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

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Abstract

In this article we assess the role of educational mismatch on unemployment risk for secondary and tertiary educated workers, taking into account the interrelation between skills and routine biased Technical Change (RBTC). 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. The econometric strategy consists in estimating transition probabilities from employment to unemployment and other jobs between 2014 and 2016, and between 2016 and 2018. The main findings are: first, mismatches in the field of study are associated with a higher unemployment risk of tertiary educated workers, especially if graduated in non-STEM fields; second, over education is associated with higher unemployment risk among young workers with secondary education, in line with the negative effect of RBTC on medium skilled workers which leads to job polarization; third, we do not find a clear impact of the RTI on transition probabilities. Our results show that the main problem for tertiary educated workers is the mismatch in the field of studies. This adds evidence to the problem of skill gap in Italy, as educational choices are not aligned to market needs. In this respect, both demand side and supply side policies are needed, especially to increase the supply of STEM graduates and to allow firms to better use this human capital.

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). Moreover, empirical evidence has shown that the share of tertiary-educated workers in routine occupations is significant (Marcolin et al. 2016).

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. 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, educational and skill mismatches can increase unemployment risk for several reasons. On the one hand, using a simple matching model, overeducated workers represent a bad match for firms thus increasing the risk to be fired. Cognitive decline (De Grip et al., 2008) and low participation in training activities (Verhaest and Omey, 2006) are factors causing a skill deteriorations process which further worsen the quality of the match. Within this framework, mismatched workers might experience longer unemployment periods during their working life, with negative consequences on their skill endowment and on the probability to find a suitable job (Ordine and Rose, 2015; Berton et al. 2018). On the other hand, educational misamtches reduce job satisfaction thus increasing voluntary unemployment as well as job mobility (Verhaest and Omey, 2006). This adds to a reduction in ability of firms to accumulate human capital. All in all, these dynamics indicate that educational and skill mismatches are a potential determinant of unemployment risk and thus negatively contributing to the overall economic performance of a country.

The Italian case is peculiar with respect to both technological change and skill mismatch as the country lags behind European partners in several indicators of technological advancement and human capital. With regard to the RBTC, Italy is the only country in the G7 where most graduates are involved in routine tasks. This is why *Increasing access to tertiary education while improving quality and relevance of skills* and *Promoting skills assessment and anticipation to reduce skills mismatch* are two of the main challenges for Italian economy (OECD, 2017) 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. 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 the negative consequences of crisis on unemployment levels in Italy seem to be still in place (Izquierdo et al. 2017), although labour market reforms seem to improve matches between workers and jobs (Berton 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. In this paper, we use different measures of educational mismatch, having in mind that the mismatch is a multidimensional theme and that it is necessary to improve its complex measurement (Cedefop, 2015). We use empirical measures of vertical and horizontal mismatch and two self-reported measure of educational mismatch based on questions about the actual and legal educational requirements of worker’s occupations. We estimate unemployment risk using a multinomial logit model where employed workers are observed between two consecutive waves of the PLUS dataset. Possible transitions are toward unemployment and toward another job. Estimates are run separately for secondary and tertiary educated workers due to differences in the labour markets and the different policy implications. Tertiary educated workers can face a problem of horizontal mismatch due to a mismatch between educational choices and technological requirements. The lack of STEM competences is usually taken as a main cause of skill mismatch. Secondary educated workers instead might be more at risk of technological unemployment since they represent the medium skilled category that suffers the most the consequences of job polarization. In this respect, their use in low quality service activities (Autor and Dorn 2013) can be seen as a consequence of a vertical educational 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

Substantial literature investigated the causes of skill mismatch at micro and macro level. 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. 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, 2013). 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). 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; Marsden et al., 2002; Skott and Auerbach, 2005; and Olitsky, 2008). Reasons for over qualification to affect unemployment come both from the demand side and supply side. Job satisfaction is the main reason for voluntary unemployment and contributes to job mobility (Verhaest and Omey, 2006). Overqualified workers tend to have a lower job satisfaction and hence are more likely to leave their current job and move into unemployment. The demand side relation between educational mismatch and unemployment can be understood using a simple matching model: overeducated workers represent a bad match for firms thus increasing the risk to be fired. Cognitive decline (De Grip et al., 2008) and low participation in training activities (Verhaest and Omey, 2006) are factors causing a skill deteriorations process which further worsen the quality of the match. Within this framework, mismatched workers might experience longer unemployment periods during their working life, with negative consequences on their skill endowment and on the probability to find a suitable job (Ordine and Rose, 2015; Berton et al. 2018). Van Loo et al., (2001), find that in Netherland skill obsolescence leads to higher risks of unemployment or non-participation. Allen and van der Velden (2001), using data from for 11 European countries and Japan show that underutilisation of skills causes on-the-job search.

All in all, these dynamics indicate that educational and skill mismatches are a potential determinant of unemployment risk and thus negatively contributing to the overall economic performance of a country.

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. 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).

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

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 Jobs 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 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 that are 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.[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 of overeducation. The first measure (SAOE) 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. The second measure (SASE) is a proxy for the sheepskin effect and tells whether a worker's educational attainment is required to get the job. Workers answering no to this question are considered overeducated. 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. However, the bias is more likely to exist for the SAOE measure since the legal requirement to get a job should be precisely known by workers.

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

The empirical measure of overducaton (RMOE) is based on the comparison between workers' educational attainment and 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
Revealed match measure of overeducation (RMOE)	Comparison between educational attainment and modal category for each profession (ISCO=-2digits): positive=overeducated; null of negative=matched
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; modal=matched

Source: PLUS

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.

In Table 2, we show labour market transitions for matched and mismatched workers between 20 and 35 years, distinguishing between secondary and tertiary educated individuals. Mismatched workers with tertiary education show a higher unemployment risk with respect to well-matched ones. Unemployment risk for the former range between 7.5% and 10% against percentages ranging between 3.2% and 5.2% for the latter. For secondary educated workers the results vary according to the measure used. SASE and RMOE report higher unemployment risk for mismatch workers (12.5% and 15.3% respectively) while SAOE and RMHM report higher risk for marched workers, although for the latter the difference with mismatched workers is not statistically significant. Looking at job-to-job transitions, there seem to be no difference between matched and mismatched workers, independently of the educational attainment.

