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Educational mismatches, routine biased technological change and unemployment: evidence from Italy

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ABSTRACT

Educational mismatches, routine biased technological change and unemployment: evidence from Italy

This paper investigates the relation between educational mismatches and individual unemployment risk in Italy with a special focus on the role of technological change and labour demand characteristics. A novel dataset obtained merging two surveys (ICP and PLUS) is used to build different measures of educational mismatch and a measure of routine intensity on Italy: the Routine Task Index. The latter takes into account the effect of Routine Biased Technical Change (RBTC) in determining educational mismatches and unemployment risk. The results indicate that over-education is significantly associated with higher unemployment risk. This effect is explained by RBTC in the case of tertiary educated workers whereas for secondary educated workers the result holds after controlling for the main features of labour demand and supply. In addition, we find a significant association between unemployment risk and mismatches in the field of study for tertiary educated workers. Policy implications stressing the complementary role of demand and supply policies are derived.

KEYWORDS: economic structure, over-education, educational mismatch, routine bias technical change, unemployment, Italy

JEL CODES: D91, J24, J64, J82

1. Introduction

One of the main features characterizing labour markets in the last years has been the increasing share of educational and skill mismatches in the labour force. Recent studies based on the PIAAC survey indicate that skill mismatches range between 20% and 35% in OECD countries and, among the different dimensions of mismatch, over-education and overskill are the most pervasive (McGowan and Andrews 2017). Labour mismatches (i.e. educational or skill mismatch) bring about negative consequences on individuals and on the economy as they reduce productivity growth and innovation activities (Adalet McGowan and Andrews 2015). 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). Negative effects on productivity are also 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).

The link between educational mismatches and unemployment has been hardly investigated in the literature as mismatches and unemployment risk are considered to be the joint result of other underlying causes such us technological change (Zago 2020) or educational choices (Cabus and Somers 2018). A possible channel through which educational mismatches might increase (involuntary) individual unemployment risk is skill deterioration. Several studies evidenced the deskilling risk of mismatched workers as a consequence of employment discontinuity (Krolikowski 2017; Ordine and Rose 2015), cognitive decline (De Grip *et al.* 2008) and low participation in training activities (Verhaest and Omey 2006). An important implication of these studies is that mismatched workers are less competitive on the labour market due to the loss of skills acquired though education. In spite of that, the economic literature on the effect of educational mismatches on unemployment risk is scant.

The aim of the paper is to fill this gap by providing evidence on the relation between educational mismatches and unemployment risk in Italy. We derive an empirical specification which takes into account the main sources of heterogeneity affecting both educational mismatches and unemployment risk, with special focuses on the role of technological change and on labour demand characteristics. The literature on technological change recently explained educational mismatches and unemployment risk through the Routine Biased Technical Change (RBTC) assumption (Autor *et al.* 2003, 2006; Autor and Dorn 2013; Goos and Manning 2007), whereby job destruction due to technological change is concentrated in routine occupations and leads to job polarization. In this framework, Zago (2020) showed that the interaction between technology and cycle leads to permanent over-education and higher unemployment risk for medium skilled routine workers, while high skilled workers should experience only temporary effects in terms of mismatch and unemployment risk.

A second literature considers the structural features of the economy as determinants of labour demand. Educational mismatches, either vertical (over/under education) or horizontal (field of study), can be the result of a specialization in low-tech industries (Franzini and Raitano 2012) and of a labour demand concentrated in low-skill and routine intensive occupations (Basso 2019; Marcolin *et al.* 2018). Such structure would hamper the absorption of the increasing supply of high skilled workers documented in the last decades (Cabus and Somers 2018). Accordingly, educational mismatches might arise especially among high educated workers. In this case too, higher unemployment risk for mismatched workers arises as a result of skill deterioration.

A clear understanding of the interplay between labour demand and labour supply is of utmost importance to derive the proper policy actions. To focus exclusively on the supply of skills limits policy implications to the role of educational choices, the lock-in, and the innate ability as in Ordine and Rose (2015). However, if unemployment risk of mismatched workers is due to a low tech/low skill specialization then policies should be aimed at favouring a structural change, both between and within industries. In this respect, industrial policies should play the main role. Alternatively, if unemployment risk of mismatched workers is due to technical change then their relocation should be favoured by using active labour market policies and by incentivising training as well as lifelong learning.

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 human capital and technological advancement. According to Cedefop data, Italy ranks last in the 2020 release for the European Skills Index as a whole (composite indicator which measures the performance of European skills systems), by reporting a very low performance in each of three components, such as skills development, skills matching and skills activation. It also ranks 29th out of 30 in 'long-term unemployment'[1]. OECD (2017b) reports that skill mismatch in Italy is highly pervasive as to prevent Italy from leaving its 'low-skills low-quality trap', hence negatively affecting the capacity to develop a high sustainable growth (Scicchitano 2007). Adalet McGowan and Andrews (2015) estimated that labour productivity could increase by 10% if the country were to reduce its level of mismatch.

In Italy, the problem of mismatch might be related to both supply and demand factors as the low level of qualifications of the labour force (Pastore 2019) couples with a relatively poor return on human capital (Biagetti and Scicchitano 2011) and a sectoral specialization in low tech and low skill intensive sectors (Evangelista and Savona 2003; Franzini and Raitano 2012; Basso 2019). Compared to OECD countries, in Italy job polarization took place mostly by reducing medium skill employment (OECD 2017a). The Italian economy experienced only marginal changes the average routine intensity (Cassandro *et al*. 2020). At the same time, it has the higher share of college graduates involved in routine tasks (Marcolin *et al.* 2018). These evidences suggest that, compared to the other advanced economies, a positive relation between educational mismatch and unemployment risk should be more likely among high skilled workers.

The analysis of the mismatch-unemployment nexus in Italy 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 empirical and self-reported measures of horizontal and vertical educational mismatch. This allows testing the robustness of the different measures, an important element due to the documented high sensitivity of the results to the measure used (Muñoz-de Bustillo *et al.* 2018). The second dataset is the Italian Survey of Professions (ICP), which provides detailed information of the task-content of occupations at the 4-

[1] See: https://www.cedefop.europa.eu/.

digit occupation level. ICP is the Italian equivalent of the US Model based on the O*NET repertoire (Author and Dorn 2013). 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) (Autor and Dorn 2013), which is the most relevant and robust indicator to evaluate the effects of RBTC on the labour market. It should be noted that the ICP database is based on Italian occupations, not on those of the US: therefore it is able to grasp the specific features of the Italian productive structure, which the O*NET is not able to capture, thus avoiding potential biases. The existing literature (Goos *et al.* 2014) use instead US O*Net data and crosswalks between US and European occupations, which possibly reflect US-specific technology adoption and labour market structure.

The empirical strategy is based on the estimation of a multinomial logit model where employment transitions from employment to unemployment are estimated jointly with job-to-job transitions for secondary and tertiary educated workers respectively. Transition probabilities are estimated as a function of educational mismatches, the RTI and a number of variables including the most important features of labour demand and supply. In addition, the richness of information included in PLUS allows to control for individual and firm characteristics affecting unemployment risk both directly and indirectly through educational mismatches.

The paper contributes to the existing literature from three points of view. First, we provide evidence on the relation between unemployment risk and educational mismatches 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 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.

The remaining of the paper is structured as follows. In Section 2, we review the main literature on job polarization, skill supply and structural weaknesses of the Italian economy to derive implications for the mismatch-unemployment relation. In Section 3, we provide descriptive evidence on unemployment dynamics and on the characteristics of mismatched workers. Section 4 describes the econometric strategy while the results are discussed in Section 5. Section 6 draws summary conclusions and policy implications.

2. Educational mismatch, technology and unemployment: a survey

Among the consequences of educational mismatches, unemployment risk received little attention. Research focused mostly on wage penalties due to over-education (Caroleo and Pastore 2018; Scicchitano *et al.* 2020 among the most recent) while other studies investigated the effects on job mobility (Verhaest and Omey 2006; Frei and Sousa-Poza 2012; Verhaest *et al.* 2015) and job satisfaction (McGuinness and Sloane 2011). In terms of the mismatch-unemployment nexus, these evidences suggest that mismatched workers (either vertically or horizontally) are more likely to experience temporary and voluntary unemployment due to their higher mobility and lower satisfaction.

