill and dJobs Survey (McGuinness et al., 2018). RM measures have the advantage to be easily implemented, as data on educational attainments by profession are widely available. There are, however, several disadvantages in the use of this measure: first, mode category is not necessary the required one as it can reflect demand shortages and changes in the supply of skill which are unrelated to firm dynamics; second, the use of the mode is based on the assumption of symmetry in the distribution

[1] For a survey of literature see McGuinness et al. (2017) and Brunello and Wruuck (2019) with a focus on Europe.

of the years of schooling. SA measures have been largely used in the last years (Green and Zhu, 2010; Boll et al., 2016; Munoz de Bustillo-Lorente 2018) as workers perception can include information that is not captured by other measures, in particular a more precise understanding of the work requirements. The disadvantage is that SA measure are subject to the so call self-reporting bias, due to the fact that individuals might misestimate the requirements of a job and their own skill (Sloane 2003, McGuinness 2006). In addition, these measures can be sensitive to the way the question is asked (Green et al., 1999).

A general problem when measuring mismatch is that different measures return different results. In this respect, De Bustillo-Lorente et al. (2018) have shown that in Europe the correlation between these measures is very scarce. Low correlation between skill and educational mismatch might be due to the fact that the two measures refer to different aspects of the skill endowment, with educational levels measuring knowledge and skill levels measuring the ability to apply this knowledge. Hence, the latter might measure not only cognitive skill but also the so-called soft skills, which are usually associated with personality traits (Koch et al., 2015). Low or null correlation among educational mismatch measures is a more serious problem as results depend crucially on the measure used. This has the further shortcoming to reduce the comparability of the results of different studies across countries and over time. In this respect, policy implications should be based on a systematic assessment of all the results obtained using different measures (McGuinness at al. 2017).

In this paper, we use several measures of educational and skill mismatch. The PLUS dataset allows calculating JA, RM and SA measures of educational mismatch and a SA measure of skill mismatch. In this way, we will provide an implicit test of the robustness of the results to measurement issues and discuss their differences in the informational power.

3. Data and descriptive evidence

Data used in this article are from an innovative dataset, recently built by merging two Italian surveys, PLUS and ICP, developed and administered by National Institute for the Analysis of Public Policies (INAPP), a national research institute reporting to the Italian Ministry of Labour and Social Policy. The primary objective of the PLUS survey is to provide reliable statistically estimates of phenomena rare or marginally explored by other surveys on the Italian labour market. In fact, if Italian National Statistical Institute (ISTAT)'s Labour Force Survey provides the aggregates and official indicators on the labour market, the PLUS survey is mainly aimed at deepening specific, particularly problematic aspects. For our purposes, it is the appropriate survey, because it allows us to examine the various existing forms of mismatches on the labour market. The survey has been carried out in the years 2014, 2016 and 2018 on a sample of about 45,000 individuals.

Interviewees were contacted through a dynamic computer-assisted telephone interviewing (CATI). In the dataset only survey respondents are included (absence of proxy interviews), thus reducing the extent of measurement errors and partial nonresponses. The questionnaire was submitted to a sample of residents aged between 18 and 74 years, being the sample design stratified over the Italian population: strata are defined by region (20 administrative regions), type of city (metropolitan/nonmetropolitan), age (five classes), sex and the employment status of the individual (employed, unemployed, student, retired, other inactive/housewife). The reference population is derived from the annual averages of the ISTAT Labour Force Survey. INAPP provides weights to account for the probability of attrition based on surveyed characteristics: all estimates reported in the article use those weights (for further details, see Clementi and Giammatteo, 2014, Filippetti et al., 2019, Meliciani, and Radicchia, 2011, 2016).[2] Our analysis is conducted on the panel quota for the years 2014, 2016 and 2018. This allows us to observe labour market transitions of employed individuals between 2014 and 2016, and between 2016 and 2018.

The second survey we merge is the ICP, used to build indicators measuring the level of routinization of the labour tasks, at the level of professional groups (ISCO classes at four digit). It allows us to build a robust RTI , and to test the relevance of the RBTC (Autor, 2013 and Autor and Dorn, 2013) in terms of unemployment risk. We calculate the RTI for the year 2012, at the beginning of our time span, assuming rank-stability of tasks for the short-time span (Akçomak et al. 2016, Tamm, 2018)

First of all, using the information contained in the PLUS database we can build several measures of educational and skill mismatch (see Table 1). Alongside standard empirical measures of vertical and horizontal mismatch, we can derive two SA measures referring to educational mismatch and to skill mismatch in broad sense (SAOS and SAOE). In addition, we introduce a SA measure of the sheepskin effect which means whether a certain job requires by law a certain educational title (SASE). The self-reported measure of educational mismatch is based on the comparison of an individual's educational attainment with the answer to the question: *what is the most suitable educational level for the job you are performing?* Overeducated are those whose education attainment is higher than the required one whereas undereducated are those whose educational attainment is below the required one. The main advantage of using self-reported measures is that they might have a better information as workers might know better the skill requirements of an occupation as well as their own skills. The main disadvantage is due to the self-reporting bias due mostly to the fact that individual might tend to overestimate their abilities.