In Table 3 we report the transitions for workers between 36 and 65 years. In this cohort, both unemployment risk and job-to-job transition are lower than those of younger workers. All of the four measures indicate that mismatched workers show a higher probability to move into unemployment and this is true for both tertiary and secondary educated workers. Unemployment risk for mismatched workers with secondary education ranges between 5.6% and 8.5% while for tertiary educated workers ranges from 3.2% to 6%. As for job-to-job transitions, we find significant differences between matched and mismatched workers. Among tertiary educated workers, being mismatched implies a higher probability to move to another job, although the difference with well-matched workers is significant only in the cases of SAOE and ROME. For secondary educated workers the results are less clear-cut, with SASE showing a higher probability to change job for mismatched workers and SASE showing the opposite results. For the other two measures, probabilities do not differ between the two groups.

Table 2 Labour market transitions by mismatch measure: individuals between 20 and 35 years

	Tertiary educated				Secondary educated			
SASE	U	E	EO	Total	U	E	EO	Total
EM	5.21	84.48	10.31	100	7.34	85.25	7.41	100
EMM	**9.47**	79.8	10.73	100	**12.46**	80.34	7.19	100
	Tertiary educated				Secondary educated			
SAOE	U	E	EO	Total	U	E	EO	Total
EM	5.19	84.52	10.29	100	**10.02**	82.75	7.23	100
EMM	**7.50**	81.94	10.56	100	6.00	85.41	8.59	100
	Tertiary educated				Secondary educated			
RMOE	U	E	EO	Total	U	E	EO	Total
EM	4.88	84.52	10.6	100	8.21	84.26	7.53	100
EMM	**9.97**	80.01	10.03	100	**15.28**	78.18	6.54	100
	Tertiary educated				Secondary educated			
RMHM	U	E	EO	Total	U	E	EO	Total
EM	3.25	84.66	**12.09**	100	**11.35**	81.9	6.75	100
EMM	**9.02**	81.93	9.04	100	8.96	83.44	7.61	100

Source: own elaboration on PLUS

Table 3 Labour market transitions by mismatch measure: individuals between 36 and 65 years

	Tertiary educated				Secondary educated			
SASE	U	E	EO	Total	U	E	EO	Total
EM	1.97	96.04	1.99	100	3.25	94.97	1.78	100
EMM	**6.01**	91.88	2.11	100	**7.23**	88.95	**3.82**	100
	Tertiary educated				Secondary educated			
SAOE	U	E	EO	Total	U	E	EO	Total
EM	1.54	96.92	1.54	100	4.6	92.85	**2.56**	100
EMM	**4.69**	92.50	**2.80**	100	**6.97**	91.77	1.26	100
	Tertiary educated				Secondary educated			
RMOE	U	E	EO	Total	U	E	EO	Total
EM	2.12	96.32	1.55	100	4.05	93.37	2.58	100
EMM	**4.90**	91.41	**3.69**	100	**8.5**	89.38	2.12	100
	Tertiary educated				Secondary educated			
RMHM	U	E	EO	Total	U	E	EO	Total
EM	2.19	96.09	1.73	100	3.32	94.14	2.54	100

EMM	**3.19**	94.55	2.26	100	**5.57**	91.93	2.50	100

Source: own elaboration on PLUS

Finally, in Table 3 we report average values of the RTI by mismatch status and measure for secondary and tertiary educated workers. In both cases, the three measures of overeducation indicate that mismatched workers perform tasks with a higher degree of routinarity. Differences are particularly market for secondary educated workers, which show a gap between 10% and 17%. Tertiary educated workers show lower average values of the index and a gap between matched and mismatched around 7 percentage points. As for the measures of horizontal mismatch, differences are less marked and not statistically significant.

Table 4 Routine intensity by measure and type of mismatch

	Secondary education			
	SASE	RMOE	SAOE	RMHM
Matched	42.6	45.2	44.0	44.3
Mismatched	51.1	62.5	56.9	46.8
Total	45.8	45.9	45.8	45.8
	Tertiary education			
	SASE	RMOE	SAOE	RMHM
Matched	32.5	30.7	32.6	35.4
Mismatched	40.1	38.6	39.0	32.9
Total	34.1	34.1	34.1	34.1

Source: own elaboration on PLUS. Weighted estimates.

Summing up, educational mismatches are associated with higher unemployment probability, especially among individuals with secondary education only. At the same time, we observe no clear distinction in terms of job-to-job transitions, but we do observe that mismatch probabilities increase with the routine intensity of the occupation.

4. Econometric analysis

We estimate a multinomial logit model where the dependent variable is the probability to change employment status in t conditional to being employed in t-1 (PT). The three possible outcomes are: permanence in the same job; transition toward unemployment; transition to another job. Marginal impacts are estimated as a function of the mismatch measures alongside firm and individual characteristics. The main idea is to understand whether mismatched workers have different probabilities to become unemployed or to change job with respect to well-matched workers.