A possible channel by which educational mismatches might increase unemployment risk is skill deterioration. Early studies provide evidence of skill deterioration among overeducated workers through cognitive decline (De Grip *et al.* 2008) and low participation in training activities (Verhaest and Omey 2006). More recently, Ordine and Rose (2015) argued that over-education is an occurrence after of long periods of unemployment due to the deterioration of skills acquired through education. They also argued that mismatch is partly due to path-dependence: workers entering the labour market as mismatched are likely to remain mismatched also in future jobs. Krolikowski (2017) found similar results on the role of employment discontinuity when analysing the cyclical reallocation of workers on the job ladder. In his model, workers becoming unemployed during recessions tend to move toward jobs with lower skill intensities. The main explanation to this pattern is, again, skill deterioration due to unemployment. In this framework, the emergence of skill mismatches is not taken into account as lower skills are associated with low-skill intensive occupations, making the match efficient. However, this process will cause over-education in a way similar to Ordine and Rose (2015). Other studies point to the role of unobserved characteristics related to personality traits (Blázquez and Budria 2012; Engelhardt 2017). These evidences suggest that skill deterioration is a way through which educational mismatches can increase unemployment risk as it makes workers less competitive on the labour markets, due to their lower productivity compared to well-matched peers. In spite of these arguments, the nexus between mismatch and involuntary unemployment has been hardly investigated.

The aim of this paper is to fill this gap by providing empirical evidence on the relation between educational mismatches and unemployment. To this aim, we review the main sources of heterogeneity in the mismatch-unemployment nexus and identify the possible factors affecting both unemployment risk and educational mismatches. In particular, we focus on labour demand in terms of structure and evolution over time. Matching models like Ordine and Rose (2015) do not provide information on the determinants of labour demand structure with respect to occupations and skills, neither assume heterogeneity in human capital losses among different types of workers. Hence, policy implications mostly focus on educational choices and on the role of innate ability, while structural weaknesses in labour demand are not taken into account. To understand the role of labour demand is important not only to build the proper empirical specification, but also to derive effective policy implications.

Information in this direction can be obtained by looking at the literature on technological change and economic structure. Technological change is an important source of mismatches and unemployment risk. The Skill Biased Technical Change (SBTC) framework (Acemoglu 2002; Autor *et al.* 2003) suggests that mismatches and unemployment risk are more likely for low skilled workers. Due to its low ability to explain job polarization, i.e. the polarization of employment around occupations requiring, respectively, low and high levels of education, this theory has been replaced by the Routine Biased Technical Change (RBTC) assumption. In this framework, new technologies enable computers to perform repetitive, – so-called 'routine' – job tasks that were previously performed by human workers with medium educational levels (see Autor *et al.* 2006; Autor and Dorn 2013; Goos and Manning 2007; Marcolin *et al.* 2018). This fall in routine employment has been associated with an increase in both manual and abstract jobs, leading to job polarization.

The RBTC hypothesis provides a relation between degree of routine intensity and unemployment risk. At the same time, it explains the existence of temporary mismatches due to the disappearance of routine jobs and the creation of new occupations. A step forward is taken by Zago (2020), who investigates the skill mismatch phenomena in the context of RBTC and skill reallocation during the economic cycle. Using a model of job polarization based on a search and matching framework with cross-skill mismatch, the author provides important insights on the educational mismatch-unemployment nexus. More specifically, he argues that high educated workers tend to be mismatched during economic downturns as they move from abstract to routine cognitive jobs, but they climb up the skill ladder – thus eliminating the mismatch – during economic recoveries. Therefore, tertiary educated workers should face only temporary over-education and their unemployment risk due to skill deterioration may not differ significantly from that of well-matched peers. On the contrary, for workers with medium-low educational attainments the permanent destruction of routine occupations caused by RBTC leads to permanent over-education or unemployment.

The literature on RBTC is not able to fully explain the fact that job polarization took place at different intensities across sectors and occupational categories, with no clear relation with the reduction in routine employment. Some studies point to the role of sectoral innovation dynamics and their interaction with output demand (Croci-Angelini *et al.* 2009; Lucchese and Pianta 2012; Bogliacino *et al.* 2013; Díaz *et al.* 2020). Other studies find evidence that polarization across occupational categories does not follow the pattern predicted by RBTC but a more general pattern of increase of both high and low skilled employment, independently of the routine intensity (Cirillo *et al.* 2017). This result is, again, associated with sectoral heterogeneity in innovation dynamics, both between and within sectors.

In addition to technological change, structural factors might play a role as they contribute to both unemployment risk and educational mismatches. In a country like Italy, specialized in low-tech sectors, where the pace of technological progress is rather slow and the economy is still characterized by a high share of low-skill and manual jobs, educational mismatches are likely to arise, especially among high-educated workers. Many works documented the structural problems of the Italian economy and the relation with labour demand (Pizzuti 2006). Basso (2019) shows that labour demand in Italy is concentrated in low-skill and routine intensive jobs. Cassandro *et al.* (2020) find that unemployment risk due to RBTC is low in Italy and that the average routine intensity remained high and stable throughout the last decade. As for over-education, Marcolin *et al.* (2018) show that a high share of tertiary graduates in Italy is employed in routine occupations. Similar results are found by Franzini and Raitano (2012) which argue that over-education is mostly the result of the sectoral specialization of the Italian economy.

Another element to take into account to understand structural causes of unemployment and mismatch is the interaction between skill demand and skill supply. Skill mismatch can explain part of the increase in unemployment in the OECD countries, particularly in the UK (Manacorda and Petrongolo 1999). Kupets (2016), Figueiredo *et al.* (2017), Cabus and Somers (2018) have shown that the recent increase in the average level of education may have had effects on the intensification of (vertical) mismatch as firms are not able to absorb the new supply of skills. Somers *at al.* (2018) also showed that this process is likely to cause horizontal mismatches. Ortiz and Kucel (2008) document the concentration of graduates in fields characterized by both vertical and horizontal mismatches such as Social Sciences and Humanities. 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) with the result of increasing over-education.

These contributions point to the role of educational choices in determining educational mismatches (and indirectly unemployment risk) but do not address the role of labour demand. In a country were labour demand is concentrated in low skill and routine intensive employment, the ability to absorb the new supply of skills is reduced. Therefore, mismatches and the implied unemployment risk across the different fields of education are likely to be also due to insufficient demand. In this respect, Franzini and Raitano (2019) recently showed that employment dynamics and skill premium are not affected by the field of studies, and point to the role of innovation as their main driver. Extending the argument to educational mismatches, their occurrence and relation with unemployment should not be dependent on the field of studies.

All in all, these evidences imply different assumptions about the mismatch-unemployment nexus. The technological explanation suggests that educational mismatches and unemployment risk are more likely among workers with secondary education. The structural characteristics of the Italian economy suggest that over-education and unemployment risk are more likely among workers with tertiary education.

In this paper, we build on these strands of literature to derive testable assumptions on the relation between educational mismatches and unemployment in Italy as well as on the interplay with technological change and economic structure. We use information collected by merging two surveys carried out by the National Institute for Public Policies Analyses (Inapp) – PLUS and ICP – to derive measures of RBTC, proxies for the structure of labour demand and controls for the main sources of heterogeneity in the mismatch-unemployment nexus. To our knowledge, this is the first study on this subject.

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 Public Policies Analysis (Inapp). The first survey is the Participation, Labour and Unemployment Survey (PLUS), created with the purpose to provide reliable statistical estimates of labour market phenomena that are rare or marginally explored by the Labour Force Survey. It also provides a wide range of standard individual characteristics for approximately 50,000 individuals in each wave. The sample is representative over employment statuses, regions (NUTS2), sectors, age cohorts and educational attainments. A useful characteristic of this survey is the absence of proxy interviews: only survey respondents are included in the dataset to reduce measurement errors and partial non-responses. PLUS also provides individual weights to account for non-response and attrition issues generally affecting sample surveys: all descriptive analysis and estimates reported in this article are weighted using those individual weights[2].