The empirical version of this measure (RMOE) is based on the comparison between workers' educational attainment with the modal educational attainment of the related profession calculated at ISCO-2digits level. Contrary to the previous measures, the advantage of this one is that it can be calculated for all employed individuals not only for those having at least the secondary education. Two main disadvantages are associated with this measure: first, the modal educational attainment it is not necessary the more adequate; second, the median category based on subsamples that are too small to be representative.

Table 1 Definition of skill mismatch measures

Measure	Construction
Self-assessed overskill (SAOS)	Question: to what extent your skill match those required by your current occupation? Slightly higher/higher=overskilled; otherwise=matched)
Revealed match measure of overeducation (RMOE)	Comparison between educational attainment and modal category for each profession (ISCO=-2digits): positive=overeducated; null of negative=matched

[2] The PLUS data are available by accessing the section https://inapp.org/it/dati/plus.

Self-assess measure of overeducation (SAOE)	Question: What is the most suitable educational level to perform your job? If answer<educational attainment=overeducated; otherwise=matched
Self-assess measure of sheepskin effect (SASE)	Is your educational attainment required to get your job? YES=matched; NO=overeducated/mismatched
Revealed match measure of horizontal mismatch (RMHM)	Comparison between the field of study (13 categories) and the two model categories by ISCO-2digits occupation: Not modal=mismatched; model=matched

Source: PLUS

The self-reported measure of skill mismatch is given by the answer to the question: *to what extent are your skills suitable for the job you perform?* Individuals are classified as overskilled if the answers are slightly above and well above, matched if the answer is more or less the same, and underskilled if the answers are slightly below of well below. The question does not focus on the educational attainment; hence it can be considered a broad measure of skills.

The sheepskin effect measure is based on the legal value of education and it is based on the question: *is your educational level mandatory for the job you are performing?* In this case, individuals answering yes are classified as matched whereas those answering no are classified as overeducated. Due to the definition of this measure, there are no undereducated individuals. With respect to the other self-reported measure, the bias in this case should be reduced due to the fact that the question asks about a legal requirement that workers should know precisely.

In order to provide a complete picture of the phenomena, we also introduce a revealed match measure of horizontal mismatch based on the modal field of study for each profession (RMHM). Similar to the empirical vertical mismatch measure, we use the ISCO classification at two digits level in order to identify the main field of study. Individuals are considered well matched if their field of study is the modal one of their profession, whereas they are classified as mismatched on the other case. Fields of education are defined by using the classification produced by the ISTAT and grouped into 13 different categories. This measure shares the same disadvantages of its vertical counterpart while not having the advantage to be calculated for all educational levels.

Table 2 Distribution of mismatch measures by employment status in t+1 and age group

		By employment status in t+1				By age group		
	Status	Matched	Mismatched	Total	Age	Matched	Misamtched	Total
SAOS	Employed	94.39	93.64	94.13	20-35	25.97	25.72	25.88
	Unemployed	5.61	6.36	5.87	36-65	74.03	74.28	74.12
	Total	100	100	100	Total	100	100	100
SAOE	Employed	94.65	91.95	94.13	20-35	24.06	34.59	25.88
	Unemployed	5.35	8.05	5.87	36-65	75.94	65.41	74.12
	Total	100	100	100	Total	100	100	100
SASE	Employed	95.26	91.81	94.13	20-35	22.85	32.27	25.88
	Unemployed	4.74	8.19	5.87	36-65	77.15	67.73	74.12
	Total	100	100	100	Total	100	100	100
RMOE	Employed	94.01	94.78	94.13	20-35	23.89	34.29	25.59
	Unemployed	5.99	5.22	5.87	36-65	76.11	65.71	74.41
	Total	100	100	100	Total	100	100	100
RMHM	Employed	95.17	93.81	94.13	20-35	28.81	26.17	26.75
	Unemployed	4.83	6.19	5.87	36-65	71.19	73.83	73.25
	Total	100	100	100	Total	100	100	100

Source: own elaboration on PLUS. Weighted estimates.

In Table 2, we report the distribution of mismatch measures by transition status and age group. With respect to the former, we observe a higher unemployment probability for mismatched workers. This is true for all measures except for RMOE which shows similar rates across categories. As for age groups, three out of five measures report higher incidence of mismatch among workers up to 35 years. According to SAOE, SASE and RMOE young workers have a probability of being mismatched 10 percentage points higher than average. The remaining measures do not show significant differences between age groups. As for older workers, they experience a lower probability to be mismatched according to the same three measures. These opposite patterns are a result of the higher average educational levels of younger individuals coupled with the lack of other skill, which are usually acquired through the working life. Contrary, among older workers, undereducation is more prominent.