According to a matching model, mismatched workers should experience higher job mobility associated with periods of frictional unemployment and eventually find a job that matched the educational attainment. If this is the case, then mismatched workers should show higher probabilities of both transitions with a higher likelihood to change job with respect to that of becoming unemployed. However, if mismatch is associated with a deskilling process then these workers might experience higher unemployment risk but not a higher probability to change job

The estimated equation is the following:

$$PT_i = \beta_1 OE_i + \beta_2 RMHM_i + \sum \gamma_k X_i^k + \sum \vartheta_h Y_i^h + \sum \vartheta_h Z_i^h + \varepsilon_i \quad (1)$$

PT is the probability of transition of individual i; OE is the measure of overeducation, given respectively by SASE, SAOE or RMOE; and RMHM is the measure of horizontal mismatch. Firm characteristics X include size, sector (13 categories), whether the firm has used income support schemes in the last two years (CIG); and geographical dummies (4 area). Individual characteristics Y include age, sex, marital status, number of children, , whether a workers relocated for the current job (transf): Finally, job specific characteristics include type of contract, wage, job satisfaction, searching for a job while employed, profession (ISCO 1digit), tenure, experience (number of years since the first job) and the RTI index. Additional individual characteristics are included as observable proxies for cognitive skill. These are field of study, grade of the diploma/degree, whether the maximum grade is achieved (maxgrade) and advanced knowledge of English. Equation (1) is estimated separately on the subsamples of secondary and tertiary educated workers to account for the fact that the two groups operate in different labour markets and because of the different implications in terms of educational and industrial policies. For each of the two group, we further divide workers according to an age threshold of 35 years.

Table 5 shows the results for tertiary educated workers using the Self-Assessed Sheepskin Effect (SASE) as measure of overeducation. This measure is never significant in explaining labour market transitions whereas the measure of horizontal mismatch exerts a positive and significant effect on the probability to become unemployed. The marginal impact is 0.014 on average but for workers up to 35 years the impact increases to o.o39 whereas it falls to 0.009 for workers above 35 years of age. These results indicate that a young overeducated worker with tertiary education faces unemployment risk 4% higher than that of well-matched workers.

Among the other regressors, we find a negative impact of wages on job-to-job transitions and a positive impact of very low job satisfaction on both transitions for workers above 35 years. The other – indirect – indicator of job satisfaction, that is Job search, affect positively both transitions on the whole sample but the strongest effect is found on job-to-job transitions of young workers. Turning to cognitive skills measures, knowledge of English has very little impact on employment transitions whereas a higher final grade reduces unemployment risk among young workers. The use of income support schemes (CIG) increases unemployment risk of old workers while reducing the probability to change job. Total work experience as well as tenure reduce the probability to make a transition and this is connected with the falling tendency to change employment status with age increases, as shown by the positive impact of the square age term. Among the other individual characteristics, only the female dummy is significant, but mostly for young female workers, which experience a higher unemployment risk and a lower probability to change job. Finally, the nature of the work contract has a largely significant impact on transition probabilities, with non-permanent contracts leading to higher probabilities. Finally, the RTI is never significant. Table 6 shows that also the other two measures of overeducation are insignificant in explaining employment transitions, while the effect of RMHM is confirmed.

Table 5 Estimation results of equation (1) on tertiary educated workers.

	20-65 years		20-35 years		36-65 years	
	E to U	E to E	E to U	E to E	E to U	E to E
RMHM	0.014**	-0.002	0.039**	-0.013	0.009*	0.007
	[0.005]	[0.008]	[0.016]	[0.024]	[0.005]	[0.006]
SASE	0.001	-0.003	-0.01	-0.009	0.006	-0.002
	[0.006]	[0.009]	[0.015]	[0.024]	[0.006]	[0.008]
RTI	-0.018	-0.044	-0.027	-0.145	-0.02	0.002
	[0.027]	[0.040]	[0.072]	[0.122]	[0.029]	[0.036]
Wage	-0.001	-0.013***	0.003	-0.025	0.001	-0.005
	[0.004]	[0.005]	[0.013]	[0.016]	[0.004]	[0.005]
JS=med-hi	0.006	0.003	0.012	0.022	0.009	0.000
	[0.008]	[0.009]	[0.020]	[0.030]	[0.009]	[0.007]
JS=low	0.000	-0.002	-0.011	0.019	0.012	-0.005
	[0.009]	[0.012]	[0.026]	[0.035]	[0.009]	[0.011]
JS=very low	0.021*	0.008	0.041	0.076	0.032**	-0.316***
	[0.012]	[0.022]	[0.032]	[0.064]	[0.014]	[0.053]
Grade	-0.001*	0.001	-0.002**	0.002	0.000	0.000
	[0.000]	[0.001]	[0.001]	[0.002]	[0.001]	[0.000]
english	-0.007	0.005	-0.014	0.02	-0.009*	0.000
	[0.005]	[0.007]	[0.015]	[0.023]	[0.005]	[0.006]
Max grade	0.006	0.004	0.02	0.010	0.000	0.002
	[0.007]	[0.009]	[0.019]	[0.026]	[0.006]	[0.007]
Job search	0.017**	0.019**	0.03	0.052**	0.009	0.003
	[0.007]	[0.009]	[0.019]	[0.025]	[0.006]	[0.011]
CIG	0.038***	-0.024	-0.012	-0.015	0.042***	-0.305***
	[0.010]	[0.023]	[0.038]	[0.059]	[0.008]	[0.052]
Age	0.001	0.001	0.004	0.015**	0.001*	0.001
	[0.001]	[0.001]	[0.005]	[0.008]	[0.000]	[0.001]
Age^2	0.000**	0.000***	0.000*	0.001***	0.000	0.000*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Moved	-0.004	0.000	-0.017	-0.023	-0.003	0.007
	[0.009]	[0.010]	[0.022]	[0.032]	[0.010]	[0.007]
experience	0.000	0.000	-0.001	0.002	0.000	-0.001
	[0.001]	[0.001]	[0.002]	[0.003]	[0.000]	[0.001]
tenure	-0.001**	-0.002**	0.002	-0.007	-0.001**	-0.001*
	[0.001]	[0.001]	[0.004]	[0.005]	[0.000]	[0.000]
Female	0.020***	-0.012	0.046***	-0.051**	0.007	0.010
	[0.007]	[0.008]	[0.017]	[0.023]	[0.009]	[0.011]
Married	0.003	-0.002	0.003	0.007	-0.004	0.013
	[0.011]	[0.014]	[0.062]	[0.066]	[0.010]	[0.011]
Married*female	0.003	0.003	0.006	-0.056	0.009	-0.010
	[0.011]	[0.015]	[0.067]	[0.065]	[0.011]	[0.012]
N. Children	0.001	-0.002	0.017	0.055*	0.001	-0.004
	[0.004]	[0.005]	[0.023]	[0.028]	[0.003]	[0.003]
Temporary	0.039***	0.028***	0.071***	0.074**	0.034***	-0.323***
	[0.008]	[0.010]	[0.019]	[0.030]	[0.010]	[0.054]
Other	0.026***	0.022***	0.035*	0.063**	0.022***	0.007
	[0.007]	[0.009]	[0.019]	[0.029]	[0.007]	[0.006]
Sector	YES	YES	YES	YES	YES	YES
Area	YES	YES	YES	YES	YES	YES
Field	YES	YES	YES	YES	YES	YES

Firm size	YES	YES	YES	YES	YES	YES
N	3806	3806	1130	1130	2676	2676

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.

