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Educational mismatches, technological change and unemployment: evidence from secondary and tertiary educated workers

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Abstract

In this article, we investigate the role of several types of educational mismatch in explaining labour market transitions of workers with secondary and higher education. We focus on transitions from employment to unemployment and on job changes, to assess whether mismatch is a temporary or a permanent phenomenon. In the first case, as suggested by matching models, mismatch will be eliminated through job-to-job transitions. In the second case, it might be permanent and caused by employment discontinuity and deskilling processes. By using information from the Italian Survey of Professions (ICP) and the Survey on Labour Participation and Unemployment (PLUS), we calculate three measures of vertical mismatch. This allows comparing the outcomes from self-reported and revealed match measures in order to assess the robustness of the results. In addition, we use a measure of horizontal mismatch and evaluated the effect of Routine Bias Technical change (RBTC) in terms of unemployment risk, through a Routine Task Index (RTI) calculated on Italian data. Results indicate that mismatched workers are at risk of long-term unemployment. More specifically, among workers with higher education, the risk is due to mismatches in the field of studies whereas for secondary educated workers, over-education is the main cause of unemployment risk. The effect of the RTI is often not significant. 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 to allow firms to better use this human capital.

Keywords: higher education, over-education, educational mismatch,, routine bias technical change, unemployment, Italy.

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 surprisingly significant (Marcolin et al. 2016). These dynamics suggest that problems of labour mismatch are likely to arise: what is missing in this line of literature is precisely the link between RBTC and mismatch and their combined effect on employment dynamics: just recently, only Zago (2018) theorized the relationship between RBCT and skill mismatch . In this article, we investigate the effect of several types of educational mismatch and RBTC on unemployment risk in Italy for secondary and tertiary educated workers. Three questions are relevant here: i) How do mismatch and technological change affect unemployment risk? ii) Is there any difference between secondary and tertiary educated workers? iii) Are the results robust across the different measures of mismatch?

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 and skill upgrading might result in sub-optimal outcomes in terms of productivity and unemployment when labour 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, 2007, 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).

From a microeconomic point of view, educational and labour 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 mismatches 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. Overall, these dynamics indicate that educational and skill mismatches are potential determinants 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. 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. The educational attainment is particularly low in Italy, as compared to the other European countries (Pastore, 2019). 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). 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, p.23). The problem of mismatch 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; Pastore 2019). OECD (2017) highlights that skill mismatch is so pervasive as to prevent Italy from leaving its "low-skills low-quality trap", hence negatively affecting the 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).

The aim of the paper is to provide micro-level evidence on the effect of educational mismatch and RBTC on unemployment risk for secondary and tertiary educated workers in Italy. More specifically, we investigate the determinants of labour market transitions to assess whether mismatched workers follow a standard matching process against the alternative of a low-employment low job-quality trap. In the first case, job mobility eliminates mismatches over time whereas in the second case mismatch becomes permanent and leads to higher structural unemployment. The analysis is carried out using a uniquely detailed professional dataset on tasks, skills and work attitudes, recently built merging two surveys. The first one is the Survey on Labour Participation and Unemployment (PLUS), a sample survey on the Italian labour market. We use the panel component for the years 2014-2016-2018. PLUS contains information on several characteristics of the labour force and allows building several empirical and self-reported measures of labour mismatch. The second dataset 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, Gualtieri et al. 2018). Notably, Italy is one of the few European countries to have a dictionary of occupations similar to the US O*NET. ICP allows us to build the well-known Routine Task Index (RTI), 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 the relative contribution of RBTC and educational mismatch on unemployment risk.

Extensive research has been carried out on the way to measure labour mismatch and the results of empirical analysis have been strongly influenced by the type of measure used, making it complicate to generalize the results (Munoz-De Bustillo and Llorente, 2018). In this paper, we use different measures of educational mismatch. On the one hand, we focus on the vertical and horizontal dimensions of educational mismatches, with the former referring to over-education and the latter referring to mismatches in the field of study. On the other hand, we use three alternative measures of over-education, whereby the standard revealed match measure is associated with two self-reported measures based on questions about the actual and legal educational requirements of worker's occupations. In this way, we provide a test of the robustness of our results across measures. 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 to the different policy implications. Tertiary educated workers can face problems of both horizontal and vertical mismatch due to the misalignment between educational choices and technological requirements. 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 induced by technological change.