Using information on perceived job-specific educational requirements included in PLUS since 2014, we can build Self-Assessed (SA) and Revealed Match (RM) measures of educational mismatch (see table 1)[3]. Self-Assessed measures are derived by asking directly to workers about the education-occupation match, while RM measures compare educational attainments with modal categories

[2] Among the other topic investigated in PLUS there are risk aversion, job insecurity and personality traits. For a detailed description of the survey see Meliciani, and Radicchia (2016), Gallo and Scicchitano (2019), Van Wolleghem *et al.* (2019).

[3] See Muñoz-de Bustillo *et al.* (2018) for a survey of the different measures of educational mismatch and their properties.

within professions. We build a measure of horizontal mismatch (RMHM), i.e. mismatch in the field of study (Reis 2018) 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 belongs to the first two modal categories of their profession, whereas they are classified as mismatched on the other case. Fields of study are defined by using the classification produced by the Istat and grouped into 13 different categories (see table A1 in the appendix 1). 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 legally required to get the job. Workers answering negatively to this question are considered overeducated. While both measure might potentially suffer from a self-reporting bias (i.e. a tendency to overestimate own positive characteristics), 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 in the related occupation calculated at ISCO-2digits level.
To analyse labour market transitions, we focus on the panel quota for the years 2014-2016 and 2016-2018, which include 24,571 and 13,968 individuals respectively. We use a sub-sample of employees with at least secondary education and age ranging between 20 and 65 years. This leaves us with a final sample ranging between 9,592 and 8,412 observations depending on the availability of controls.

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

The second survey used in the paper is the Inapp-Istat Survey of Professions (ICP), which allows building indicators measuring the objective level of routinization of labour tasks for occupations defined at the fifth digit of the ISCO classification. ICP is a rather unique source of information on skill, task and work contents. In fact, it 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). Interviews cover 16.000 Italian workers and ensure the representativeness with respect to sector, occupation, firm size and geographical domain (macro-regions). The survey includes more than 400 variables on skills, work contents, attitudes and tasks[4].

With the information included in ICP we are able to construct a Routine Task Index (RTI) (Autor *et al.* 2003; Autor and Dorn 2013; Goos *et al.* 2014) which measures the objective degree of task routineness. 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 significantly 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[5].

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 formula of the RTI in occupation *i* – with *i* being the ISCO 5-digit code – is the following:

$$RTI_i = RM_i + RC_i - NRM_i - NRMIA_i - NRCI_i - NRCA_i \; (i \in ISCO2011 - 5digits) \qquad (1)$$

where RC stands for Routine cognitive; RM for Routine manual; NRCI for Non routine cognitive interpersonal; NRCA for Non routine cognitive analytical; NRM for Non routine manual; and NRMIA for Non routine manual interpersonal adaptability. Each component is the aggregation of different tasks (see appendix 2 for details) whose importance is expressed by a score ranging between 0 and 100. The index is standardized over the interval 0-1 and aggregated at the ISCO 4-digits level to merge it with PLUS.

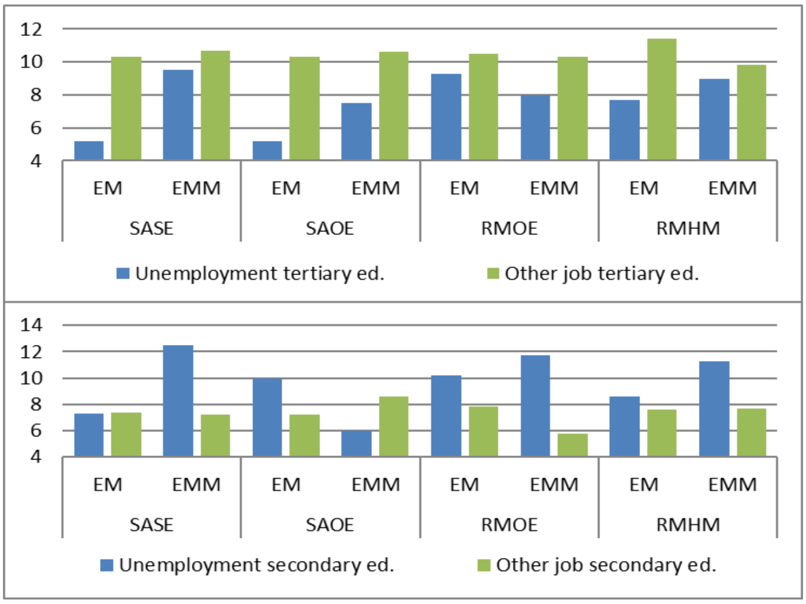
We begin the descriptive analysis by showing the bivariate association between labour market transitions and educational mismatches for secondary and tertiary educated workers, and for the two age cohorts 20-35 years (figure 1) and 36-65 years (figure 2). Starting with the cohort 20-35 years (figure 1), mismatched workers (EMM) with tertiary education show a higher unemployment risk with respect to well-matched ones (EM) 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. Secondary educated workers show similar results as unemployment risk of mismatched workers with respect to well-matched peers 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.

Turning to workers belonging to the cohort 36-65 years (figure 2), we find confirmation that unemployment risk is higher for mismatched workers independently of the educational attainment.

[4] A deeper analysis of the survey is in Cirillo *et al.* (2019) and Barbieri *et al.* (2020).

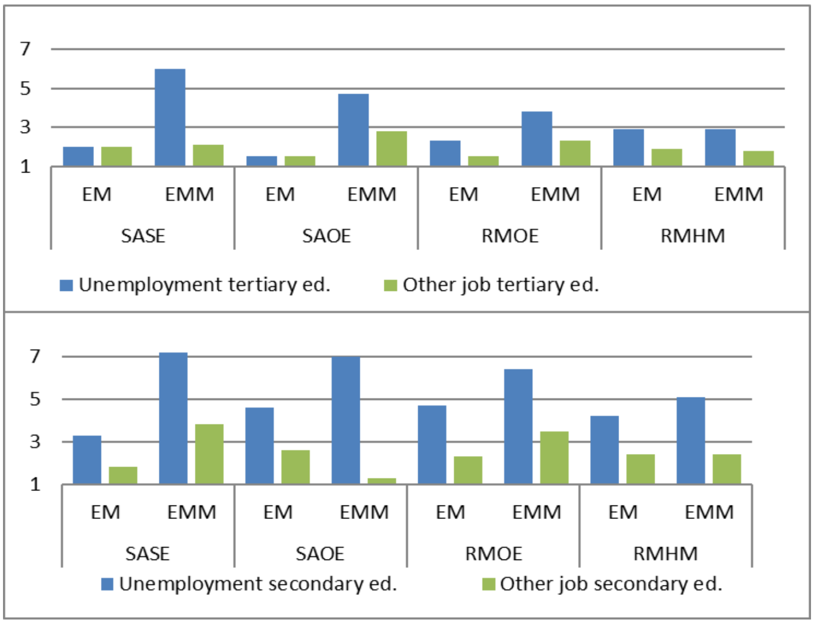
[5] The RTI derived from ICP data has been used to analyse unemployment risk (Cassandro *et al.* 2020) and the digitalization process (Cirillo *et al.* 2019).