Table 6 Estimation results of equation (1) on tertiary educated workers: specifications with SAOE and RMOE

	20-65 years		20-35 years		36-65 years	
SAOE	E to U	E to E	E to U	E to E	E to U	E to E
RMHM	0.013**	-0.001	0.038**	-0.011	0.008*	0.007
	[0.005]	[0.008]	[0.016]	[0.024]	[0.005]	[0.006]
SAOE	0.005	-0.01	0.005	-0.029	0.007	-0.004
	[0.005]	[0.008]	[0.014]	[0.024]	[0.005]	[0.008]
N	3806	3806	1130	1130	2676	2676
	20-65 years		20-35 years		36-65 years	
RMOE	E to U	E to E	E to U	E to E	E to E	E to U
	20-65 years	20-35 years	36-65 years	20-65 years	20-35 years	36-65 years
RMHM	0.014**	-0.003	0.044***	-0.014	0.009*	0.006
	[0.006]	[0.008]	[0.016]	[0.024]	[0.005]	[0.006]
RMOE	-0.002	0.005	-0.030*	-0.004	0.003	0.007
	[0.006]	[0.008]	[0.016]	[0.025]	[0.005]	[0.008]
N	3806	3806	1130	1130	2676	2676

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.

The results for workers with secondary education only are shown in Tables 7 and 8. Differently from tertiary educated workers, SASE is significant in explaining employment transitions. More specifically, we find that being overeducated increases the probabilities of both transition, but unemployment risk is concentrated in the cohort up to 35 years whereas higher job-to-job transitions probsbility is found for workers above 35 years only. The negative impact of the RTI on unemployment risk for this same group provides important details on the underlying employment dynamics of this group. More specifically, young workers with secondary education only tend to be employed in routine intensive tasks but when they are overeducated they face higher unemployment risk. This might indicate that job opportunities are concentrated in occupations requiring only basic primary and lower secondary education, in line with the job-polarization phenomena implied by the RBTC theory whereby medium skilled workers are more at risk of unemployment.

As for the other repressors (Table 7), the main difference with tertiary educated workers lies in the negative and significant impact of wages on unemployment risk. While this impact might be biased due to reverse causality, it suggests that high-pay jobs are less likely to be destroyed. This might be because these jobs require a high level of skills that are not captured by the educational attainment. Other differences with repsect to tertiary educated workers are the insignificance of total work experience and, in most case, of horizontal mismatch.

The impact shown in Table 8 provide a partial confirmation of the impact of overeducation employment transitions. The SAOE measure confirms that young overeducated workers with secondary education face higher unemployment risk whereas workers above 35 years experience a higher probability to change job. These results, however, are not confirmed by the RMOE measure but this might be an effect of the way the variable is built. Since the median educational level is high school diploma in most cases, the number of overeducated workers is very low, resulting in a weak power of this variable in explaining employment transitions. Summing up, the results provide some clear indications on the role of educational mismatch in explaining labour market transitions. First, horizontal mismatch is a significant determinant of unemployment of tertiary educated workers. Second, overeducation increases unemployment risk of workers with secondary education only. Third, the results are robust to the inclusion of several determinants of labour market transitions and overeducation. More specifically, job satisfaction and measures of cognitive skills do not affect the results. Finally, we do not find a clear evidence on the role of routine biased technical change. Sectoral heterogeneity and differences in the demand for routine cognitive and routine manual workers might explain the variability of the results (Cassandro et al. 2019).

Table 7 Estimation results of equation (1) on secondary educated workers.

	20-65 years		20-35 years		36-65 years	
	E to U	E to E	E to U	E to E	E to U	E to E
RMHM	-0.01	-0.005	-0.048***	0.002	0.002	-0.008
	[0.007]	[0.008]	[0.018]	[0.021]	[0.006]	[0.007]
SASE	0.011*	0.015**	0.053***	0.023	-0.006	0.013*
	[0.006]	[0.007]	[0.015]	[0.018]	[0.006]	[0.007]
RTI	-0.04	-0.038	-0.134**	-0.051	0.012	-0.051*
	[0.026]	[0.032]	[0.061]	[0.091]	[0.025]	[0.028]
Wage	-0.028***	-0.005	-0.054***	-0.005	-0.015***	-0.011
	[0.005]	[0.007]	[0.012]	[0.014]	[0.006]	[0.009]
JS=med-hi	-0.005	0.007	-0.013	0.026	0.000	-0.004
	[0.007]	[0.010]	[0.018]	[0.023]	[0.008]	[0.009]
JS=low	0.006	0.019*	-0.025	0.045*	0.016*	0.004
	[0.009]	[0.011]	[0.024]	[0.026]	[0.008]	[0.010]
JS=very low	0.020*	0.015	-0.014	0.045	0.028***	-0.002
	[0.011]	[0.014]	[0.031]	[0.044]	[0.010]	[0.013]
Grade	0.001*	0.000	0.000	0.001	0.001**	0.000
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]
english	0.001	-0.006	0.020	0.007	-0.004	-0.015**
	[0.006]	[0.007]	[0.014]	[0.016]	[0.006]	[0.008]
Max grade	0.001	-0.011	0.025	-0.008	-0.01	-0.012
	[0.012]	[0.020]	[0.029]	[0.042]	[0.012]	[0.018]
Job search	0.01	0.020**	0.008	0.033*	0.014*	0.011
	[0.008]	[0.008]	[0.019]	[0.019]	[0.008]	[0.009]
CIG	0.022***	0.009	-0.008	-0.01	0.018**	0.013*
	[0.009]	[0.010]	[0.029]	[0.032]	[0.007]	[0.007]
Age	0.002***	0.000	0.011***	0.006	0.002***	0.000
	[0.001]	[0.001]	[0.004]	[0.006]	[0.001]	[0.001]