In Table 3 we take a closer look at the relation between mismatch and educational attainment. For workers with secondary education the picture is unclear, with SAOE and RMOE reporting lower incidence of mismatch whereas SARE and RMHM report a higher share of mismatched workers. As for tertiary educated workers, the incidence of mismatch is below average according to SASE and RMHM whereas the other measures do not show significant differences. Lastly, workers with post-graduate education show higher levels of overeducation according to SAOE and RMOE.

In table 4 we provide evidence on the relationship between mismatch and type of contract. The evidence for permanent workers is unclear, but based on 4 measures out of 5, there is a higher incidence of mismatch among fixed-term contracts. Mismatch does not seem to be a problem for self-employed workers.

Finally, in Table 5 we report average values of the RTI by mismatch. While the two RM measures do not show significant differences in the routine intensity of mismatched workers compared to matched ones, all three SA measures indicate that mismatched workers are employed in occupation with a higher degree of routine intensity.

Table 3 Distribution of mismatch measures by educational attainment

		Matched	Mismatched	Total
SAOS	Secondary	67.91	65.29	66.9
	Tertiary	28.44	29.98	29.03
	Post-grad	3.65	4.73	4.07
	Total	100	100	100
SAOE	Secondary	69.34	55.19	66.9
	Tertiary	29.03	29.07	29.03
	Post-grad	1.64	15.74	4.07
	Total	100	100	100
SASE	Secondary	60.63	80.15	66.9
	Tertiary	34	18.53	29.03
	Post-grad	5.37	1.32	4.07
	Total	100	100	100
RMOE	Secondary	77.24	13.11	66.59
	Tertiary	22.76	62.16	29.3
	Post-grad	0	24.74	4.11
	Total	100	100	100
RMHM	Secondary	29.32	77.56	66.92

Tertiary	61.84	19.7	29
Post-grad	8.84	2.73	4.08
Total	100	100	100

Source: own elaboration on PLUS and ICP. Weighted estimates.

Table 4 Distribution of mismatch measures by type of contract

		Matched	Mismatched	Total
SAOS	Permanent	72.08	73.5	72.63
	Fixed	6.69	6.73	6.71
	Other	9.68	9.52	9.62
	Self-empl	11.55	10.25	11.05
	Total	100	100	100
SAOE	Permanent	73.75	67.22	72.63
	Fixed	5.75	11.29	6.71
	Other	9.01	12.53	9.62
	Self-empl	11.48	8.96	11.05
	Total	100	100	100
SASE	Permanent	74.06	69.61	72.63
	Fixed	5.61	9.02	6.71
	Other	8.09	12.86	9.62
	Self-empl	12.25	8.52	11.05
	Total	100	100	100
RMOE	Permanent	73.02	68.78	72.33
	Fixed	6.43	8.31	6.74
	Other	9.38	11.68	9.76
	Self-empl	11.16	11.23	11.17
	Total	100	100	100
RMHM	Permanent	65.6	74.32	72.33
	Fixed	7.25	6.59	6.74
	Other	9.85	9.73	9.76
	Self-empl	17.31	9.35	11.17
	Total	100	100	100

Source: own elaboration on PLUS. Weighted estimates.

Table 5 Routine intensity by measure and type of mismatch

	SAOS	SAOE	SASE	RMOE	RMHM
Matched	41.6	40.5	38.6	42.1	42.0
Mismatched	42.5	48.9	49.0	41.8	42.0
Total	41.9	41.9	41.9	41.9	41.9

Source: own elaboration on PLUS. Weighted estimates.

Summing up, educational and skill mismatches are associated with higher unemployment probability, lower age, fixed-term contracts and higher routine intensity. The implication are substantial, as negative effects of being overeducated would add the destruction of human capital arising with long periods of unemployment. In addition, mismatched workers could be particularly vulnerable to technological change due to their specialization in routine intensive jobs.

4. Econometric analysis

We estimate a probit model where the probability to be unemployed in t conditional to being employed in t-1 (PU) is estimated as a function of the mismatch measures alongside firm and individual characteristics. The estimated equation is the following:

$$PU_{i,t} = \beta_1 SAOS_{i,t} + \beta_2 SAOE_{i,t} + \beta_3 SASE_{i,t} + \beta_4 RMOE_{i,t} + \beta_5 RMHM_{i,t} + \sum \pi_n \, UE_{i,t}^n + \sum \gamma_k \, X_{i,t}^k + \sum \vartheta_h Y_{i,t}^h + \varepsilon_{i,t} \qquad (1)$$

The first five variables are the indicators of overeducation and horizontal mismatch described in the previous section. Variables UE are three indicators of undereducation and underskill derived by the same questions used to derive SA and RM measures. More specifically, we introduce a self-assessed measure of underskill (SAUS), a self-assessed measure of underducation (SAUE) and a revealed match measure of undereducation (RMUE). These measure are introduced to control for differences between matched and overeducated individuals which could affect the estimation overeducation and overskill impacts. Firm characteristics X include size, sector (13 categories) and geographical dummies (20 regions). Individual characteristics include age (dummies, 5 years interval), sex, marital status, presence and number of children, type of contract, educational attainment, profession (ISCO 1digit) and the RTI index.