Figure 1. Labour market transitions by mismatch measure: individuals between 20 and 35 years



Source: own elaboration on PLUS, 2014-2018. Weighted estimates

Figure 2. Labour market transitions by mismatch measure: individuals between 36 and 65 years



Source: own elaboration on PLUS, 2014-2018. Weighted estimates

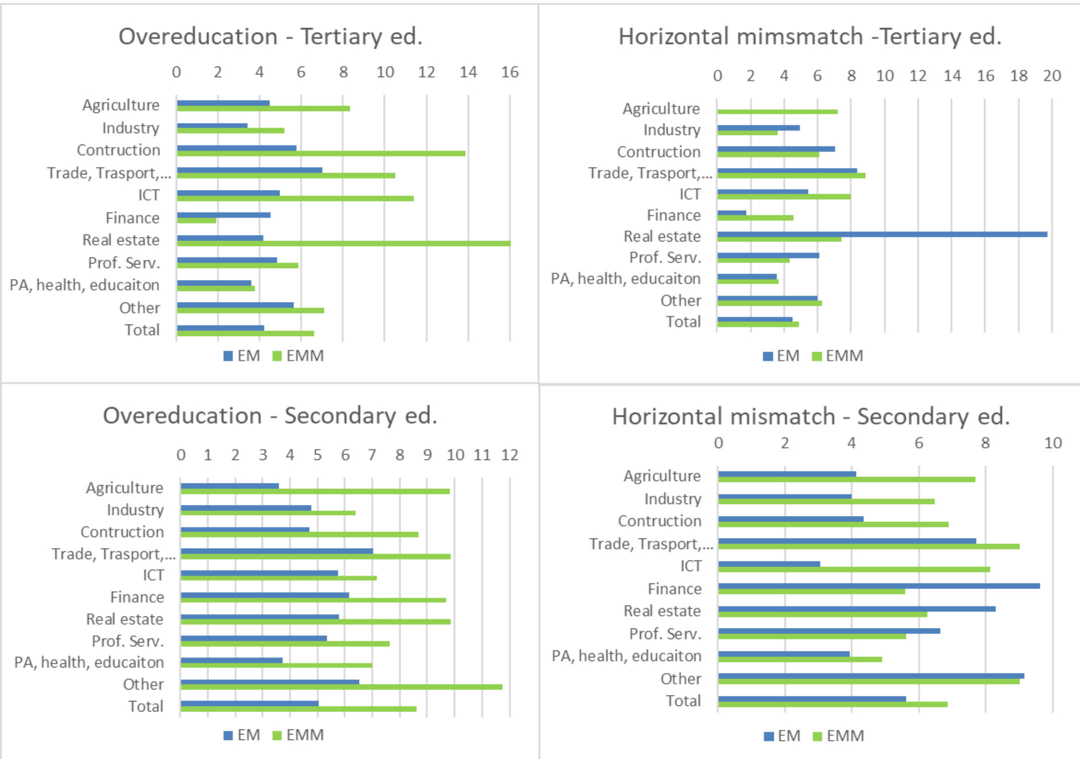
Among tertiary educated workers, unemployment risk ranges between 2.9% and 6% for mismatched individuals against percentages ranging from 1.5% to 2.9% for well-matched workers. Among secondary educated workers, the gap is lower, with mismatched individuals showing unemployment risk between 5.1% and 7.2% 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.

Figure 3. Routine intensity by measure and type of mismatch

Source: own elaboration on PLUS, 2014-2018

To understand the role of RBTC in the mismatch-unemployment nexus, in Figure 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 over-education indicate that mismatched workers perform tasks with high routine-intensity. 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.

Figure 4. Unemployment risk for horizontally and vertically mismatched individuals by sector of activity

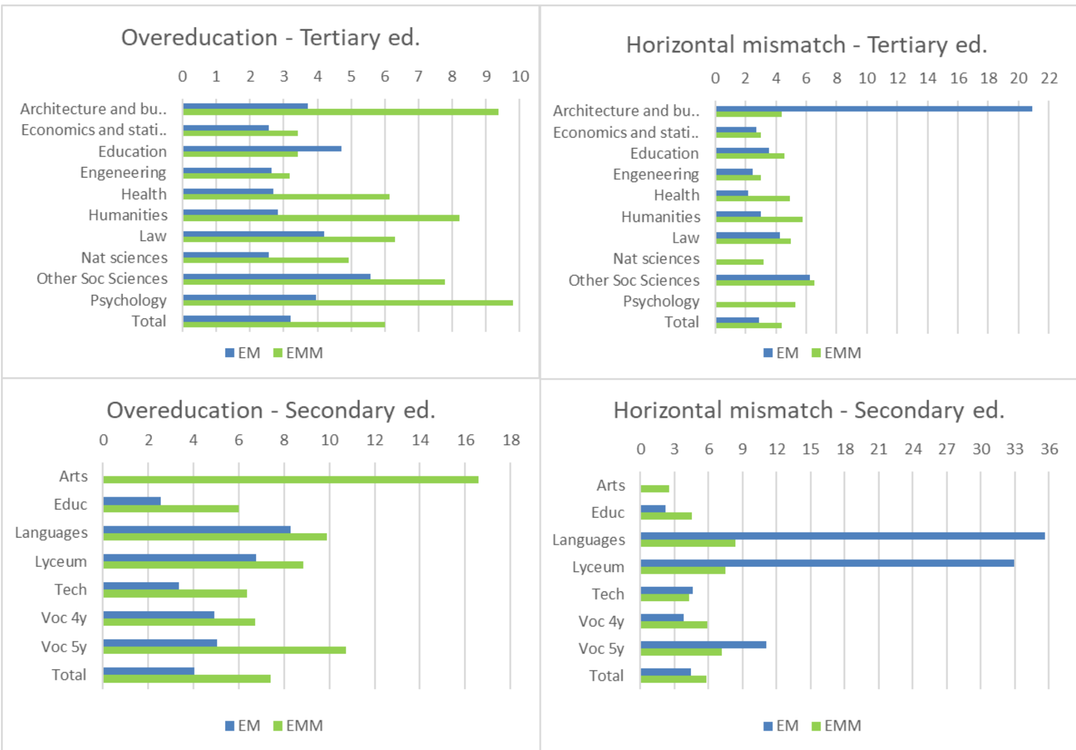


Source: own elaboration on PLUS, 2014-2018

A first indication on the role of sectoral specialization is provided in figure 4, which shows unemployment risk of well-matched and mismatched workers by sector of activity. Among tertiary educated individuals (upper panel) and considering over-education, unemployment risk of mismatched workers is higher in all sectors but Finance. In terms of horizontal mismatch, sectoral heterogeneity is relatively large, with sectors like Agriculture, ICT and Finance reporting higher unemployment risk for mismatched workers, and others like industry, real estate and professional services reporting a higher unemployment risk for well-matched workers. In terms of over-education, the picture is similar when looking at workers with secondary education. However, when we look at horizontal mismatch, all but Real Estate, Finance and Professional Services show higher unemployment probabilities for mismatched workers.

Finally, in figure 5 we look at unemployment risk across fields of study. Mismatched workers show higher unemployment probabilities across all fields but education for overeducated workers. A similar pattern is found – with the exception of Architecture and Buildings - when looking at horizontal mismatch. Turning to workers with secondary education (lower panel), the higher unemployment risk of overeducated workers is confirmed in all fields while the evidence in terms of horizontal mismatch is not clear-cut[6].

Figure 5. Unemployment risk for horizontally and vertically mismatched individuals by field of education



Source: own elaboration on PLUS, 2014-2018

[6] The high unemployment risk of those having studies Languages or Lyceum is due to the fact that these schools typically prepare students for tertiary education as they focus on general scientific and humanistic studies.

Summing up, the descriptive evidence suggests that educational mismatches are – on average – associated with higher risk to become unemployment, 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.

As for the main causes of the mismatch-unemployment nexus, there is a positive association between (vertical) mismatch and routine intensity whereas both sectoral specialization and fields of study seem not to play a particular role as the higher unemployment risk of overeducated workers is confirmed within both dimensions.

4. Econometric model and strategy

To assess the association between educational mismatches and unemployment risk, we estimate a multinomial logit model where transition probabilities toward unemployment and other jobs are estimated as a function of horizontal mismatch, vertical mismatch, the main characteristics of labour demand described in the previous section and a number of individual controls. In a standard matching framework, mismatched workers should experience higher mobility and unemployment risk is expected to be temporary. Since we are observing transitions after two years, we should not detect any difference in unemployment risk. On the contrary, the skill deterioration assumption implies that mismatched workers face significantly higher unemployment risk. The empirical specification is the following:

$$PT_i = \beta_1 RTI_i + \beta_2 OE_i + \beta_3 RMHM_i + \sum \gamma_k X_i^k + \sum \vartheta_h SEC_i^h + \sum \tau_l Field_i^l + \sum \varphi_l Y_i^l + \varepsilon_i \qquad (2)$$

where the dependent variable is the probability to change employment status in t conditional to being employed in t-1 (PT). There are three possible outcomes: permanence in the same job; transition to unemployment (E to U); transition to another job (E to E). RTI is the Routine Task Index; OE is the measure of other education (SASE, SAOE or RMOE); RMHM is the measure of horizontal mismatch; SEC is a group of 18 sectoral dummies; Field is a group of dummies for 13 fields of tertiary education and 8 fields of secondary education. The vector X includes *k* standard sources of heterogeneity in employment transitions. These are age, sex, marital status, number of children, type of contract, wage, geographical dummies (4 area), firm size, employed in the public sector, and a dummy equal to 1 if units belong to the 2014-2016 panel. The vector of controls Y includes variables that might affect the mismatch-unemployment nexus. First, we control for factors causing voluntary unemployment and job changes (job satisfaction, searching for a job while employed, whether a worker relocated for the current job, tenure). Second, following Agarwal *et al.* (2019), we control for the endowment of cognitive skills when entering the labour market (grade of the diploma/degree, whether the maximum grade is achieved). Third, we control for unemployment risk due to adverse economic conditions by adding a dummy equal to 1 if the firm in which the worker is employed used income support schemes in the last two years. A full description of the variables used in the analysis is provided in table A1 in the appendix 1.

