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What drives employment-unemployment transitions?

Evidence from Italian task-based data

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Abstract

Relying on a unique longitudinal integrated database supplying micro-level information on labor market transitions (concerning the 2011-2017 period) and occupation task characteristics (e.g. routine-task intensity), this paper provides fresh evidence of the determinants of unemployment risk in Italy. We find that workers employed in routine-intensive occupations (measured with the RTI proposed by Acemoglu and Autor, 2011) do not display – on average - higher unemployment risks than the rest of the workforce. However, on distinguishing between cognitive and manual tasks, it turns out that workers employed in occupations entailing a large proportion of routine cognitive tasks (such as workers employed in service occupations as cashiers or call-center operators) are in fact exposed to a relatively higher risk of becoming unemployed. By contrast, a rather lower risk seems to be faced by workers employed in occupations entailing a large proportion of routine-manual tasks. Finally, the distribution of unemployment risk and its relation with routine-task intensity varies significantly across sectors – with higher risk in manufacturing and construction - confirming the importance of industry-level economic, technological and institutional heterogeneities.

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1. Introduction

In the recent past, labor markets have become increasingly 'flexible'. The process is driven by several factors: i) rising competition on the global markets; ii) the increasing importance of the service sector wherein internal (i.e. continuous rotation of tasks among employees) and external (i.e. frequent entry and exit of workers) flexibility characterizes the prevailing organizational mode; iii) changes in labor legislation implying a generalized weakening of protection against dismissal accompanied by the spread of temporary employment. These changes have fueled a broad process of 'risk-shifting' from firms to workers with the latter bearing an increasing share of the (economic and occupational) risks related to market volatility (Brian and Rafferty, 2018; Cetrulo et al. 2019a). On the other hand, the diffusion of digital technologies and automated machinery has heightened the threat for workers performing repetitive and encodable tasks. As an extensive literature has documented (see, among the others, Autor et al. 2003; Goos et al. 2009; Autor and Dorn, 2013), the larger the proportion of routine-task, the greater the risk of being substituted by a machine.

While a vast amount of empirical literature has explored the relationship between task characteristics and changes in employment composition building upon the well-known 'routinization hypothesis' (for a review, see Autor, 2015), less attention has been paid to the determinants of unemployment risk (i.e. the risk of moving from employment to unemployment) measured at the individual level. In particular, there is scant empirical evidence on the relative importance of routine-task vis-à-vis other supply and demand factors in accounting for individuals' employment-unemployment transitions. In fact, technological unemployment risks have to a large extent been investigated by looking into long-term changes in employment composition across countries and sectors (Acemoglu and Restepo, 2017; Feldman, 2013; Van Roy et al. 2018), while less is known about what happens in terms of individual risks (a notable exception is the recent contribution by Sacchi et al. 2020). This is mostly due to the lack of comprehensive micro-level databases providing information on the evolution of individuals' labor market status (i.e. employed, unemployed, inactive and relative transitions) or indeed on the qualitative characteristics of their jobs, including the degree of routineness of the tasks they perform.

Both supply and demand factors may affect firms' decisions concerning hiring and layoff. As for the supply-side, labor-saving technologies can increase the attractiveness of capital input vis-à-vis labor, thus raising the probability of technology-driven layoffs. On the other hand, the same technology may contribute to modifying the workforce structure, fueling the demand for non-routine occupations while at the same time favoring the contraction of sectors characterized by routine-intensive jobs (Autor et al. 2003). As a result, the unemployment risk is expected to be greater for workers belonging to routine-intensive occupations given the potential obsolescence of their tasks – i.e. expected to be easily replicable, encodable and thus substitutable by machines – as compared with the rest of the workforce. Nevertheless, workers (even those employed in occupations characterized by a relatively high degree of routine-intensive tasks) could be carriers of experience and firm-specific knowledge, making their layoff too costly for their employer (considering potential loss of firm-specific capabilities), despite the potential cost reduction offered by labor-saving technologies (on this point, see Dosi and Marengo, 2015; Dosi et al. 2019). The extent of the efficiency gains entailed by new technologies could depend significantly on the degree of technological and organizational capabilities. The latter, however, are known to be unevenly distributed across firms, sectors and countries (Cetrulo et al. 2019b). Consequently, the diffusion (and impact on employment) of new technologies tends to be heterogeneous in terms of time, space and organizational set-up. Turning to the demand-side, it is worth noting that companies' decisions in terms of technological and organizational innovation (eventually implying layoffs and/or hires) are constrained by expected demand flows or, more generally, by medium-to-long-run growth prospects. Demand-related constraints could also have to do with the differentiated positioning along the Global Value Chains (GVCs) and to the associated (heterogeneous) ability of firms to capture demand flows and value added shares (Bramucci et al. 2018). As an additional but no less relevant element, the institutions (e.g. labor market characteristics in terms of layoff discipline, prevalent contractual arrangement and industrial relations) could be a crucial factor shaping the effect that new technologies might ultimately have on variables such as employment, unemployment and incomes. In this respect, it might be possible to reduce the risk of a massive rise in technological unemployment with contractual safeguards protecting workers against layoffs. The same applies to changes in the workplace organization that can have labor-saving effects. Even if changes of this kind may be technically feasible, they can be blocked by the existing legislation or the opposition of the trade unions (Deery, 2018).