Age^2	0.000***	0.000	0.000***	0.000	0.000***	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Moved	0.015	-0.024	0.034	-0.044	0.008	-0.009
	[0.012]	[0.017]	[0.032]	[0.050]	[0.011]	[0.013]
experience	0.000	-0.001	0.001	-0.003	0.000	0.000
	[0.001]	[0.001]	[0.003]	[0.003]	[0.000]	[0.001]
tenure	0.000	-0.002**	-0.003	-0.012**	0.000	-0.001
	[0.000]	[0.001]	[0.003]	[0.006]	[0.000]	[0.000]
Female	0.023***	-0.029***	0.062***	-0.052***	-0.001	-0.026**
	[0.008]	[0.009]	[0.016]	[0.018]	[0.009]	[0.012]
Married	-0.001	0.014	0.009	-0.028	-0.011	0.011
	[0.010]	[0.010]	[0.041]	[0.050]	[0.009]	[0.008]
Married*female	0.002	-0.001	0.025	0.034	0.016	0.007
	[0.011]	[0.013]	[0.047]	[0.056]	[0.011]	[0.014]
N. Children	-0.005	0.002	-0.006	0.033	-0.003	0.000
	[0.004]	[0.005]	[0.019]	[0.025]	[0.003]	[0.004]
Temporary	0.046***	0.024**	0.076***	0.019	0.026**	0.030*
	[0.009]	[0.012]	[0.019]	[0.027]	[0.011]	[0.016]
Other	0.046***	0.033***	0.049***	0.039*	0.049***	0.021*
	[0.008]	[0.009]	[0.019]	[0.023]	[0.009]	[0.011]
Sector	YES	YES	YES	YES	YES	YES
Area	YES	YES	YES	YES	YES	YES
Field	YES	YES	YES	YES	YES	YES
Firm size	YES	YES	YES	YES	YES	YES
N	4606	4606	1254	1254	3352	3352

Table 8 Estimation results of equation (1) on secondary educated workers: specifications with SAOE and RMOE

	20-65 years		20-35 years		36-65 years	
	E to U	E to E	E to U	E to U	E to E	E to U
RMHM	-0.009	-0.004	-0.045**	0.005	0.002	-0.008
	[0.007]	[0.008]	[0.018]	[0.021]	[0.006]	[0.007]
SAOE	0.008	0.012	0.038**	0.005	-0.007	0.015*
	[0.007]	[0.008]	[0.017]	[0.019]	[0.007]	[0.008]
N	4606	4606	1254	1254	3352	3352
	20-65 years		20-35 years		36-65 years	
	E to U	E to E	E to U	E to U	E to E	E to U
RMHM	-0.009	-0.004	-0.043**	0.005	0.001	-0.008
	[0.007]	[0.008]	[0.018]	[0.021]	[0.006]	[0.007]
RMOE	-0.005	0.007	-0.032	0.052	0.012	-0.017
	[0.016]	[0.017]	[0.045]	[0.045]	[0.012]	[0.019]
	4606	4606	1254	1254	3352	3352

5. Robustness checks

5.1 Previous unemployment and mismatchIn this section, we provide a robustness check of the results by adding to the baseline specification additional variables with might affect the relation between mismatch and labour market transitions. In specific, we deal with the role of previous unemployment spells as the core element in determining labour market transitions. Rose and Ordine (2015) argue that longer periods of unemployed increase the probability to be mismatched because of skill deterioration associated with the periods of inactivity and personal traits. In this framework, the higher unemployment risk mismatched workers face might not only be a temporary consequence of the matching process, but a long-term consequence of the lower competitiveness of these workers in the labour market. If mismatch is a consequence of skill deterioration caused by long unemployment spells then controlling for the latter should turn mismatch indicators insignificant. In order to take into account this channel, we introduce two alternative variables in the specification. The first one is the variable used by Rose and Ordine (2019), that is the last unemployment spell before finding the current job, which is derived from a specific question on PLUS. The second one is a proxy for the total period of inactivity /unemployment, and is calculated as the difference between the time distance from the first occupation and the number of years of contribution. While this measure might be not precise due to the potential presence of unpaid work (stages, training, intervals between temporary contracts), it can be associated with lower competitiveness on the labour market as a consequence of underemployment. Positive values of this variable indicate that working experience has not been continuous although there might be cases where no contribution is recorded even if the individual was employed. This is the case for example of unpaid internships or illegal jobs.

Specifications with the last unemployment spell are shown in Table 9 whereas Table 10 shows the results using our proxy for the total unemployment spell. Marginal impacts of mismatch measures and RTI are unchanged, but the search variable turns to be a significant determinant of unemployment risk for workers with secondary education. More specifically, when the previous unemployment spell is longer than 3 months the risk to become unemployed again increases substantially, but above that threshold, impacts are uniform. The results using the total period of non-employment are similar as shown in Tables 10. The variable is insignificant for tertiary educated workers, positive, and significant in most cases in explaining unemployment risk of secondary educated workers. The implication of this result is that skill deterioration due to long periods of non-employment is not the main channel through educational mismatch affects unemployment.