To disentangle the role of technology and the structural features of labour demand in determining a positive relation between mismatch and unemployment risk we begin by estimating a basic specification A) including the two mismatch measures (*OE* and *RMHM*) and the vector of controls X. We then augment this basic specification by progressively adding: B) the *RTI*; C) sectoral dummies (*SEC*), D) fields of study (*Field*); and E) the group of controls *Y*.

Equation (2) is estimated separately on the subsamples of secondary and tertiary educated workers to account for the different effect that technological change and labour demand have on medium and high skilled workers. Unemployment risk due to short and long-run polarization should be significantly higher for mismatched workers with secondary education (Zago 2020), while the specialization of the Italian economy in low tech industries and low skilled jobs (Basso 2019; Marcolin *et al.* 2018; Franzini and Raitano 2012) suggests that mismatched workers with tertiary education should be more at risk of unemployment.

For each of the two groups, 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.

5. Discussion of the results

Table 2 shows the results for tertiary educated workers using the self-assessed sheepskin effect measure (SASE). The table has five panels reporting the main results[7] for the specifications A) to E) described in the previous section. Stating with specification A), we can see that estimates differ between the two age cohorts. For workers above 35 years, the marginal effect of over-education on unemployment risk is positive and significant. This effect disappears when introducing the RTI (Panel B) but the significance of the RTI falls substantially when adding sectoral dummies (Panel C) and it disappears when controlling for fields of education (Panel D).

Among workers between 20 and 35 years, we find a moderate impact of horizontal mismatch in Panel A. This effect increases both in magnitude and significance when fields of education are introduced (Panel D). Mismatches in field of study are associated with higher unemployment risk – by approximately 4.3% – m within each sector and field of education. As for the RTI, its marginal effect is positive and significant in Panel B but it turns insignificant when controlling for sectors and fields of education.

The results for tertiary educated workers suggest that unemployment risk associated to over-education is due to their concentration in occupations with a high degree of routineness, hence they face a pure risk of technological unemployment. This is coherent with the findings of Marcolin *et al.* (2018).

[7] Results for the full list of covariates is shown in tables A2 and A3 in the appendix.

At the same time, the significance of horizontal mismatch within sectors and fields of education indicates that the higher unemployment risk of (horizontally) mismatched workers must be due to other causes affecting all workers, independently of their title and occupation. Employment discontinuity, path dependence in mismatch (Ordine and Rose 2015) and unobserved individual characteristics related to innate abilities might be the main drivers of this result.
Finally, we find that technological unemployment as described by the RTI is completely determined by the distribution of workers across sectors and fields of education. This confirms that unemployment risk due to technological change is only partially captured by the routine intensity of occupations and that the country's sectoral specialization (Cassandro *et al.* 2020; Cirillo *et al.* 2017; Bogliacino *et al.* 2013) as well as workers' educational choices (Cabus and Somers 2018) play an important role.

The results for workers with secondary education are shown in table 3. Panel A indicates that over-education positively related to unemployment risk among workers up to 35 years while it is associated with higher job to job transitions among older workers.
The introduction of the RTI (Panel B) does not alter the results and routine intensity is associated with higher unemployment risk of older workers. The effect of the RTI vanishes when adding sectoral dummies (Panel C) and it turns negative when fields of education are introduced (Panel D). Over-education remains significant after adding both sectoral and field dummies. The results indicate that over-education is significantly associated with unemployment risk and this result holds across sectors and fields of study.

According to the estimates, over-education is associated with unemployment risk 5% higher with respect to well-matched peers. The results are in line with the assumption that secondary educated workers experience permanent mismatch (Zago 2020) and are, by consequence, more at risk of deskilling and unemployment. The significance of the result across sectors and fields of education points again to a pervasive effect which might be due to employment discontinuity, cognitive decline or unobserved individual characteristics. In addition, the higher probability to change jobs of workers above 35 years indicates that over-education leads to higher job mobility but this process is rather slow. As for the RTI, we confirm that its impact is completely determined by the structural characteristics of the economy.

Tables 4-7 report estimation results using the alternative measures of over-education SAOE and RMOE. As of workers with tertiary education, both SAOE and RMOE (tables 4 and 5) confirm the results: over-education is significantly associated with higher unemployment risk but its impact is captured by the RTI, while the effect of RMHM is unchanged. Looking at workers with secondary education (tables 6 and 7), some differences across measures emerge. In particular, the higher probability of job-to-job transitions is confirmed by SAOE but not by RMOE. Nevertheless, the result in terms of unemployment risk holds across measures.

Table 2. Estimation results of equation (2) on tertiary educated workers

	Panel A: Individual controls only					
	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
SASE	0.011*	-0.003	0.007	-0.003	0.011**	-0.006
	[0.006]	[0.007]	[0.015]	[0.023]	[0.005]	[0.006]
RMHM	0.005	-0.008	0.027*	-0.029	-0.002	0.000
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4029	4029	1163	1163	2866	2866
	Panel B: Individual controls and RTI					
	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
RTI	0.079***	-0.025	0.112*	-0.108	0.074***	-0.026
	[0.025]	[0.028]	[0.066]	[0.092]	[0.025]	[0.025]
SASE	0.003	-0.001	-0.004	0.006	0.004	-0.003
	[0.006]	[0.008]	[0.016]	[0.024]	[0.006]	[0.007]
RMHM	0.006	-0.009	0.028*	-0.031	-0.002	0.000
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4019	4019	1162	1162	2857	2857
	Panel C: Individual controls, RTI and sectoral dummies					
	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
RTI	0.063**	-0.019	0.103	-0.112	0.056*	-0.013
	[0.028]	[0.033]	[0.071]	[0.104]	[0.029]	[0.030]
SASE	0.003	-0.001	-0.004	0.004	0.003	-0.001
	[0.006]	[0.008]	[0.017]	[0.025]	[0.006]	[0.007]
RMHM	0.005	-0.008	0.026*	-0.029	-0.002	0.001
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4019	4019	1162	1162	2857	2857
	Panel D: Individual controls, RTI, sectoral dummies and field of studies					
	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
RTI	0.025	-0.02	-0.002	-0.112	0.02	-0.006
	[0.024]	[0.036]	[0.068]	[0.116]	[0.022]	[0.035]
SASE	0.006	0	-0.001	0.001	0.008	0.002
	[0.006]	[0.008]	[0.015]	[0.025]	[0.005]	[0.007]
RMHM	0.009	-0.009	0.037**	-0.024	0	0.002
	[0.006]	[0.008]	[0.018]	[0.024]	[0.005]	[0.007]
N	3935	3935	1148	1148	2787	2787
	Panel E: All controls					
	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
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]
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]
RMHM	0.012*	-0.008	0.042**	-0.022	0	0.003
	[0.006]	[0.008]	[0.019]	[0.023]	[0.005]	[0.007]
N	3806	3806	1130	1130	2676	2676

Note: marginal effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.
Source: own elaborations on PLUS and ICP, 2014-2018

Table 3. Estimation results of equation (2) on secondary educated workers

Panel A: Individual controls only

	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
SASE	0.011*	0.015**	0.033**	0.021	0.003	0.011*
	[0.007]	[0.006]	[0.014]	[0.016]	[0.008]	[0.006]
RMHM	0.002	-0.003	-0.011	-0.002	0.005	-0.003
	[0.007]	[0.006]	[0.014]	[0.017]	[0.007]	[0.006]
N	5606	5606	1379	1379	4227	4227