Estimation results for the whole sample and for the two subsamples of individuals below and above 35 years of age are shown in Table 6. In order to assess the interplay between RBTC and mismatch the first three columns report the specification including the RTI only; columns 4-6 add the empirical horizontal and vertical educational mismatch measures; columns 7-9 add the self-reported measures of educational mismatch; and columns 10-12further add the self-reported skill mismatch measure and the sheepskin effect. Individual and firm characteristics are included in any estimation model.

Starting from the RTI, its impact is significant and positive when mismatch measures are not included and it is not significant for young workers. The effect appears to be driven by workers above 35 years. Instead, it becomes insignificant for all workers but negative (positive) and significant for workers up to (over) 35 years when all the other measures of mismatch are added. This result indicates that, on the one hand younger workers employed in routine intensive tasks face a lower unemployment risk once controlled for their perceived condition in terms of skill mismatch. In other words, the positive correlation between unemployment risk and RTI observed on Italian data might be due to the fact that workers specialized in routine intensive tasks are more likely to be overeducated, especially among young age cohorts. On the other hand, for older workers technology driven unemployment risk seems to be more relevant than the skill-mismatch one, because workers over 35 engaged in routine tasks have a 3.6% higher risk of unemployment.

As for the revealed match measures, workers with a mismatch in their field of study show a higher probability to become unemployed. The effect for the entire labour force is driven by older workers. This suggests that while graduates of all ages experience a higher probability to move into unemployment when they are horizontally mismatched, for young workers this effect is in part captured by the other self-reported measure of overeducation. A possible explanation is that overeducated graduates are also horizontally mismatched but the vertical component is the dominant factor in explaining labour mobility decision. This explanation is supported by the positive and significant impact of SROE for the groups of workers up to 35 years. For this group, unemployment risk increases 4.5% if they are overeducated. This result confirms that, among younger workers, unemployment probability is explained by the vertical rather than the horizontal dimension of mismatch while changing educational requirements might explain the higher importance of RMHM among workers above 35 years. The sheepskin effect is also significant for younger workers only.

Finally, it is worth noticing that RMUE is negative and significant especially for the group of older workers. This result is in line with the evidence of a larger incidence of underducation among high age cohorts documented by ISTAT and it is likely to be due to the lower average educational level of this group. In addition, this result could be explained by a stability-qualification trade off whereby workers chose a stable but relatively low skill job when better jobs are more precarious or unavailable in the local labour market.

Looking at the other variables the work experience and the tenure show a small negative and significant effect and this happens, as expected, above all among older workers. Being woman and having a fixed-term contract increases the probability of unemployment regardless of age, while being married has a positive and significant effect only amongst young workers. As the size of the business increases, the risk of unemployment decreases. Working in the public sectors reduces the probability of unemployment, but not for young workers.

All in all, these results indicate that workers of both age groups face a higher unemployment risk when they are mismatched and that both horizontal and vertical dimension of mismatch matter. Within this general picture, older workers seem to face mostly a problem of horizontal mismatch whereas for younger workers, unemployment risk is mostly associated with overeducation. Further, the effect of RTI is positive (negative) and significant for adult (young) workers: hence this is in line with the *Age-biased technical change* (ABTC) (Aubert et al., 2006; Behaghel et al., 2014). The negative effect for young may be related the structure of the Italian economy, more focused on routinary jobs.

Table 6 Estimation results of equation (1)