The paper contributes to the existing literature from three points of view. First, we provide evidence on the relation between unemployment risk and educational mismatch in Italy for the most recent years (2014-2018), and by distinguishing secondary and higher education. To our knowledge, this is the first study investigating the issue. Second, we use different measures of educational mismatch and compare the robustness of the results across empirical (revealed match) 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 causes of labour 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 draws summary conclusions and policy implications.

2. Literature on the causes and consequences of labour mismatch

Substantial literature investigated the causes of labour mismatch at micro and macro level. Macroeconomic dynamics might affect labour 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. In the long-run, a mismatch can arise because of technology-driven structural changes in the economy, shifting labour demand toward new skills and different fields of study (Mendes de Oliveira et al. 2000, Peng et al. 2016). At the same time, changes in the labour supply can also be a cause of mismatch. In this respect, Figueiredo et al. (2017) as well as Cabus and Somers (2018) have shown that the recent increase in the average level of education may have had effects on the intensification of mismatch. From the point of view of skill supply, academic achievement and field of study are 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; Frenette, 2004). In these fields, the skill assessment by employer is more complicate as it cannot rely on specific definition of competencies. 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). Moreover, in terms of transferability of higher education, mismatches can also be generated by having obtained educational qualifications abroad (Wiers, Jenssen and Try, 2005).

As for the consequences of skill mismatch, substantial research have shown that overeducated workers incur in wage penalty compered to individuals with similar educational levels but well matched (Sanchez-Sanchez and McGuinness, 2015, Caroleo and Pastore, 2018, Gaeta et al. 2017, Scicchitano et al. 2018 among the most recent). Other studies investigated the relation between skill mismatch and job satisfaction (McGuinness and Sloane, 2011; McGuinness and Byrne, 2015; Mateos-Romero and Salinas-Jimenez 2018). Overqualification affects job mobility (Verhaest and Omey, 2006) both between and within jobs. In this respect, young workers have a higher tendency to be overeducated, but vertical mobility allows moving to jobs 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.

Focusing on the relation between mismatch and unemployment, several works have proved the existence of a causal link from mismatch to size and duration of unemployment (Skott and Auerbach, 2005; Berton et al. 2017). Reasons for over qualification to affect unemployment come from both 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 (McGuinness and Sloane, 2011; McGuinness and Byrne, 2015; Mateos-Romero and Salinas-Jimenez 2018), hence they are more likely to engage in on the job search (Allen and van der Velden, 2001) or 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 (Van Loo et al., (2001), with additional negative consequences on their skill endowment and on their employability (Ordine and Rose, 2015; Berton et al. 2017).

The unemployment risk due to technological change has been recently investigated within the literature on RBTC, whereby most vulnerable workers are those employed in routine intensive tasks (Autor and Dorn, 2013). It emerges that technological change, in determining a growing obsolescence of skills, tends to exacerbate the mismatch between skills and tasks (Zago, 2018). In this respect Frey and Obsorne (2017) estimate that 47% of existing jobs in the US are at risk of automation in the next 20 years.

In summary, these studies indicate that educational and skill mismatches are potential determinants of unemployment risk and thus negatively contributing to the overall economic performance of a country in terms of GDP (Ramos et al., 2012) and productivity (McGowan and Andrews, 2015).