Panel B: Individual controls and RTI

	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
RTI	0.055**	-0.026	-0.082	-0.049	0.102***	-0.017
	[0.026]	[0.024]	[0.056]	[0.070]	[0.028]	[0.022]
SASE	0.007	0.015**	0.040***	0.023	-0.006	0.011*
	[0.007]	[0.006]	[0.014]	[0.016]	[0.008]	[0.006]
RMHM	0.002	-0.005	-0.011	-0.005	0.004	-0.004
	[0.007]	[0.006]	[0.014]	[0.018]	[0.008]	[0.006]
N	5573	5573	1369	1369	4204	4204

Panel C: Individual controls, RTI and sectoral dummies

	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
RTI	0.033	-0.029	-0.098	-0.019	0.062	-0.013
	[0.030]	[0.027]	[0.061]	[0.085]	[0.038]	[0.032]
SASE	0.007	0.013**	0.040***	0.019	-0.006	0.011*
	[0.007]	[0.006]	[0.014]	[0.016]	[0.008]	[0.006]
RMHM	0.003	-0.005	-0.011	-0.004	0.004	-0.005
	[0.007]	[0.006]	[0.014]	[0.018]	[0.008]	[0.006]
N	5573	5573	1369	1369	4204	4204

Panel D: Individual controls, RTI, sectoral dummies and field of studies

	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
RTI	-0.031	-0.034	-0.136**	-0.030	0.043	-0.031*
	[0.026]	[0.033]	[0.061]	[0.085]	[0.031]	[0.030]
SASE	0.011	0.014**	0.050***	0.023	-0.007	0.014**
	[0.007]	[0.007]	[0.015]	[0.018]	[0.006]	[0.007]
RMHM	-0.002	-0.010	-0.027	-0.019	-0.004	-0.01
	[0.007]	[0.009]	[0.018]	[0.020]	[0.008]	[0.007]
N	4606	4606	1254	1254	3352	3352

Panel E: All controls

	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
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]
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]
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]
N	4606	4606	1254	1254	3352	3352

Note: marginal effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.
Source: own elaborations on PLUS and ICP, 2014-2018

Table 4. Estimation results of equation (1) on tertiary educated workers: specifications with SAOE

	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
Panel A: Individual controls only						
SASE	0.011**	-0.011	0.018	-0.019	0.009*	-0.008
	[0.005]	[0.007]	[0.015]	[0.023]	[0.005]	[0.006]
RMHM	0.006	-0.008	0.026*	-0.028	-0.002	0
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4029	4029	1163	1163	2866	2866
Panel B: Individual controls and RTI						
	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
RTI	0.078***	-0.015	0.093	-0.084	0.076***	-0.022
	[0.024]	[0.028]	[0.060]	[0.091]	[0.025]	[0.025]
SASE	0.004	-0.009	0.01	-0.013	0.003	-0.007
	[0.006]	[0.008]	[0.014]	[0.023]	[0.005]	[0.007]
RMHM	0.006	-0.008	0.026*	-0.028	-0.002	0
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4019	4019	1162	1162	2857	2857
Panel C: Individual controls, RTI and sectoral dummies						
	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
RTI	0.062**	-0.011	0.085	-0.09	0.058**	-0.011
	[0.027]	[0.032]	[0.067]	[0.102]	[0.029]	[0.030]
SASE	0.004	-0.01	0.01	-0.015	0.002	-0.005
	[0.006]	[0.008]	[0.015]	[0.023]	[0.006]	[0.007]
RMHM	0.005	-0.007	0.025*	-0.027	-0.002	0.001
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4019	4019	1162	1162	2857	2857
Panel D: Individual controls, RTI, sectoral dummies and field of studies						
	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
RTI	0.023	-0.011	-0.014	-0.09	0.022	-0.001
	[0.024]	[0.035]	[0.066]	[0.102]	[0.022]	[0.035]
SASE	0.007	-0.008	0.01	-0.015	0.007	-0.003
	[0.005]	[0.008]	[0.014]	[0.023]	[0.005]	[0.007]
RMHM	0.009	-0.008	0.036**	-0.027	0	0.002
	[0.006]	[0.008]	[0.018]	[0.020]	[0.005]	[0.007]
N	3935	3935	1148	1162	2787	2787
Panel E: All controls						
	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
RTI	-0.018	-0.03	-0.032	-0.123	-0.023	-0.003
	[0.027]	[0.040]	[0.070]	[0.120]	[0.029]	[0.038]
SASE	0.004	-0.01	0.003	-0.028	0.008	-0.004
	[0.005]	[0.008]	[0.014]	[0.023]	[0.005]	[0.008]
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]
N	3806	3806	1130	1130	2676	2676

Note: marginal effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.
Source: own elaborations on PLUS and ICP, 2014-2018

Table 5. Estimation results of equation (1) on tertiary educated workers: specifications with 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
Panel A: Individual controls only						
SASE	0.012**	-0.002	-0.004	-0.004	0.017***	-0.004
	[0.006]	[0.006]	[0.014]	[0.018]	[0.006]	[0.005]
RMHM	0.006	-0.009	0.028*	-0.029	-0.002	0
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4029	4029	1163	1163	2866	2866
Panel B: Individual controls and RTI						
RTI	0.077***	-0.029	0.154**	-0.116	0.055*	-0.027
	[0.027]	[0.031]	[0.066]	[0.101]	[0.029]	[0.029]
SASE	0.003	0.001	-0.022	0.008	0.011	-0.001
	[0.007]	[0.007]	[0.015]	[0.021]	[0.007]	[0.006]
RMHM	0.006	-0.009	0.029*	-0.031	-0.002	0
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4019	4019	1162	1162	2857	2857
Panel C: Individual controls, RTI and sectoral dummies						
RTI	0.058**	-0.024	0.134*	-0.12	0.035	-0.013
	[0.029]	[0.035]	[0.072]	[0.110]	[0.031]	[0.032]
SASE	0.004	0.002	-0.021	0.007	0.012*	0
	[0.007]	[0.007]	[0.016]	[0.022]	[0.007]	[0.006]
RMHM	0.005	-0.008	0.027*	-0.029	-0.002	0.001
	[0.006]	[0.006]	[0.015]	[0.020]	[0.006]	[0.005]
N	4019	4019	1162	1162	2857	2857
Panel D: Individual controls, RTI, sectoral dummies and field of studies						
RTI	0.034	-0.025	0.032	-0.12	0.019	-0.008
	[0.025]	[0.039]	[0.069]	[0.110]	[0.024]	[0.039]
SASE	-0.002	0.003	-0.021	0.007	0.006	0.002
	[0.005]	[0.008]	[0.015]	[0.022]	[0.005]	[0.007]
RMHM	0.010*	-0.009	0.040**	-0.029	0	0.002
	[0.006]	[0.008]	[0.018]	[0.020]	[0.005]	[0.007]
N	3935	3935	1148	1162	2787	2787
Panel E: All controls						
RTI	-0.009	-0.046	0.013	-0.152	-0.018	-0.012
	[0.028]	[0.043]	[0.072]	[0.129]	[0.030]	[0.041]
SASE	-0.002	0.004	-0.025	0	0.003	0.003
	[0.006]	[0.008]	[0.016]	[0.024]	[0.005]	[0.008]
RMHM	0.012*	-0.008	0.043**	-0.023	0	0.003
	[0.006]	[0.008]	[0.018]	[0.023]	[0.005]	[0.007]
N	3806	3806	1130	1130	2676	2676

Note: marginal effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.
Source: own elaborations on PLUS and ICP, 2014-2018

Table 6. Estimation results of equation (1) on secondary educated workers: specifications with SAOE