This study analyses the relationship between the probability of becoming unemployed and the amount of routine task characterizing Italian jobs, verifying for a large range of supply and demand factors likely to affect the relationship in question (sectoral demand dynamics, contract types, educational attainment, gender, age and other socio-demographic characteristics). Routineness is measured with the Routine Task Index as formulated by Acemoglu and Autor (2011). The role of routine-task as a factor contributing to shape employment dynamics is further explored by distinguishing between cognitive and manual tasks (on this point, see Gualtieri et al. 2018 and Cirillo et al. 2019). The database adopted integrates information on employment status - derived from the ISTAT 'Italian Labor Force Survey' (ILFS) - with data on task, skills and work attitudes - drawn for the INAPP 'Indagine Campionaria sulle Professioni' (ICP). The latter provides O*Net-type information for the Italian economy (see Cirillo et al. 2019 for a thorough description of the database). Although an ample literature has explored the relationship between task characteristics and employment at the occupation and industry level (for a review, see Autor 2015), few attempts have been made so far to study the role of task characteristics in accounting for employment-unemployment transitions at the individual-level. We aim to fill this literature gap by analyzing a unique integrated longitudinal database reporting information on the Italian labor market. Italy represents a case of significant interest due to the intense process of labor market 'flexibilization' underway from the early 2000s onwards (Cirillo et al. 2017). Italy, moreover, is an advanced industrialized economy with a considerable share of manufacturing productions. In this respect, the economy is significantly exposed to the current wave of automation and digitalization which, in turn, lies behind the revived fears of an incoming wave of mass technological unemployment (Vivarelli, 2014; Autor, 2015; Frey and Osborne, 2017).

The paper is structured thus: the next section briefly reviews the literature on technology, task and labor market dynamics; section 3 spells out the research questions while section 4 illustrates the data and provides some evidence concerning the key relationships in question. Section 4 sets out the econometric strategy and the results, both for the sample as a whole and by industry. Some final conclusions are drawn in section 5.

2. Task characteristics and Technological Unemployment

In the *General Theory*, Keynes (1936) conceptualizes technological change as the continuous 'discovery of means of economizing the use of labor'. Four years after the explosion of the great crisis of 1929, Keynes seems to have identified a link between the continuous search for greater efficiency (i.e. cost-reduction) characterizing capitalist organizations and the 'social casualties' which were before his very eyes in the form of mass unemployment and poverty.

In what follows, we briefly review the literature analyzing the technology-unemployment nexus with the focus on tasks. The first element to be pointed out is the transition from the Skill Biased Technical Change (SBTC) (Katz and Murphy 1992; Bound and Johnson 1992; Murphy, Riddell, and Romer 1998; Katz 1999; Card and Lemieux 2000; Acemoglu 2002) to the Routine Biased Technical Change (RBTC) approach. According to the former, the introduction of computers is expected to boost the demand for high-skilled workers – due to the complementarity between computers and this set of skills – while penalizing low-skilled jobs with the drawback of a poor complementarity with ICT technologies. Moving to the RBTC approach, a switch in the conceptualization of occupations takes place. To evaluate their relative exposure to technological unemployment risks, occupations are no longer ranked and categorized in terms of skills. In turn, the RBTC literature conceives occupations as 'bundles of tasks'. As pointed out in Autor et al. (2003), it is tasks rather than skills or jobs that are subject to (potential) replacement by machines. Therefore, it is on the basis of task characteristics (as well as job composition in terms of tasks) that, according to this stream of literature, occupations can be properly evaluated with respect to the amount of technology-related risk.