		20-70	20-35	36-65	20-70	20-35	36-65	20-70	20-35	36-65	20-70	20-35	36-65
RBTC	RTI	0.036**	-0.004	0.048**	0.013	-0.046	0.035	0.005	-0.082**	0.035	0.003	-0.091**	0.036*
		[0.017]	[0.036]	[0.019]	[0.020]	[0.036]	[0.021]	[0.020]	[0.036]	[0.022]	[0.020]	[0.037]	[0.021]
Mismatch	RMHM				0.010**	0.016	0.009*	0.009*	0.012	0.009*	0.009*	0.010	0.009*
					[0.005]	[0.011]	[0.005]	[0.005]	[0.011]	[0.005]	[0.005]	[0.011]	[0.005]
	RMOE				-0.001	-0.009	0.001	-0.005	-0.021*	0.001	-0.005	-0.024*	0.001
					[0.006]	[0.012]	[0.006]	[0.006]	[0.013]	[0.006]	[0.006]	[0.013]	[0.006]
	RMUE				-0.024***	-0.02	-0.020***	-0.022***	-0.01	-0.020***	-0.021***	-0.008	-0.020***
					[0.008]	[0.020]	[0.007]	[0.008]	[0.021]	[0.008]	[0.008]	[0.020]	[0.008]
	SAOE							0.011**	0.045***	-0.001	0.007	0.033***	-0.001
								[0.005]	[0.011]	[0.005]	[0.005]	[0.012]	[0.006]
	SAUE							-0.007	-0.016	-0.002	-0.006	-0.012	-0.002
								[0.007]	[0.018]	[0.006]	[0.007]	[0.018]	[0.006]
	SAOS										0.002	0.000	0.005
											[0.004]	[0.010]	[0.004]
	SAUS										-0.006	-0.019	0.001
											[0.010]	[0.021]	[0.011]
	SASE										0.007	0.029***	-0.002
											[0.010]	[0.021]	[0.011]
Individual	experience	0.000	0.002	-0.001***	-0.001*	0.001	-0.001***	-0.001**	0.001	-0.001***	-0.001**	0.001	-0.001***
		[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]
	tenure	-0.001**	0.001	-0.000*	-0.001***	0.000	-0.001**	-0.001***	0.001	-0.001**	-0.001***	0.000	-0.001**
		[0.000]	[0.002]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.002]	[0.000]
	female	0.031***	0.063***	0.018***	0.029***	0.058***	0.017***	0.029***	0.058***	0.017***	0.029***	0.058***	0.017***
		[0.005]	[0.010]	[0.005]	[0.004]	[0.009]	[0.005]	[0.004]	[0.009]	[0.005]	[0.004]	[0.009]	[0.005]
	married	0.013**	0.028*	0.006	0.009	0.035**	0.001	0.009	0.036**	0.001	0.009	0.036**	0.001
		[0.006]	[0.016]	[0.006]	[0.006]	[0.016]	[0.006]	[0.006]	[0.016]	[0.006]	[0.006]	[0.016]	[0.006]
	children	-0.031***	-0.007	-0.036***	-0.023**	-0.052	-0.023***	-0.024**	-0.05	-0.023***	-0.023**	-0.05	-0.022***
		[0.009]	[0.032]	[0.009]	[0.009]	[0.038]	[0.008]	[0.009]	[0.038]	[0.008]	[0.009]	[0.038]	[0.008]
	n. children	0.003	0.022	0.004	0.003	0.043*	0.003	0.003	0.041*	0.003	0.003	0.041*	0.003

		[0.004]	[0.017]	[0.004]	[0.004]	[0.022]	[0.003]	[0.004]	[0.022]	[0.003]	[0.004]	[0.022]	[0.003]
	Tertiary ed.	-0.011**	-0.002	-0.015***	-0.01	0.005	-0.012*	-0.012*	-0.002	-0.013*	-0.011	0.003	-0.013*
		[0.005]	[0.010]	[0.006]	[0.007]	[0.016]	[0.007]	[0.007]	[0.017]	[0.007]	[0.007]	[0.016]	[0.007]
Contract	Employer	-0.001	0.060***	-0.022**	0.006	0.054***	-0.01	0.007	0.055***	-0.01	0.007	0.055***	-0.01
		[0.009]	[0.018]	[0.010]	[0.008]	[0.017]	[0.009]	[0.008]	[0.017]	[0.009]	[0.008]	[0.017]	[0.009]
	Other	0.051***	0.083***	0.047***	0.048***	0.087***	0.037***	0.048***	0.086***	0.037***	0.048***	0.085***	0.038***
		[0.007]	[0.013]	[0.009]	[0.006]	[0.013]	[0.008]	[0.006]	[0.013]	[0.008]	[0.006]	[0.013]	[0.008]
	Self-employed	-0.034***	-0.004	-0.042***	-0.020**	0.000	-0.027***	-0.019**	0.006	-0.027***	-0.019**	0.005	-0.027***
		[0.009]	[0.020]	[0.009]	[0.008]	[0.020]	[0.008]	[0.008]	[0.020]	[0.008]	[0.008]	[0.020]	[0.008]
	Fixed term	0.051***	0.062***	0.053***	0.044***	0.067***	0.043***	0.044***	0.064***	0.043***	0.044***	0.064***	0.043***
		[0.006]	[0.012]	[0.008]	[0.006]	[0.012]	[0.007]	[0.006]	[0.012]	[0.007]	[0.006]	[0.012]	[0.007]
Firm size	<10 employees	-0.006	0.003	-0.013*	0.002	0.000	-0.001	0.002	0.000	-0.001	0.002	0.000	-0.001
		[0.006]	[0.013]	[0.007]	[0.006]	[0.012]	[0.006]	[0.006]	[0.012]	[0.006]	[0.006]	[0.012]	[0.006]
	11<emplyees<50	-0.014*	-0.019	-0.018**	-0.018**	-0.032**	-0.018**	-0.018**	-0.030*	-0.018**	-0.018**	-0.031**	-0.018**
		[0.008]	[0.016]	[0.008]	[0.007]	[0.016]	[0.008]	[0.007]	[0.016]	[0.008]	[0.007]	[0.016]	[0.008]
	51<emplyees<250	-0.033***	-0.049**	-0.033***	-0.027***	-0.041*	-0.026**	-0.027***	-0.041*	-0.026**	-0.027***	-0.041*	-0.026**
		[0.010]	[0.022]	[0.011]	[0.010]	[0.023]	[0.010]	[0.010]	[0.023]	[0.010]	[0.010]	[0.023]	[0.010]
	>250 employees	-0.031***	0.002	-0.041***	-0.013	0.004	-0.020*	-0.012	0.008	-0.020*	-0.012	0.01	-0.020*
		[0.011]	[0.025]	[0.013]	[0.011]	[0.026]	[0.011]	[0.011]	[0.026]	[0.011]	[0.011]	[0.026]	[0.011]
	Public	-0.042***	0.009	-0.055***	-0.041***	0.002	-0.052***	-0.041***	0.003	-0.052***	-0.040***	0.003	-0.052***
		[0.008]	[0.015]	[0.009]	[0.007]	[0.014]	[0.008]	[0.007]	[0.014]	[0.008]	[0.007]	[0.014]	[0.008]
	N	13651	3597	10054	11957	3401	8556	11957	3401	8556	11957	3401	8556