	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
Panel A: Individual controls only						
SASE	0.005	0.009	0.029*	0.019	-0.008	0.004
	[0.007]	[0.007]	[0.015]	[0.017]	[0.009]	[0.007]
RMHM	0.003	-0.003	-0.01	-0.003	0.006	-0.003
	[0.007]	[0.006]	[0.014]	[0.017]	[0.007]	[0.006]
N	5606	5606	1379	1379	4227	4227
Panel B: Individual controls and RTI						
RTI	0.064**	-0.023	-0.083	-0.051	0.109***	-0.011
	[0.027]	[0.024]	[0.059]	[0.073]	[0.028]	[0.023]
SASE	-0.001	0.011	0.036**	0.024	-0.019*	0.005
	[0.008]	[0.007]	[0.016]	[0.018]	[0.010]	[0.008]
RMHM	0.002	-0.005	-0.009	-0.005	0.005	-0.003
	[0.007]	[0.006]	[0.014]	[0.018]	[0.007]	[0.006]
N	5573	5573	1369	1369	4204	4204
Panel C: Individual controls, RTI and sectoral dummies						
RTI	0.04	-0.026	-0.097	-0.023	0.069	-0.021
	[0.031]	[0.028]	[0.064]	[0.088]	[0.048]	[0.023]
SASE	-0.001	0.01	0.034**	0.022	-0.003	0.008
	[0.008]	[0.007]	[0.016]	[0.018]	[0.008]	[0.008]
RMHM	0.003	-0.005	-0.009	-0.005	0.006	-0.001
	[0.007]	[0.006]	[0.014]	[0.017]	[0.007]	[0.005]
N	5573	5573	1369	1369	4204	4204
Panel D: Individual controls, RTI, sectoral dummies and field of studies						
RTI	0.025	-0.028	-0.104	-0.028	0.028	-0.026
	[0.030]	[0.030]	[0.064]	[0.091]	[0.038]	[0.026]
SASE	-0.003	0.011	0.035**	0.012	-0.004	0.010
	[0.007]	[0.008]	[0.016]	[0.018]	[0.008]	[0.008]
RMHM	0.005	-0.008	-0.015	-0.013	0.001	-0.001
	[0.007]	[0.0068]	[0.016]	[0.017]	[0.007]	[0.005]
N	5573	5573	1369	1369	4204	4204
Panel E: All controls						
RTI	-0.032	-0.032	-0.124*	-0.031	0.012	-0.050*
	[0.026]	[0.033]	[0.064]	[0.093]	[0.025]	[0.029]
SASE	0.008	0.012	0.038**	0.005	-0.007	0.015**
	[0.007]	[0.008]	[0.017]	[0.019]	[0.007]	[0.008]
RMHM	-0.009	-0.011	-0.026	-0.018	-0.004	-0.010
	[0.007]	[0.009]	[0.019]	[0.023]	[0.007]	[0.008]
N	4606	4606	1254	1254	3352	3352

Note: marginal effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.
Source: own elaborations on PLUS and ICP, 2014-2018

Table 7. Estimation results of equation (1) on secondary educated workers: specifications with RMOE

	20-65 years		20-35 years		36-65 years	
Panel A: Individual controls only						
	E to U	E to E	E to U	E to E	E to U	E to E
SASE	0.01	0.000	0.049**	-0.01	-0.006	0.004
	[0.012]	[0.011]	[0.023]	[0.036]	[0.014]	[0.010]
RMHM	0.003	-0.003	-0.007	-0.002	0.006	-0.002
	[0.007]	[0.006]	[0.014]	[0.017]	[0.007]	[0.006]
N	5606	5606	1379	1379	4227	4227
Panel B: Individual controls and RTI						
	E to U	E to E	E to U	E to E	E to U	E to E
RTI	0.062**	-0.013	-0.063	-0.025	0.102***	-0.009
	[0.027]	[0.022]	[0.056]	[0.066]	[0.028]	[0.021]
SASE	0.003	0.002	0.056**	-0.007	-0.018	0.006
	[0.012]	[0.011]	[0.023]	[0.035]	[0.015]	[0.010]
RMHM	0.002	-0.004	-0.005	-0.004	0.004	-0.003
	[0.007]	[0.006]	[0.014]	[0.018]	[0.007]	[0.006]
N	5573	5573	1369	1369	4204	4204
Panel C: Individual controls, RTI and sectoral dummies						
	E to U	E to E	E to U	E to E	E to U	E to E
RTI	0.038	-0.019	-0.084	-0.001	0.069	-0.012
	[0.031]	[0.027]	[0.062]	[0.082]	[0.043]	[0.041]
SASE	0.004	0.003	0.048**	-0.007	-0.008	0.006
	[0.013]	[0.011]	[0.024]	[0.034]	[0.016]	[0.011]
RMHM	0.003	-0.004	-0.005	-0.004	0.004	-0.003
	[0.007]	[0.006]	[0.014]	[0.017]	[0.007]	[0.006]
N	5573	5573	1369	1369	4204	4204
Panel D: Individual controls, RTI, sectoral dummies and field of studies						
	E to U	E to E	E to U	E to E	E to U	E to E
RTI	-0.037	-0.020	-0.091	-0.002	0.066	-0.013
	[0.031]	[0.028]	[0.063]	[0.083]	[0.045]	[0.040]
SASE	0.006*	0.003	0.048**	-0.006	-0.005	0.005
	[0.013]	[0.011]	[0.025]	[0.034]	[0.015]	[0.011]
RMHM	0.003	-0.010	-0.030	-0.005	0.004	-0.004
	[0.007]	[0.009]	[0.019]	[0.018]	[0.007]	[0.006]
N	5573	5573	1369	1369	4204	4204
Panel E: All controls						
	E to U	E to E	E to U	E to E	E to U	E to E
RTI	-0.032	-0.024	-0.111*	-0.028	0.005	-0.038
	[0.026]	[0.031]	[0.063]	[0.087]	[0.025]	[0.028]
SASE	0.021*	0.003	0.066**	-0.005	0.005	0.005
	[0.011]	[0.013]	[0.027]	[0.034]	[0.010]	[0.010]
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]
N	4606	4606	1254	1254	3352	3352

Note: marginal effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.
Source: own elaborations on PLUS and ICP, 2014-2018

6. Conclusions and policy implications

In this article we investigated the existence of a positive relation between educational mismatches and unemployment risk in Italy. We built our empirical investigation on the assumption that mismatched workers are less competitive on the labour market due to human capital deterioration and derived an empirical specification taking into account the different aspects that might affect both unemployment risk and educational mismatches. In particular, based on the literature on RBTC and labour demand in Italy, we derived assumptions on existence of a nexus between educational mismatches and unemployment for workers with different educational attainments

The empirical analysis relied on a novel dataset obtained by merging information from the ICP and PLUS surveys. PLUS includes information to build alternative 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 (Cedefop 2015). In addition, we evaluated the effect of RBTC in terms of unemployment risk through a Routine Task Index (RTI) derived from the ICP survey, which uses Italian-specific data.

The main findings of the paper can be summarized as follow. First, over-education is significantly associated with higher unemployment risk of tertiary educated workers. This result holds for the group 36-65 years and it is due to the concentration of overeducated workers in occupations with high routine intensity. This means that the problem of skills obsolescence of older workers couples with structural problems as labour demand is concentrated in routine intensive occupations. Second, over-education is significantly associated with higher unemployment risk among young workers with secondary education and this result holds after controlling the main features of labour demand and supply. Third, a mismatch in the field of study is associated with higher unemployment risk among workers with tertiary education and this result holds within sectors and fields of study. These two findings suggest that human capital deterioration is due to factors affecting all workers independently of their field of education and the characteristics of their occupation. Finally, we find that the effect of technological unemployment due to RBTC, as shown by the RTI, is due to the country's specialization across sectors and fields of study. This finding is coherent with the hypothesis of a general impoverishment of the Italian labour market due to the growth of low-skills occupations during the last decades (Basso 2019) and to the specialization in the most traditional sectors (Evangelista and Savona 2003).