In this paper, we focus on the relation between educational 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. The Italian case is relevant as the country is one of the worst affected from the Global and European crises in terms of GDP and employment (Izquierdo et al. 2017). By using a multinomial framework, we analyse the effect of education mismatch on job-to-job mobility to understand whether mismatched workers follow a standard matching process whereby unemployment risk is temporary. If this is not the case, mismatched workers are at risk of long-term unemployment and skill deterioration as in the framework of Ordine and Rose (2015). Our analysis is linked to the literature on technology driven unemployment risk (Autor and Dorn, 2013; Autor et al. 2003, Cassandro et al., 2019). In addition, we innovate with respect to the previous studies by disentangling the effect educational mismatches from that of technological unemployment by introducing a measure of Routine Biased Technical Change (RBTC) in the analysis.

3. Data and descriptive evidence

Data used in this article are from an innovative dataset recently built by merging two Italian surveys developed and administered by National Institute for the Analysis of Public Policies (INAPP): PLUS and ICP. The primary objective of the PLUS survey is to provide reliable statistical estimates of phenomena that are rare or marginally explored by other surveys on the Italian labour market while retaining most of the information provided by the Labour Force Survey. For our purposes, it is the appropriate survey because it allows examining 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 50,000 individuals.[1] 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 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). In line with the current literature (Autor et al., 2003, Autor and Dorn 2003, Goos et al., 2014), we measure the objective degree of task routineness according to the RTI index. Using the ICP questionnaire, we account for the same task-related dimensions used by Goos et al., 2014 and followers in their empirical studies. In our case, however, we can significally improve the quality of data in Goos et al. (2014). They use the RTI index built by Autor and Dorn (2013) and mapped into their European occupational classification: a key point of our data is that our task and skill variables directly refer to the Italian economy. In fact, the availability of ICP variables avoid potential methodological problems arising when information referring to the American occupational structure (i.e. contained in the US O*Net repertoire) are linked

[1] For a detailed description of the survey see Clementi and Giammatteo, 2014, Filippetti et al., 2019, Meliciani, and Radicchia, 2011, 2016), Van Wolleghem et al. (2019), Gallo and Scicchitano (2019).

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to labour market data referring to different economies as the European ones[2]. 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)

The literature[3] has provided several ways to measure educational and skill mismatch. According to Munoz-De Bustillo and Llorente (2018) measures can be divided into three groups: Job Assessment measures (JA); Revealed 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 using experts' or employers' information. JA measures have the advantage to assess precisely what is the required educational or skill level for a given occupation but they rely on information that is rarely available for a large number of countries and time periods. Recent studies used 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 use the median or mean educational attainment for each profession calculated on disaggregated ISCO categories. They have the advantage to be easily implemented, as data on educational attainments by profession are widely available. However, they suffer from several shortcomings, among which the inappropriateness of the median levels and the assumption of symmetry in the distribution. 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). 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, because individuals might misestimate the requirements of a job and their own skill (Sloane 2003, McGuinness 2006).

Using the information contained in the PLUS database we can build SA and RM measures of educational mismatch (see Table 1). First, we build a measure of horizontal mismatch (RMHM), i.e. mismatch in the field of study (Reis, 2018; Cabus et al., 2019) using a Revealed Match approach. 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 category 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.

[2] A detailed description of data used for building the RTI is in Appendix.

[3] See McGuinness et al. (2018) for a survey.

Second, we build three different measures of over-education: two SA measures and a RM measure. 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. While both measure might potentially suffer from self-reporting bias, the bias is more likely to exist for SAOE since the legal requirement to get a job should be precisely known by workers. The revealed match measure of over-education (RMOE) is based on the comparison between workers' educational attainment and the modal educational attainment of the related profession calculated at ISCO-2digits level.

(Table 1 here)

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 in all measures but RMOE. Unemployment risk for the former ranges between 7.5% and 9.5% against percentages between 5.3% and 9.3% for the latter. For secondary educated workers too unemployment risk of mismatched workers is higher in three out of four measures. At the same time, unemployment risk is higher for secondary educated workers with respect to tertiary educated ones. Looking at job-to-job transitions, tertiary educated workers have a higher probability to change job if horizontally mismatched whereas for secondary educated workers the evidence is unclear.