In this context, the extent to which a task can be considered more or less routine-intensive became of paramount importance. The birth of the RBTC literature is the result of the failure of its predecessor, the SBTC approach, in explaining polarization patterns that have been characterizing the American occupational structure since the beginning of the 1990s. Building upon the RBTC hypotheses, a number of contributions found links between employment and income polarization and job routineness (see, among others, Autor et al. 2006 and Goos and Manning 2007). These authors assume that the 'hollowing out of the middle' is closely related to the fact that creative high-skill jobs as well as low-skilled ones, implying a great deal of manual dexterity and/or intensive social interactions, are less likely to be crowded out by the diffusion of computers and ICT devices. In their seminal paper, Autor et al. (2003) propose the 'Routine Task Index' to rank US occupations according to the relative importance of repetitive and encodable tasks in carrying out such work activities. On the evidence of long time-series (1960 to 1998) these authors document the fact that computerization is associated with a drop in routine intensive employment paralleled by an increasing demand for non-routine jobs. Following along the same line, Autor and Dorn (2013) document the fact that polarization stems from the interaction between consumer preferences, which favor variety over specialization, and the falling cost of automating routine, codifiable job tasks.[1]

The routine concept has a multidimensional nature given the multitude of elements exposing tasks to the risk of becoming 'obsolete'. The key elements are: degree of repetitiveness; formalization and proceduralization; propensity towards standardization; and codifiability. Indeed, the current wave of digitization and automation of production is allowing machines - mostly thanks to the rapid development of Artificial Intelligence (AI) – to perform tasks so far considered 'strictly human', such as those entailing significant amounts of knowledge and learning. Brynjolfsson and McAfee (2014) identify the advances in computing power as a major cause of the rapidly expanding set of tasks that machines can perform. Thanks to AI, machines are also capable of adjusting and refining (thus becoming increasingly efficient) their execution mode by learning from their own 'mistakes'. Among the examples of this increasing 'multi-tasking' nature of machines (Deming, 2017), we might mention operations such as automated financial management, tax preparation to legal e-discovery, or cancer diagnosis and treatment. Of course, these developments entail a proliferation of technological unemployment risks also at the top of the skill distribution (Levy and Murnane 2012; Brynjolfsson and McAfee 2014; Remus and Levy 2015). In a recent paper, Deming (2017) argued that cognitive tasks are increasingly replicable, supporting the idea that technology-related risks are also spreading among high-skilled and knowledge-intensive occupations. However, Deming (2017) emphasizes the growing importance of 'social skills' as drivers of employability, occupation resilience and wage dynamics.

Another strand of the literature focuses on estimating the risk of a job or a task being digitized and, as a consequence, substituted by a machine (Frey and Osborne 2017; Arntz, Gregory and Zierhan 2016; McKinsey 2017). The paper by Frey and Osborne (2017) gave rise to a great deal of debate on the issue. They built a routine index, partly based on the US O*Net data and partly on experts' judgement, estimating that nearly 47% of US occupations are doomed to disappear due to AI-driven substitution. A common criticism concerning Frey and Osbourne's evidence is that routineness is a specific feature characterizing tasks and not occupations as a whole: new machines, robots, and

[1] Many other studies have empirically investigated the dynamics of employment and income polarization in the western economies. Among others, Spitz-Oener (2006), Mazzolari and Ragusa (2007), Autor and Dorn (2009, 2013), Goos, Manning and Salomons (2009), Acemoglu and Autor (2011), OECD (2017), Ross, (2017), Vom Lehm (2018), Naticchioni et al. (2014). Another approach has been proposed by authors like Fernandez-Macias and Hurley (2016) and Cirillo (2016), relating employment patterns to industry-level technological trajectories, country-level heterogeneities, institutional and demand factors.

software can replicate a repetitive task, but, on the other hand, they cannot replicate the whole set of tasks characterizing an occupation. Moreover, these authors take no account of macroeconomic, institutional, technological and cultural factors that may prevent technology-driven labor destruction from occurring. Another attempt to estimate the number of jobs at risk was made by Arntz et al. (2016). Relying on individual data derived from the PIAAC survey and focusing on the 21 European member countries of the OECD, the authors estimate that only 9% of European occupations are at high risk of automation.[2] In a more recent study, Marcolin (2018) formulated a measure of task routineness based, again, on PIAAC: the Routine Intensity Index (RII). The RII focuses on the degree of freedom that workers have in organizing their activities and builds upon four PIAAC items regarding the design and organization of working activities. Analyzing a panel of 20 OECD counties, Marcolin (2018) finds that employment increases in non-routine occupations with particularly significant results in services as opposed to manufacturing. A study by Cortes et al. (2020) - which adopts a long-run perspective - shows that the increase in non-routine employment in the US is mostly due to a reduction in the propensity of non-employed individuals to move into routine jobs. This couples with an increased propensity to move into non-routine jobs.