Source: own elaborations on PLUS and ICP. Weighted estimates. Marginal impacts. Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01. Sectors, professions and Regions controls included but not reported.

5. Understanding sectoral differences

The negative effect of the RTI on unemployment risk might be the result of different sectoral dynamics in the relation between technical change, skill mismatch and unemployment. Centra et al. (2019) using LFS data find a small but positive overall impact of the RTI on unemployment risk. However, their result is mostly driven by construction and industry while in other sectors the impact is null or even negative. In this section we will provide some evidence on sectoral dynamics by estimating separate specifications for industry, services and the public sector.

Table 7 Estimation results of equation (1) for workers employed in the production of goods:

	All	20-35	36-70	All	20-35	36-70	All	20-35	36-70
RTI	0.067	0.067	0.065	0.045	0.016	0.057	0.036	-0.031	0.062
	[0.056]	[0.108]	[0.065]	[0.057]	[0.108]	[0.066]	[0.058]	[0.110]	[0.067]
RMHM	0.017	0.052	0.002	0.017	0.049	0.003	0.017	0.046	0.003
	[0.017]	[0.031]	[0.019]	[0.017]	[0.031]	[0.019]	[0.017]	[0.031]	[0.019]
RMOE	-0.004	-0.019	0.006	-0.013	-0.037	0.003	-0.015	-0.047	0.002
	[0.021]	[0.041]	[0.023]	[0.021]	[0.042]	[0.024]	[0.021]	[0.041]	[0.024]
RMUE	-0.025	-0.057	-0.014	-0.021	-0.051	-0.013	-0.023	-0.04	-0.015
	[0.040]	[0.111]	[0.040]	[0.040]	[0.108]	[0.040]	[0.040]	[0.109]	[0.041]
SAOE				0.038**	0.087***	0.01	0.028	0.053	0.011
				[0.016]	[0.030]	[0.020]	[0.018]	[0.034]	[0.022]
SAUE				-0.002	0.002	-0.01	-0.002	0.008	-0.012
				[0.027]	[0.063]	[0.029]	[0.027]	[0.063]	[0.029]
SAOS							0.017	-0.005	0.021
							[0.015]	[0.030]	[0.016]
SAUS							-0.011	-0.158*	0.070*
							[0.038]	[0.083]	[0.043]
SASE							0.014	0.071**	-0.01
							[0.017]	[0.032]	[0.019]
N	1867	607	1260	1867	607	1260	1867	607	1260

Source: own elaborations on PLUS and ICP. Weighted estimates. Marginal impacts. Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01. Individual and firm characteristics, as well as sectors, professions and Regions controls included but not reported.

In Table 7 we report the estimates for workers employed in the production of goods. The RTI exerts a positive but insignificant effect on unemployment risk. RM measures of horizontal and vertical mismatch are insignificant too whereas SROE and SRSE remain significant, especially for younger workers. In addition, there is a weak evidence that underskilled workers have a lower unemployment risk.

Turning to services (Table 8), the RTI is insignificant while most mismatch measures retain their significance compared to the estimations on the whole sample. There are, however, few worth noticing differences: first, RMUE turns significant for young workers too; second, SROS turns insignificant for older workers. These results suggest that the stability-qualification trade off might be the most appropriate explanation of the lower unemployment risk of undereducated workers.

Finally, in the public sector (Table 9) the only significant relations between mismatch and unemployment are due to horizontal mismatch and to undereducation.