In Table 3 we report the transitions of workers between 36 and 65 years. In this cohort, both unemployment risk and job-to-job transition are lower than those of younger workers. There is a general evidence that, in this group too, unemployment risk is higher for mismatched workers independently of the educational attainment. Among tertiary educated workers, unemployment risk ranges between 2.9% and 6% for mismatched individuals against percentages ranging from 1.5% to 2.9% for well-matched workers. Among secondary educated workers, the gap is lower, with mismatched individuals showing unemployment risk between 5.1% and 7.2% against probabilities between 3.3% and 4.7% for well-matched ones. Turning to job-to-job transitions, 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 RMOE. For secondary educated workers the results are less clear-cut, with SASE and RMOE showing a higher probability to change job for mismatched workers and SAOE showing the opposite results.

(Table 2 and 3 here)

Finally, in Table 4 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 over-education indicate that mismatched workers perform tasks with a higher degree of routinarity. Differences are particularly marked for secondary educated workers, which show a gap between 8.5% and 12.9%. 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 here)

Summing up, educational mismatches are – on average - associated with higher unemployment probability, especially among individuals with secondary education only. At the same time, for mismatched workers transitions to unemployment are more likely than job-to-job transitions whereas the opposite is true for well-matched workers. This suggests that the matching process for mismatched workers does not improve over time and the risk of a low-employment low-quality job trap is substantial. Finally, we observe that overeducated workers tend to be employed in occupation with a high routine intensity.

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 effects are estimated as a function of 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 matching models and to previous studies (see Section 2), 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. However, if mismatch is associated with a deskilling process, then workers might experience higher unemployment risk but not a higher probability to change job.

The estimated equation is the following:

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

PT is the probability of transition of individual *i*; OE is the measure of over-education, 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 worker 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. The use of variables assessing job satisfaction and cognitive skills allows disentangling voluntary transitions from performance–related transitions.

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. Such division is important to take into account the criticisms of Leuven and Oosterbeek (2011) which point out that the analysis of educational mismatch is flawed because of the role of skills acquired during the working career. For workers up to 35 years this problem is minimized due to the reduced working experience.

Table 5 shows the results for tertiary educated workers using the Self-Assessed Sheepskin Effect (SASE) as measure of over-education. 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 effect is 0.012 on average but for workers up to 35 years the effect increases to 0.039, whereas it turns insignificant 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 effect of wages on job-to-job transitions and a positive effect of very low job satisfaction on both transitions for workers above 35 years. The other – indirect – indicator of job satisfaction, that is Job search, affects positively both transitions for 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 effet 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. 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 RTI is never significant. Table 6 shows that the other two measures of over-education are insignificant too in explaining employment transitions, while the effect of RMHM is confirmed.

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 unemployment risk in the cohort 20-35 years (+5%) whereas a higher job-to-job transition probability is found for workers above 35 years (+1.4%). The RTI reduces unemployment risk for workers up to 35 years. 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.

As for the other regressors (Table 7), the main difference with tertiary educated workers lies in the stronger negative and significant association between wages and unemployment risk. While this relationship might be biased due to reverse causality, it suggests that high-pay jobs are less likely to be destroyed. Other differences with respect to tertiary educated workers are the insignificance of total work experience and, in most case, of horizontal mismatch.

(Table 7 here)

The results shown in Table 8 provide a confirmation of the effect of overeducation on employment transitions. Both SAOE and RMOE confirm that young, overeducated workers with secondary education face higher unemployment risk, with marginal effects between 3.8% and 6.6%. As for the job-to-job transition of workers above 35 years, the higher probability is confirmed by SAOE only. 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, over-education increases unemployment risk of workers with secondary education only and this result holds independently of the measure used. Third, the results are robust to the inclusion of several determinants of labour market transitions and over-education. 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. While there is a weak evidence in favour of the RBTC hypothesis, 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 8 here)