Our results imply that structural characteristics in terms of sectoral distribution and routine intensity play a role in the positive relation between educational mismatches and unemployment, thus showing that both demand side and supply side policies are needed. From the demand point of view, firms need to efficiently select and allocate workers and to create enough high-skilled jobs in innovative high-tech and knowledge-intensive sectors. On-the-job training policies aimed at reducing skills obsolescence are also relevant especially in sectors with higher technological intensity. Improving human capital through on-the-job training positively affects innovation capacity and helps firms make fuller and more efficient use of skills. This, in turn, positively affects their innovative capacity, thus generating a virtuous cycle. As to the skill supply, Italy needs measures aimed at reducing mismatch among graduates. Some recent reforms of the higher education system seem to be designed to this end. 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 (*lauree professionalizzanti*). These programmes are defined to produce professional technical skills at the tertiary education level in several disciplines, tailored on local needs (OECD 2019).

All in all, this article has showed that, in the absence of structural changes, educational mismatch is likely to be a dead-end for many workers in Italy. We have demonstrated the complexity of the mismatch-unemployment nexus and showed that robust analyses investigating all aspects of the mismatch as well as their interplay with technological change and labour demand are needed to be able to adopt tailored policies for both secondary and tertiary educated workers.

Appendix

Appendix 1: additional tables

Table A1. Variables description

Variable	Description	Source
RTI	Routine Task Index (see table A3)	ICP
SEC	Sectoral dummies classified according to 18 industries: Agriculture; Mining and Gas extraction; Manufacturing; Constructions; Trade; Hotels and Restaurants; Transports; ICT; Finance; Business Services; Professional and Scientific Services; Public Administration; Health; Education; Activity of Households; Extraterritorial Bodies.	PLUS
Field Tertiary	Field of education, 13 categories: Agrarian; Architecture/Buildings; Chemistry/Pharmaceutical; Economics/Statistics; Geology/Biology; Law; Humanities; Engineering; Education; Medicine; Political Sciences; Psichology; Science	PLUS
Field Secondary	Field of education, 7 categories: Arts; Education; Languages; Lyceum; Technical; Vocational 5 years; Vocational 4 years	PLUS
Wage	log of net monthly wage	PLUS
Tenure	Number of years since the begin of the current job	PLUS
Sex	Female=1	PLUS
Married	Married=1 if a worker is married	PLUS
Sex*Married	Female=1 and Married=1	PLUS
Children	Number of children	PLUS
Age	Age categories: 20-24; ,25-29; 30-34; 35-39; 40-44; 45-49; 50-54; 55-59; 60-65	PLUS
Temporary	=1 if a worker is employed with a temporary contract	PLUS
Other n.s.	=1 if a worker is employed with non-standard contractual arrangements	
CIG	=1 if the employer used the Italian Employment Protection Scheme (CIG) by the firm in the last two years	PLUS
Size	Firm size, 5 categories: micro (<10 empl.); small (10-25 empl); medium (26-50 empl.); large (51-250 empl); very large (>250 empl)	PLUS
Public	=1 if a worker is employed in the public sector	PLUS
Grade	Final grade for the higher level of educational attainment	PLUS
Transf	=1 if a worker relocated to accept the current job	PLUS
Search	=1 if a worker is searching for a job while employed	PLUS
Maxgrade	=1 if the maximum grade in the higher educational attainment is achieved	PLUS
JobSat	Job satisfaction, 5 categories: low; medium-low; medium-high; high	PLUS
Area	Dummies for the 4 main regions: North-East; north-West; Centre; South and Islands	PLUS

Table A2. Estimation results for workers with tertiary education: other controls

	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
RTI	-0.018	-0.026	0.002	-0.124	-0.03	-0.003
	[0.030]	[0.039]	[0.071]	[0.118]	[0.034]	[0.038]
Wage	0.000	-0.014***	-0.005	-0.026*	0.004	-0.005
	[0.005]	[0.005]	[0.013]	[0.015]	[0.005]	[0.005]
Grade	-0.001***	0.001	-0.003**	0.002	-0.001	0.000
	[0.000]	[0.001]	[0.001]	[0.002]	[0.000]	[0.000]
Max grade	0.008	0.007	0.017	0.010	0.002	0.004
	[0.007]	[0.009]	[0.020]	[0.026]	[0.007]	[0.007]
Search	0.013*	0.017*	0.024	0.051**	0.005	0.003
	[0.008]	[0.009]	[0.020]	[0.025]	[0.007]	[0.009]
Transf	-0.004	0.000	-0.018	-0.025	-0.003	0.008
	[0.009]	[0.010]	[0.022]	[0.031]	[0.009]	[0.007]
CIG	0.037***	-0.024	0.001	-0.02	0.039***	-0.312***
	[0.010]	[0.022]	[0.034]	[0.058]	[0.008]	[0.052]
JobSat=med-low	-0.005	0.002	-0.002	0.019	-0.004	0.000
	[0.007]	[0.009]	[0.020]	[0.029]	[0.007]	[0.007]
JobSat=med-high	-0.006	-0.003	-0.024	0.017	0.004	-0.004
	[0.009]	[0.012]	[0.025]	[0.034]	[0.008]	[0.011]
JobSat=high	0.015	0.007	0.034	0.07	0.023*	-0.320***
	[0.013]	[0.021]	[0.031]	[0.063]	[0.013]	[0.054]
Tenure	-0.001**	-0.002**	0.002	-0.003	0	-0.001*
	[0.000]	[0.001]	[0.002]	[0.007]	[0.000]	[0.000]
Sex	0.026***	-0.01	0.063***	-0.039*	0.007	0.011
	[0.008]	[0.008]	[0.018]	[0.022]	[0.009]	[0.011]
Married	0.008	-0.003	-0.086	0.004	0.002	0.016
	[0.011]	[0.014]	[0.093]	[0.071]	[0.009]	[0.011]
Sex*Married	-0.011	0.001	0.083	-0.065	0.001	-0.013
	[0.011]	[0.015]	[0.093]	[0.069]	[0.011]	[0.012]
Children	0.001	-0.005	0.025	0.062**	0	-0.004
	[0.003]	[0.005]	[0.021]	[0.027]	[0.002]	[0.003]
Temporary	0.049***	0.033***	0.077***	0.083***	0.041***	-0.331***
	[0.008]	[0.010]	[0.019]	[0.031]	[0.011]	[0.055]
Other n.s.	0.030***	0.025***	0.038**	0.075**	0.028***	0.008
	[0.007]	[0.009]	[0.019]	[0.030]	[0.007]	[0.007]
Area=North-West	0.017**	-0.017*	0.033*	-0.03	0.004	-0.011
	[0.008]	[0.009]	[0.020]	[0.026]	[0.009]	[0.008]
Area=Centre	0.012	-0.012	0.008	0.003	0.009	-0.014*
	[0.008]	[0.009]	[0.022]	[0.028]	[0.007]	[0.008]
Area=South/Islands	0.030***	-0.018**	0.052***	-0.016	0.015*	-0.013**
	[0.008]	[0.008]	[0.019]	[0.025]	[0.008]	[0.007]
Waves 2016-2018	-0.018***	-0.004	-0.032**	-0.014	-0.016***	-0.002
	[0.005]	[0.007]	[0.014]	[0.019]	[0.005]	[0.005]
Size=small	0.005	-0.014	0.026	-0.036	-0.009	-0.002
	[0.007]	[0.010]	[0.017]	[0.027]	[0.008]	[0.013]
Size=medium	-0.015	-0.011	-0.016	-0.028	-0.020**	-0.002
	[0.010]	[0.012]	[0.027]	[0.033]	[0.009]	[0.012]
Size=large	-0.021	-0.023	-0.044	-0.057	-0.01	-0.314***
	[0.013]	[0.016]	[0.034]	[0.043]	[0.013]	[0.053]
Size=very large	-0.049***	-0.014	-1.197***	0.109*	-0.028**	-0.01
	[0.019]	[0.021]	[0.098]	[0.062]	[0.013]	[0.019]
Public	-0.017*	-0.025**	0.016	-0.051	-0.029***	-0.01
	[0.009]	[0.011]	[0.019]	[0.035]	[0.010]	[0.011]
Sec	YES	YES	YES	YES	YES	YES
Field	YES	YES	YES	YES	YES	YES
N	3864	3864	1140	1140	2724	2724

Note: marginal effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.
Source: own elaborations on PLUS and ICP, 2014-2018

Appendix 2: building the Routine Task Index for Italy

As shown in equation (3), 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; Non routine 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. Table A3 shows the indicators included in each component of the RTI.

Table A3. 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

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