All in all, sectoral differences are not particularly marked, especially when comparing industry and services. There seem to be a higher incidence of horizontal mismatch and undereducation in the service sector whereas the effect of overeducation is more pronounced for workers employed in the production of goods. As for the RTI, sectoral estimates do not provide additional insights even though there is a weak evidence that the risk of technological unemployment is higher among worker of the goods industry.

Table 8 Estimation results of equation (1) for workers employed in services

	All	20-35	36-70	All	20-35	36-70	All	20-35	36-70
RTI	-0.005	-0.05	0.031	-0.023	-0.101	0.03	-0.025	-0.109	0.031
	[0.036]	[0.068]	[0.041]	[0.037]	[0.069]	[0.041]	[0.037]	[0.070]	[0.042]
RMHM	0.028**	0.033	0.026*	0.027**	0.027	0.026*	0.026**	0.024	0.026*
	[0.012]	[0.022]	[0.014]	[0.012]	[0.022]	[0.014]	[0.012]	[0.022]	[0.014]
RMOE	-0.011	-0.019	-0.007	-0.018	-0.038	-0.008	-0.019	-0.039	-0.008
	[0.014]	[0.027]	[0.017]	[0.015]	[0.027]	[0.017]	[0.015]	[0.027]	[0.017]
RMUE	-0.061***	-0.088*	-0.047**	-0.059**	-0.078	-0.048**	-0.058**	-0.075	-0.048**
	[0.023]	[0.052]	[0.024]	[0.024]	[0.053]	[0.024]	[0.024]	[0.053]	[0.024]
SAOE				0.024**	0.062***	0.002	0.019	0.048**	0.002
				[0.011]	[0.019]	[0.012]	[0.012]	[0.022]	[0.014]
SAUE				-0.004	-0.019	0.004	-0.003	-0.016	0.003
				[0.016]	[0.036]	[0.015]	[0.016]	[0.036]	[0.016]
SAOS							0.001	-0.004	0.006
							[0.009]	[0.018]	[0.010]
SAUS							-0.008	-0.01	-0.012
							[0.023]	[0.039]	[0.030]
SASE							0.011	0.032	-0.003
							[0.010]	[0.020]	[0.011]
N	5381	1948	3433	5381	1948	3433	5381	1948	3433

Source: own elaborations on PLUS and ICP. Weighted estimates. Marginal impacts. Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01. Individual and firm characteristics, as well as sectors, professions and Regions controls included but not reported.

Table 9 Estimation results of equation (1) for workers employed in the public sector

	All	20-35	36-70	All	20-35	36-70	All	20-35	36-70
RTI	-0.011	0.022	-0.018	-0.016	0.006	-0.018	-0.016	0.009	-0.018
	[0.028]	[0.102]	[0.026]	[0.029]	[0.103]	[0.026]	[0.029]	[0.103]	[0.026]
RMHM	0.017**	0.053*	0.012	0.017**	0.051*	0.012	0.017**	0.053*	0.011
	[0.008]	[0.029]	[0.008]	[0.008]	[0.029]	[0.008]	[0.008]	[0.029]	[0.008]
RMOE	-0.003	0.016	-0.005	-0.003	0.015	-0.005	-0.004	0.018	-0.006
	[0.010]	[0.044]	[0.008]	[0.010]	[0.044]	[0.008]	[0.010]	[0.045]	[0.008]
RMUE	0.007	-0.038	0.013	0.003	-0.049	0.012	0.003	-0.048	0.012
	[0.010]	[0.035]	[0.009]	[0.010]	[0.038]	[0.010]	[0.010]	[0.039]	[0.010]
SROE	-0.021*	-0.022	-0.017*	-0.017	-0.01	-0.018*	-0.017	-0.013	-0.017*
	[0.011]	[0.042]	[0.010]	[0.011]	[0.045]	[0.010]	[0.011]	[0.045]	[0.010]
SAUE				0.009	0.027	0.002	0.008	0.038	0.000
				[0.010]	[0.037]	[0.009]	[0.011]	[0.040]	[0.009]
SAOS				-0.008	-0.023	0.002	-0.01	-0.027	0.000
				[0.010]	[0.043]	[0.009]	[0.010]	[0.043]	[0.009]
SAUS							0.002	-0.023	0.009
							[0.007]	[0.027]	[0.006]
SASE							0.027	0.032	0.023
							[0.017]	[0.069]	[0.015]
RTI							0.000	-0.019	-0.002
							[0.009]	[0.036]	[0.008]
N	4698	846	3833	4698	846	3833	4698	846	3833

Source: own elaborations on PLUS and ICP. Weighted estimates. Marginal impacts. Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01. Individual and firm characteristics, as well as sectors, professions and Regions controls included but not reported.