5. Conclusions

In this article, we investigated the role of educational mismatch in explaining labour market transitions of workers with secondary and higher education. We focused on transitions from employment to unemployment and on job changes to assess whether mismatch is a temporary or a permanent phenomenon. In the first case, as suggested by matching models, mismatch will be eliminated though job-to-job transitions. In the second case, it might be permanent and caused by employment discontinuity and deskilling processes. By using information from the ICP and the PLUS surveys, we calculated four measures of educational mismatch. This allowed comparing 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 evaluated the effect of 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 workers with higher education. Second, overeducation is associated with higher unemployment risk among young workers with secondary education only, whereas for older workers with the same educational level overeducation increases the likelihood of job changes. These results indicate that mismatched workers face substantial risks to be locked in a situation characterized by employment discontinuity and low quality of the matches. At the same time, the behaviour of older workers is coherent with a matching process toward a better job. Finally, we do not find a clear effect of the RTI on transition probabilities. In other words, results seem to indicate that the technology driven unemployment risk – measured through RTI - seems to be less relevant than the labour mismatch one.

Our results show that the main problem for tertiary educated workers is the mismatch in the field of study. This adds evidence to the problem of skill gap in Italy, as educational choices are not aligned to market needs. 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 to allow firms to better use this human capital. In order to address these issues some reforms in the Italian higher education system have been recently introduced. Universities are now forced to consult external stakeholders before developing existing courses or implementing new study programmes. In addition, students' internship programs are now much more encouraged to promote a better school-to-work transition. Finally, a recent innovation in the higher education system was the introduction of a professional bachelor's programme or *Lauree Professionalizzanti* in Italian (OECD, 2017). These programmes are defined to produce professional technical skills at the tertiary education level in several disciplines, tailored on local needs.

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 for both secondary and tertiary educated workers (Cedefop, 2015). Thus, our results confirm that improvements measurement of skill mismatch and understanding its consequences are currently crucial research areas, particularly for higher education (Cedefop, 2009).

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Table 1 Definition of skill mismatch measures

Measure	Construction
Revealed match measure of over-education (RMOE)	Comparison between educational attainment and modal category for each profession (ISCO=-2digits): positive=overeducated; null of negative=matched
Self-assess measure of over-education (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

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	5.2	84.5	10.3	100	7.3	85.3	7.4	100
EMM	**9.5**	79.8	10.7	100	**12.5**	80.3	7.2	100
	Tertiary educated				Secondary educated			
SAOE	U	E	EO	Total	U	E	EO	Total
EM	5.2	84.5	10.3	100	**10.0**	82.8	7.2	100
EMM	**7.5**	81.9	10.6	100	6.0	85.4	8.6	100
	Tertiary educated				Secondary educated			
RMOE	U	E	EO	Total	U	E	EO	Total
EM	9.3	80.2	10.5	100	10.2	82.0	7.8	100
EMM	8.0	81.7	10.3	100	**11.7**	82.5	5.8	100
	Tertiary educated				Secondary educated			
RMHM	U	E	EO	Total	U	E	EO	Total
EM	7.7	80.9	11.4	100	8.6	83.8	7.6	100
EMM	**9.0**	81.1	9.8	100	**11.3**	81.0	7.7	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	2.0	96.0	2.0	100	3.3	95.0	1.8	100
EMM	**6.0**	91.9	2.1	100	**7.2**	89.0	**3.8**	100
	Tertiary educated				Secondary educated			
SAOE	U	E	EO	Total	U	E	EO	Total
EM	1.5	96.9	1.5	100	4.6	92.9	**2.6**	100
EMM	**4.7**	92.5	**2.8**	100	**7.0**	91.8	1.3	100
	Tertiary educated				Secondary educated			
RMOE	U	E	EO	Total	U	E	EO	Total
EM	2.3	96.1	1.5	100	4.7	93.0	2.3	100
EMM	**3.8**	94.0	**2.3**	100	**6.4**	90.2	**3.5**	100
	Tertiary educated				Secondary educated			
RMHM	U	E	EO	Total	U	E	EO	Total
EM	2.9	95.2	1.9	100	4.2	93.4	2.4	100
EMM	2.9	95.3	1.8	100	**5.1**	92.5	2.4	100

Source: own elaboration on PLUS. Weighted estimates

Table 4 Routine intensity by measure and type of mismatch

	Secondary education			
	SASE	RMOE	SAOE	RMHM
Matched	42.6	45.5	44.0	44.7
Mismatched	51.1	56.3	56.9	46.5
Total	45.8	45.8	45.8	45.8
	Tertiary education			
	SASE	RMOE	SAOE	RMHM
Matched	32.5	31.2	32.6	34.2
Mismatched	40.1	38.0	39.0	34.1
Total	34.1	34.1	34.1	34.1

Source: own elaboration on PLUS. Weighted estimates.