Table 9 Specification with last unemployment spell

	Workers with tertiary education																	
	20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years	
	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U
RTI	-0.021	-0.032	-0.034	-0.123	-0.022	0.01	-0.017	-0.04	-0.021	-0.144	-0.021	0.008	-0.013	-0.05	0.006	-0.149	-0.019	-0.007
	[0.027]	[0.040]	[0.071]	[0.118]	[0.030]	[0.037]	[0.027]	[0.040]	[0.071]	[0.122]	[0.030]	[0.035]	[0.027]	[0.041]	[0.072]	[0.125]	[0.030]	[0.039]
Search 1-3m	0.008	-0.015	0.016	-0.019	0.007	-0.029**	0.008	-0.015	0.016	-0.02	0.007	-0.029**	0.008	-0.015	0.017	-0.02	0.007	-0.028**
	[0.007]	[0.010]	[0.019]	[0.026]	[0.006]	[0.013]	[0.007]	[0.010]	[0.019]	[0.026]	[0.006]	[0.013]	[0.007]	[0.010]	[0.019]	[0.026]	[0.006]	[0.014]
Search 4-12m	-0.014*	0	-0.018	-0.003	-0.013	0.004	-0.014*	0	-0.018	-0.004	-0.013	0.005	-0.014*	0	-0.019	-0.005	-0.014	0.006
	[0.007]	[0.009]	[0.019]	[0.026]	[0.008]	[0.007]	[0.007]	[0.009]	[0.019]	[0.026]	[0.008]	[0.007]	[0.007]	[0.009]	[0.019]	[0.026]	[0.008]	[0.007]
Search >12m	0.002	-0.006	0.006	-0.015	0.006	-0.003	0.003	-0.006	0.007	-0.019	0.006	-0.002	0.003	-0.006	0.007	-0.019	0.006	-0.002
	[0.008]	[0.012]	[0.024]	[0.039]	[0.008]	[0.009]	[0.008]	[0.013]	[0.023]	[0.039]	[0.008]	[0.009]	[0.008]	[0.013]	[0.023]	[0.039]	[0.008]	[0.009]
RMHM	0.014**	-0.001	0.038**	-0.01	0.009*	0.008	0.014***	-0.002	0.040**	-0.012	0.009*	0.008	0.015***	-0.003	0.045***	-0.013	0.009*	0.007
	[0.006]	[0.008]	[0.016]	[0.024]	[0.005]	[0.006]	[0.006]	[0.008]	[0.016]	[0.024]	[0.005]	[0.006]	[0.006]	[0.008]	[0.016]	[0.024]	[0.005]	[0.006]
SAOE	0.005	-0.011	0.003	-0.03	0.006	-0.003												
	[0.005]	[0.008]	[0.014]	[0.024]	[0.005]	[0.008]												
SASE							0.001	-0.003	-0.011	-0.01	0.006	-0.002						
							[0.006]	[0.009]	[0.015]	[0.024]	[0.005]	[0.008]						
RMOE													-0.002	0.004	-0.031*	-0.004	0.004	0.007
													[0.006]	[0.008]	[0.016]	[0.025]	[0.005]	[0.008]
N	3806	3806	1130	1130	2676	2676	3806	3806	1130	1130	2676	2676	3806	3806	1130	1130	2676	2676

	Workers with secondary education																	
	20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years	
	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U
RTI	-0.038	-0.031	-0.123*	-0.018	0.008	-0.051*	-0.043	-0.035	-0.137**	-0.027	0.009	-0.050*	-0.029	-0.024	-0.07	-0.041	0	-0.032
	[0.026]	[0.033]	[0.064]	[0.096]	[0.025]	[0.030]	[0.026]	[0.032]	[0.060]	[0.091]	[0.025]	[0.029]	[0.025]	[0.030]	[0.062]	[0.084]	[0.025]	[0.028]
Search 1-3m	0.016*	-0.007	0.028	-0.041**	0.013	-0.001	0.016*	-0.007	0.025	-0.042**	0.013	0	0.016*	-0.007	0.027	-0.042**	0.013	0.001
	[0.009]	[0.009]	[0.020]	[0.021]	[0.009]	[0.010]	[0.009]	[0.009]	[0.020]	[0.021]	[0.009]	[0.010]	[0.009]	[0.009]	[0.020]	[0.020]	[0.009]	[0.010]
Search 4-12m	0.028***	-0.005	0.042**	-0.043*	0.021**	0.006	0.027***	-0.005	0.040**	-0.042*	0.021**	0.006	0.028***	-0.005	0.042**	-0.043*	0.021**	0.007
	[0.009]	[0.009]	[0.020]	[0.023]	[0.009]	[0.009]	[0.008]	[0.009]	[0.019]	[0.023]	[0.009]	[0.009]	[0.009]	[0.009]	[0.020]	[0.023]	[0.009]	[0.009]
Search >12m	0.026***	-0.017	0.049**	-0.106***	0.020**	0.006	0.026***	-0.017	0.050**	-0.104***	0.020**	0.006	0.026***	-0.017	0.053**	-0.106***	0.019**	0.007
	[0.009]	[0.012]	[0.024]	[0.037]	[0.009]	[0.010]	[0.009]	[0.012]	[0.024]	[0.036]	[0.009]	[0.010]	[0.009]	[0.012]	[0.024]	[0.038]	[0.009]	[0.010]
RMHM	-0.009	-0.004	-0.041**	-0.002	0.001	-0.007	-0.01	-0.004	-0.044**	-0.005	0.001	-0.007	-0.009	-0.003	-0.040**	-0.002	0.001	-0.007
	[0.007]	[0.008]	[0.018]	[0.022]	[0.006]	[0.007]	[0.007]	[0.008]	[0.018]	[0.022]	[0.006]	[0.007]	[0.007]	[0.008]	[0.018]	[0.022]	[0.006]	[0.007]
L.smm2o	0.008	0.011	0.037**	0.005	-0.007	0.015*												
	[0.007]	[0.008]	[0.018]	[0.019]	[0.007]	[0.008]												
							0.011*	0.015**	0.051***	0.023	-0.006	0.013*						
							[0.006]	[0.007]	[0.015]	[0.017]	[0.006]	[0.007]						
													-0.005	0.007	-0.031	0.05	0.01	-0.015
													[0.016]	[0.017]	[0.045]	[0.043]	[0.012]	[0.018]
N	4606	4606	1254	1254	3352	3352	4606	4606	1254	1254	3352	3352	4606	4606	1254	1254	3352	3352