6. Sample selection into employment

In this section we provide a robusteness check by addressing the problem of self-selection into employment. This will be done by estimating a Heckmann (1979) selection model where the probit regression of equation (1) is associated with the following selection equation:

$$PE_{i,t} = b_1 FathEMP_{i,t} + b_2 MothEMP_{i,t} + b_3 FathEduc_{i,t} + b_4 MothEduc_{i,t} + \sum \vartheta_h Y_{i,t}^h + \varepsilon_{i,t} \quad (2)$$

Where the additional instruments are given by parents' education level (MothEduc and FathEduc) and occupation (*FathEMP* and *MothEMP*). Other instruments are individual characteristics Y previously described. The estimation results of equation (1) with the Mills ratio (rho) derived from the selection equation (2) are shown in Table 10. The first evidence is that the selection equation is significantly correlated with the main equation (rho is significant) for the whole sample and for younger workers. For workers above 35 years, there seem to be no correlation between the two equations (rho is insignificant). The second result is that RTI becomes insignificant for both young and old workers. Finally, all mismatch measures retain their sign and significance, indicating that although the sample of employed and unemployed individuals differ, the selection bias does not affect the results.

Table 10 Estimation results of equation (1) with selection into employment

	All	20-35	36-70	All	20-35	36-70	All	20-35	36-70
RTI	0.003	-0.013	0.016	-0.007	-0.039	0.014	-0.009	-0.045	0.015
	[0.017]	[0.030]	[0.017]	[0.017]	[0.032]	[0.017]	[0.017]	[0.032]	[0.017]
RMHM	0.016***	0.024**	0.012**	0.016***	0.021**	0.012**	0.015***	0.019*	0.012**
	[0.005]	[0.011]	[0.006]	[0.005]	[0.010]	[0.006]	[0.005]	[0.010]	[0.006]
RMOE	0.001	-0.01	0.007	-0.004	-0.021*	0.006	-0.004	-0.023*	0.006
	[0.006]	[0.011]	[0.006]	[0.006]	[0.012]	[0.006]	[0.006]	[0.013]	[0.006]
RMUE	-0.024***	-0.015	-0.018**	-0.022**	-0.008	-0.018**	-0.022**	-0.006	-0.019**
	[0.009]	[0.018]	[0.009]	[0.009]	[0.018]	[0.009]	[0.009]	[0.018]	[0.009]
SAOE				0.016***	0.038***	0.003	0.013**	0.030**	0.003
				[0.005]	[0.012]	[0.005]	[0.006]	[0.012]	[0.006]
SAUE				-0.004	-0.008	0.001	-0.004	-0.005	0.000
				[0.007]	[0.015]	[0.006]	[0.007]	[0.015]	[0.006]
SAOS							0.003	-0.005	0.007*
							[0.004]	[0.008]	[0.004]
SAUS							0.003	-0.014	0.013
							[0.011]	[0.019]	[0.011]
SASE							0.006	0.021**	-0.003
							[0.005]	[0.010]	[0.005]
N	11957	3401	8556	11957	3401	8556	11957	3401	8556
rho	0.308**	0.535**	0.435	0.311**	0.541**	0.431	0.31**	0.541**	0.423

Source: own elaborations on PLUS and ICP. Weighted estimates. Marginal impacts. Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01. Individual and firm characteristics, as well as sectors, professions and Regions controls included but not reported.

7. Conclusions

In this paper we investigated the role of educational and skill mismatch in explaining unemployment risk, with a special focus on the interplay with RBTC. By using information collected from merging the ICP and the PLUS survey for the years 2014-2018 we calculated five measures of educational and skill mismatch. This allowed to compare the results from self-reported and revealed match measures in order to assess the robustness of the results. Moreover, we were able to evaluate the effect of the RBTC in terms of risk of unemployment, through the classic RTI.

The main findings of the paper can be summarized as follow. First, the effect of overeducation depends on the age cohort, with young overeducated workers experiencing unemployment risk 4 percentage points higher than average. Second, for young workers, the sheepskin effect is positive and significant too, leading to an increase in unemployment risk by 3%. Third, horizontal mismatch is positively related to unemployment risk in all age cohorts. Fourth, these effects are stronger in the private sector and the sheepskin effect is particularly important for manufacturing employment. Fifth, all results about mismatch are robust to the sample selection. As to the RTI index, after controlling for mismatch, it remains positive and significant for adult workers, while becomes negative and significant for youngers. Moreover, after also controlling for sample selection, RTI becomes insignificant for all age cohort. This means that technological unemployment affects mostly overeducated workers as they tend to be employed in more routine intensive occupations. In other words, the technology driven unemployment risk seems to be less robust than the skill-mismatch one.

The main implication of the results is that overeducation and overskilling are associated with higher unemployment risk. Therefore, policies aimed at improving the quality of matches should be encouraged not only to increase potential growth but also to avoid human capital losses and the risk that short-term unemployment becomes structural. In this respect, both demand side and supply side policies are needed.

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