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	0.012*	-0.008	0.042**	-0.022	0	0.003
	[0.006]	[0.008]	[0.019]	[0.023]	[0.005]	[0.007]
SASE	0.001	-0.002	-0.009	-0.008	0.007	-0.001
	[0.006]	[0.009]	[0.015]	[0.024]	[0.005]	[0.008]
RTI	-0.014	-0.039	-0.02	-0.144	-0.023	-0.006
	[0.027]	[0.041]	[0.071]	[0.124]	[0.029]	[0.037]
Wage	-0.001	-0.015***	0	-0.028*	0.001	-0.005
	[0.004]	[0.005]	[0.012]	[0.016]	[0.004]	[0.005]
JS=med-high	0.005	0.001	0.011	0.017	0.008	-0.001
	[0.008]	[0.010]	[0.020]	[0.030]	[0.009]	[0.007]
JS=med-low	0	-0.005	-0.014	0.012	0.013	-0.006
	[0.009]	[0.012]	[0.026]	[0.035]	[0.010]	[0.011]
JS=very low	0.02	0.005	0.036	0.067	0.032**	-0.320***
	[0.013]	[0.022]	[0.031]	[0.064]	[0.014]	[0.054]
Grade	-0.001**	0.001	-0.002**	0.002	0	0
	[0.000]	[0.001]	[0.001]	[0.002]	[0.001]	[0.000]
English	-0.007	0.004	-0.013	0.009	-0.010*	-0.001
	[0.005]	[0.007]	[0.015]	[0.023]	[0.005]	[0.006]
Max grade	0.007	0.005	0.018	0.008	0.001	0.003
	[0.007]	[0.009]	[0.019]	[0.026]	[0.006]	[0.007]
Job search	0.016**	0.017*	0.031	0.049*	0.009	0.002
	[0.007]	[0.009]	[0.019]	[0.026]	[0.006]	[0.010]
CIG	0.037***	-0.022	-0.014	-0.017	0.039***	-0.307***
	[0.010]	[0.023]	[0.040]	[0.059]	[0.007]	[0.052]
Transf	-0.004	0	-0.018	-0.025	-0.003	0.008
	[0.009]	[0.010]	[0.022]	[0.031]	[0.009]	[0.007]
Female	0.021***	-0.011	0.052***	-0.041*	0.008	0.012
	[0.007]	[0.008]	[0.017]	[0.023]	[0.008]	[0.011]
Female*married	-0.001	-0.003	-0.023	-0.061	0.007	-0.014
	[0.011]	[0.015]	[0.060]	[0.067]	[0.011]	[0.012]
N	3806	3806	1130	1130	2676	2676

Source: own elaborations on PLUS and ICP. Weighted estimates. Marginal effects. Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01. Sectors, professions, contract, tenure, experience 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	
	E to U	E to E	E to U	E to E	E to U	E to E
RMHM	0.011*	-0.007	0.040**	-0.02	-0.001	0.003
	[0.006]	[0.008]	[0.019]	[0.023]	[0.005]	[0.007]
SAOE	0.004	-0.01	0.003	-0.028	0.008	-0.004
	[0.005]	[0.008]	[0.014]	[0.023]	[0.005]	[0.008]
N	3806	3806	1130	1130	2676	2676
	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	0.012*	-0.008	0.043**	-0.023	0	0.003
	[0.006]	[0.008]	[0.018]	[0.023]	[0.005]	[0.007]
RMOE	-0.002	0.004	-0.025	0	0.003	0.003
	[0.006]	[0.008]	[0.016]	[0.024]	[0.005]	[0.008]
N	3806	3806	1130	1130	2676	2676