Table 10 Specification with total unemployment spell

	Workers with tertiary education																	
	20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years	
	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U
RTI	-0.021	-0.022	-0.03	-0.096	-0.015	0.006	-0.017	-0.036	-0.017	-0.133	-0.017	0.001	-0.013	-0.036	0.012	-0.121	-0.012	-0.013
	[0.027]	[0.038]	[0.073]	[0.120]	[0.027]	[0.028]	[0.028]	[0.039]	[0.074]	[0.124]	[0.027]	[0.026]	[0.028]	[0.039]	[0.075]	[0.128]	[0.028]	[0.032]
U tot	0.001	0.002	0.004	0.004	0.001	0.001	0.001	0.002	0.004	0.004	0.001	0.001	0.001	0.002	0.004	0.004	0.001	0.001
	[0.001]	[0.001]	[0.003]	[0.006]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.006]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.006]	[0.001]	[0.001]
RMHM	0.013**	-0.004	0.037**	-0.015	0.009*	0.002	0.013**	-0.005	0.039**	-0.018	0.008*	0.002	0.014**	-0.005	0.043***	-0.017	0.009*	0.002
	[0.006]	[0.008]	[0.016]	[0.024]	[0.005]	[0.006]	[0.006]	[0.008]	[0.016]	[0.024]	[0.005]	[0.006]	[0.006]	[0.008]	[0.017]	[0.024]	[0.005]	[0.006]
SAOE	0.006	-0.013	0.003	-0.034	0.008	-0.004												
	[0.005]	[0.008]	[0.014]	[0.024]	[0.005]	[0.008]												
SASE							0.003	0.000	-0.011	-0.002	0.008	0.000						
							[0.006]	[0.009]	[0.015]	[0.024]	[0.005]	[0.007]						
RMOE													-0.001	0.000	-0.031*	-0.011	0.005	0.006
													[0.006]	[0.008]	[0.016]	[0.025]	[0.006]	[0.008]
N	3646	3646	1113	1113	2533	2533	3646	3646	1113	1113	2533	2533	3646	3646	1113	1113	2533	2533
	Workers with secondary education																	
	20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years	
	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U	E to U	E to E	E to U
RTI	-0.033	-0.03	-0.119*	-0.028	0.014	-0.052*	-0.038	-0.034	-0.130**	-0.044	0.015	-0.053*	-0.024	-0.024	-0.067	-0.056	0.006	-0.033
	[0.026]	[0.033]	[0.065]	[0.094]	[0.025]	[0.029]	[0.026]	[0.032]	[0.061]	[0.090]	[0.025]	[0.028]	[0.026]	[0.030]	[0.063]	[0.083]	[0.025]	[0.028]
U tot	0.001*	0.000	0.008***	-0.003	0.000	0.000	0.001*	0.000	0.008***	-0.003	0.000	0.001	0.001*	0.000	0.008***	-0.003	0.000	0.001
	[0.001]	[0.001]	[0.003]	[0.003]	[0.000]	[0.001]	[0.001]	[0.001]	[0.003]	[0.003]	[0.000]	[0.001]	[0.001]	[0.001]	[0.003]	[0.003]	[0.000]	[0.001]
RMHM	-0.009	-0.005	-0.039**	0.000	0.002	-0.009	-0.009	-0.006	-0.043**	-0.002	0.002	-0.009	-0.008	-0.005	-0.038**	0.001	0.002	-0.009
	[0.007]	[0.008]	[0.018]	[0.021]	[0.006]	[0.007]	[0.007]	[0.008]	[0.018]	[0.021]	[0.007]	[0.007]	[0.007]	[0.008]	[0.018]	[0.021]	[0.006]	[0.007]
SAOE	0.008	0.01	0.036**	-0.001	-0.008	0.015*												
	[0.007]	[0.008]	[0.017]	[0.019]	[0.007]	[0.008]												
SASE							0.011*	0.014*	0.050***	0.021	-0.006	0.013*						
							[0.006]	[0.007]	[0.014]	[0.018]	[0.006]	[0.007]						
RMOE													-0.005	0.007	-0.03	0.052	0.011	-0.018
													[0.016]	[0.017]	[0.045]	[0.044]	[0.013]	[0.020]
N	4493	4493	1243	1243	3250	3250	4493	4493	1243	1243	3250	3250	4493	4493	1243	1243	3250	3250

5.2 Horizontal mismatch and STEM competencies

In this section, we aim to extend the analyses by taking into account the role of STEM competencies. Specifically, we test whether workers whose field of study does not belong to the group of STEM degrees drive this result. This is done by estimating equation (1) separately for the two groups of STEM and non-STEM graduates. STEM degrees include the group of geology-biology, engineering, science, architecture, chemical-pharmaceutical and some degrees of the group of statistics and humanities. STEM graduates are 1309, accounting for 26% of the total sample of tertiary educated workers.

Marginal impacts from multinomial logit estimates are shown in Table 11. The results for non-STEM graduates (upper panel) confirm the significance of RMHM for the whole sample and for the groups of workers up to 35 years. In addition, non-STEM graduates show a lower probability to change job but only in the cohort 20-35 years. The impact of overeducation is not robust to the measure usesd: according to SAOE young overeducated workers have a lower probability to change job but this result is not confirmed by the other measures. Turning to STEM graduates (lower panel), horizontal mismatch is insignificant in explaining labour market transitions and, again, the impact of overeducation in not robust across measures but the results point to a higher probability to change job among workers between 20 and 35 years. These results confirm that unemployment risk due to mismatches in the field of study are driven by non-STEM graduates whereas holding a degree in one of the STEM fields does not lead to increased unemployment risk even in presence of a mismatch with the median categories within occupations. This highlights the importance of STEM competences in the labour market and suggests that policies aimed at increasing the share of individuals with such competencies would be effective in reducing the unemployment rate alongside positive effects of firms' productivity.