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

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 U	E to E	E to U	E to E	E to U
RMHM	-0.009	-0.011	-0.027	-0.019	-0.004	-0.01
	[0.007]	[0.009]	[0.019]	[0.024]	[0.007]	[0.008]
SASE	0.01	0.015**	0.051***	0.023	-0.007	0.014**
	[0.006]	[0.007]	[0.015]	[0.018]	[0.006]	[0.007]
RTI	-0.035	-0.036	-0.133**	-0.045	0.013	-0.051*
	[0.026]	[0.032]	[0.060]	[0.089]	[0.025]	[0.029]
Wage	-0.029***	-0.005	-0.053***	-0.003	-0.015**	-0.011
	[0.005]	[0.007]	[0.013]	[0.015]	[0.006]	[0.008]
JS=med-high	-0.005	0.007	-0.01	0.026	0	-0.004
	[0.007]	[0.009]	[0.018]	[0.023]	[0.008]	[0.008]
JS=med-low	0.006	0.019*	-0.025	0.045*	0.017**	0.003
	[0.009]	[0.011]	[0.024]	[0.026]	[0.009]	[0.010]
JS=very low	0.021*	0.015	-0.016	0.044	0.030***	-0.002
	[0.011]	[0.014]	[0.032]	[0.043]	[0.010]	[0.013]
Grade	0.001*	0	0	0.001	0.001**	0
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]
English	0.001	-0.006	0.02	0.006	-0.006	-0.015*
	[0.006]	[0.007]	[0.014]	[0.016]	[0.006]	[0.007]
Max grade	0	-0.011	0.019	-0.008	-0.011	-0.011
	[0.012]	[0.020]	[0.029]	[0.043]	[0.012]	[0.019]
Job search	0.009	0.020**	0.01	0.034*	0.011	0.012
	[0.008]	[0.008]	[0.019]	[0.019]	[0.008]	[0.009]
CIG	0.019**	0.009	-0.016	-0.009	0.016**	0.013*
	[0.009]	[0.010]	[0.031]	[0.033]	[0.007]	[0.008]
Transf	0.011	-0.023	0.027	-0.044	0.005	-0.008
	[0.013]	[0.017]	[0.032]	[0.051]	[0.012]	[0.013]
Female	0.025***	-0.030***	0.062***	-0.053***	0.001	-0.027**
	[0.008]	[0.009]	[0.017]	[0.018]	[0.009]	[0.012]
Female*married	-0.006	-0.001	0.006	0.038	0.011	0.008
	[0.011]	[0.013]	[0.041]	[0.057]	[0.011]	[0.014]
N	4606	4606	1254	1254	3352	3352

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

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 E	E to U	E to E
RMHM	-0.009	-0.011	-0.026	-0.018	-0.004	-0.01
	[0.007]	[0.009]	[0.019]	[0.023]	[0.007]	[0.008]
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 E	E to U	E to E
RMHM	-0.008	-0.01	-0.02	-0.019	-0.004	-0.009
	[0.007]	[0.009]	[0.020]	[0.023]	[0.007]	[0.008]
RMOE	0.021*	0.003	0.066**	-0.005	0.005	0.005
	[0.011]	[0.013]	[0.027]	[0.034]	[0.010]	[0.010]
N	4606	4606	1254	1254	3352	3352