Table 11 Estimation results for STEM and non-STEM tertiary education

	Non-STEM degrees																	
	20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years	
	E to U	E to U	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E
RTI	0.007	-0.027	0.033	-0.031	0.023	-0.028	0.023	-0.037	0.052	-0.054	0.03	-0.03	0.014	-0.03	0.104	-0.06	0.014	-0.022
	[0.039]	[0.039]	[0.093]	[0.129]	[0.043]	[0.036]	[0.035]	[0.034]	[0.093]	[0.131]	[0.042]	[0.035]	[0.041]	[0.041]	[0.096]	[0.132]	[0.048]	[0.038]
RMHM	0.013*	-0.005	0.040**	-0.043*	0.002	0.004	0.013*	-0.006	0.041**	-0.042*	0.003	0.004	0.012*	-0.005	0.046**	-0.044*	0.001	0.004
	[0.007]	[0.007]	[0.018]	[0.024]	[0.007]	[0.005]	[0.007]	[0.008]	[0.018]	[0.025]	[0.007]	[0.005]	[0.007]	[0.007]	[0.018]	[0.024]	[0.007]	[0.005]
SAOE	0.006	-0.019**	0.016	-0.058**	0.004	-0.006												
	[0.007]	[0.009]	[0.019]	[0.027]	[0.007]	[0.007]												
SASE							-0.001	-0.008	0.002	-0.038	-0.002	-0.002						
							[0.008]	[0.009]	[0.022]	[0.029]	[0.008]	[0.007]						
RMOE													0.000	-0.015	-0.042*	-0.039	0.008	-0.007
													[0.009]	[0.009]	[0.024]	[0.028]	[0.009]	[0.008]
N	2876	2876	836	836	2040	2040	2876	2876	836	836	2040	2040	2876	2876	836	836	2040	2040
	STEM degrees																	
	20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years		20-65 years		20-35 years		36-65 years	
	E to U	E to U	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E	E to U	E to E
RTI	0.01	-0.032	-0.095	-0.054	0.025	-0.003	-0.007	-0.044	-0.108	-0.05	-0.003	-0.032	0.003	-0.095	-0.116	-0.179	0.008	-0.063
	[0.045]	[0.080]	[0.103]	[0.225]	[0.043]	[0.128]	[0.045]	[0.081]	[0.098]	[0.230]	[0.045]	[0.121]	[0.048]	[0.080]	[0.113]	[0.244]	[0.040]	[0.131]
RMHM	0.012	-0.001	0.039	0.052	0.004	-0.061	0.009	-0.003	0.036	0.044	-0.005	-0.015	0.011	-0.011	0.039	0.016	0.005	-0.019
	[0.012]	[0.017]	[0.025]	[0.042]	[0.015]	[0.028]	[0.012]	[0.016]	[0.026]	[0.038]	[0.016]	[0.031]	[0.012]	[0.016]	[0.029]	[0.034]	[0.018]	[0.026]
SAOE	-0.017	0.01	-0.046*	0.034	0.002	-0.028												
	[0.011]	[0.017]	[0.027]	[0.047]	[0.013]	[0.023]												
SASE							-0.002	0.023	-0.031	0.070**	0.009	0.015						
							[0.010]	[0.017]	[0.021]	[0.034]	[0.015]	[0.029]						
RMOE													-0.006	0.042***	-0.018	0.098**	-0.005	0.030*
													[0.009]	[0.015]	[0.022]	[0.038]	[0.013]	[0.018]
N	1002	1002	305	305	697	697	1002	1002	305	305	697	697	1002	1002	305	305	697	697

6. Conclusions

In this paper, we investigated the role of educational and skill mismatch in explaining labour market transitions, of secondary and tertiary educated workers. We focused on transitions from employment to unemployment and on job changes. By using information collected from merging the ICP and the PLUS survey for the years 2014-2018 we calculated four measures of educational mismatch. This allowed to compare the outcomes from self-reported and revealed match measures in order to assess the robustness of the results. In addition, we used a measure of horizontal mismatch and tested whether they are driven by non-STEM fields. Finally, 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, mismatches in the field of study are associated with a higher unemployment risk of tertiary educated workers, especially if graduated in non-STEM fields. Second, over education is associated with higher unemployment risk among young workers with secondary education only whereas older for older workers with the same educational level overeducation increases the likelihood of job changes. This is coherent with the negative effect of RBTC on medium skilled workers which leads to job polarization. At the same time, the behaviour of older workers is coherent with a matching process toward a better job. Third, our results confirm the finding of Rose and Ordine (2010) as workers experiencing longer periods of unemployment are more at risk of losing their job once employed. However, we do not find that this effect is stronger for mismatched workers. This means that deskilling and competitiveness losses associated with long unemployment periods affect unemployment risk of all workers, with no distinction between matched and mismatched workers. Finally, we do not find a clear impact of the RTI on transition probabilities.

Our results show that the main problem for tertiary educated workers is the mismatch in the field of studies. This adds evidence to the problem of skill gap in Italy, as educational choices are not aligned to market needs. The shortage of STEM graduates seem to be one of the main reasons behind this result. This finding has two consequences: on the one hand, large horizontal mismatches reduce the potential for productivity growth and cause a waste of human capital; on the other hand, these individuals are particularly vulnerable as they are less competitive on the labour market and potentially at risk of becoming long-term unemployed. In this respect, both demand side and supply side policies are needed, especially to increase the supply of STEM graduates and to allow firms to better use this human capital.

This study has demonstrated how complex and multidimensional the mismatch topic is and that a robust analysis that investigates all aspects of the mismatch is necessary to be able to adopt tailored policies (Cedefop, 2015). Thus, our results confirm that improvements measurement of skill mismatch and understanding its consequences are currently crucial research areas (Cedefop, 2009).

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