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

Appendix: building the Routine Task Index for Italy

On the other side, to measure objective level of routinarity, we exploit detailed information on the task-content of jobs at the 4-digit occupation-level, using data drawn from the INAPP-ISTAT Survey of Professions (ICP). The ICP is a rather unique source of information on skill, task and work contents. In fact, the ICP is the only European survey replicating extensively American O*Net . The latter is the most comprehensive repertoire reporting qualitative and quantitative information on tasks, work context, organizational features of work places at a very detailed level. Both the American O*Net and the Italian ICP focus on occupations (i.e. occupation-level variables are built relying on both survey-based worker-level information as well as on post-survey validation by experts' focus groups). The ICP survey has been realized twice (2007 and 2012) being based the whole spectrum of the Italian 5-digit occupations (i.e. 811 occupational codes). The interviews cover to 16.000 Italian workers ensuring representativeness with respect to sector, occupation, firm size and geographical domain (macro-regions). On average, 20 workers per each Italian occupation are interviewed providing representative information at the 5th digit. The survey includes more than 400 variables on skill, work contents, attitudes and tasks.

In line with the current literature (Autor et al., 2003, Autor and Dorn 2003, Goos et al., 2014), we measure the objective degree of task routineness according to the Routine Task Intensity (RTI) index. Using the ICP questionnaire, we account for the same task-related dimensions used by Goos et al., 2014 and followers in their empirical studies. In our case, however, we can significally improve the quality of data in Goos et al. (2014). They use the RTI index built by Autor and Dorn (2013) and mapped into their European occupational classification: a key point of our data is that our task and skill variables directly refer to the Italian economy. In fact, the availability of ICP variables avoid potential methodological problems arising when information referring to the American occupational structure (i.e. contained in the US O*Net repertoire) are linked to labour market data referring to different economies as the European ones.

As in Autor et al. (2003), we build upon five dimensions allowing to qualify jobs according to their relative degree of routineness. The RTI covers three dimensions (two related to the degree of manual and cognitive task routineness, the other to the degree of 'non-routineness' of tasks) resulting from the combination of the five DOT dimensions used by Autor et al. (2003). The detailed description of the RTI we use in our estimates is reported in table 1. Thus, the RTI adopted here is significantly close to the one in Autor and Dorn (2013) and Goos et al. (2014) and can be formalized as follows:

$$RTIk = RCk + RMk - (NRCAk + NRCIk + NRMk + NRMIAk) \quad (1)$$

Where for each 5-digit occupation k (k = 1,…,811) the RTI index is computed as the sum of the standardized values of the Routine Cognitive (RC) indicator capturing dimensions as the degree of repetitiveness and standardization of tasks as well as the importance of being exact and accurate; Routine Manual (RM) indicator proxying the degree of repetitiveness and of predetermination of manual operations minus the Non Routine Cognitive Analytical (NRCA) reporting the relevance of tasks related to think creatively as well as to analyse and interpret data and information; Nonroutine Cognitive Interpersonal (NRCI) referring to the importance of social relationships, interaction, managing and coaching colleagues; Non Routine Manual (NRM) capturing the degree of manual dexterity needed to perform operations; Non Routine Manual Interpersonal Adaptability (NRMIA) referring to degree of social perceptiveness. The indicator in (1) rises with the importance of routine task in each 4-digit occupation, while declines with the importance of abstract and non-routine tasks. Based on this information, we define a worker as being employed in an objectively routine job if he works in a job with an RTI index above the sample average. The RTI is calculated for the year 2012, assuming rank-stability of tasks for the short-time span (Akçomak et al. 2016).

Table 1: The structure of the Routine Task Index

Routine cognitive (RC)	
	Importance of repeating the same tasks
	Importance of being exact or accurate
	Structured v. Unstructured work (reverse)
Routine manual (RM)	
	Pace determined by speed of equipment
	Controlling machines and processes
	Spend time making repetitive motions
Non-routine cognitive: Analytical (NRCA)	
	Analyzing data/information
	Thinking creatively
	Interpreting information for others
Non-routine cognitive: Interpersonal (NRCI)	
	Establishing and maintaining personal relationships
	Guiding, directing and motivating subordinates
	Coaching/developing others
Non-routine manual (NRM)	
	Operating vehicles, mechanized devices, or equipment
	Spend time using hands to handle, control or feel objects, tools or controls
	Manual dexterity
	Spatial orientation
Non-routine manual: interpersonal adaptability (NRMIA)	
	Social Perceptiveness