This study adds to the empirical literature by exploring the role of tasks in accounting for the risk of becoming unemployed (Goos et al. 2009; Fernandez-Macias and Hurley, 2016). The key contributions are: i) analysis of the effects of task characteristics (i.e. routine-task intensity) in accounting for the risk of becoming unemployed faced by Italian workers ii) highlighting the distinct part played by manual and cognitive tasks looking beyond the standard routine-task indicator (i.e. the RTI) iii) to explore in depth sectoral-level heterogeneities and so to take into account key structural factors likely to affect the relationship at stake.

3. Unemployment risk and task characteristics: research questions

In what follows, we spell out our key research questions. As discussed above, unemployment risks are affected by a multitude of supply and demand factors. Upswings (downswings) of the business cycle are of course associated with a higher (lower) probability of losing job and income. Unemployment risks are also unevenly distributed across geographical areas and sectors. The latter are in fact exposed to differentiated degrees of competition that may in turn be reflected in differentiated unemployment risks. By the same token, heterogeneous technological and organizational characteristics of firms may be associated with differentiated attitudes and strategies in terms of hiring, firing and HR management. Moreover, regulations and contractual arrangements, often heterogeneous across labor market segments, are likely to affect unemployment risks. A number of individual elements are also important to determine the probability of becoming unemployed. Age, gender, marital status and educational endowment could contribute to accounting for individuals' transition from employment to unemployment.

[2] The Programme for the International Assessment of Adult Competencies (PIAAC) is a programme of assessment and analysis of adult skills carried out by the OECD.

In this study, we place the internal characteristics of labor – i.e. the type of tasks that workers perform according to their occupation – at the center of the stage. Verifying for all the above mentioned supply and demand factors, we aim to capture the relative contribution of routine tasks – i.e. relying on both the standard RTI indicator (Acemoglu and Autor, 2011) and its subcomponents to distinguish between manual and cognitive tasks – in accounting for the probability of moving from employment to unemployment.

The first research question (RQ1) can be formalized as follows:

$$\Pr\left(TUE_{i,t}\right) = \alpha + \beta RTI_{i,k,t} + \sum_{k=1}^{H} \gamma_k X_k + \varepsilon_{i,t} \qquad (1)$$

the probability of becoming unemployed - Pr(TUE), is a dummy variable standing at 1 if an individual is employed in t and unemployed in t+1, whereas it is 0 if an individual is employed in both t and t+1. The degree of routineness is captured, for each worker i belonging to a certain occupation k (k ∈ ISCO-5 digit)[3], by the RTI (Acemoglu and Autor, 2011) while the matrix X includes controls such as: age, gender, marital status, type of contract, educational attainment, geographical area and sector of activity. According to the RBTC hypothesis (Autor et al. 2003), the immediate expectation would be that workers performing operations characterized by a considerable proportion of routine tasks are, ceteris paribus, more likely to become unemployed as compared to other workers. This reflects the idea that routine-intensive jobs are more likely to be substituted by labor-saving machines and ICT devices. If structural factors prevail (see the discussion above), however, it would not be surprising to find that task are not the key element accounting for employment-unemployment transitions in the Italian labor market.

This first research question, formalized as follows, (1) is further explored by distinguishing between routine tasks and cognitive and manual operations. The underlying idea is that manual and cognitive tasks are heterogeneously exposed to technology-related unemployment risks. Given the still large share of manufacturing productions characterizing the Italian economy, a significant quantity of traditional blue-collar jobs is at risk of machine-driven substitution. In this case, manual tasks are the key object of the substitution process. Even in Italy, however, the service sector dominates the industrial structure with the share of low value added and low-tech services growing significantly after the 2008 crisis (Cirillo et al. 2016). As a result, cognitive tasks characterized by low levels of embedded knowledge, experience and creativity are similarly exposed to the risk of being substituted by computers and ICT devices, thus raising the probability of becoming unemployed. This distinction between manual and cognitive routine tasks gives rise to our RQ2:

$$\Pr\left(TUE_{i,t}\right) = \alpha + \beta_1 RTCI_{i,t} + \beta_2 RTMI_{i,t} + \sum_{k=1}^{H} \gamma_k X_k + \varepsilon_{i,t} \qquad (2)$$

where the only difference with respect to equation (1) lies in the presence of the RTMI (Routine Task Cognitive Index) and the RTMI (Routine Task Manual Index). With regard to (2), the

[3] As illustrated in the data section, the RTI is shown for each ISCO 5-digit occupation.

expectations are mixed. A positive association between the probability of becoming unemployed and the proportion of routine manual tasks could be driven by the introduction of labor-saving technologies in the manufacturing sector. At the same time, however, a contraction of the manufacturing production base eventually induced by a drop in aggregate demand – as was the case in Italy between 2010 and 2014 (on this point, see Lucchese et al. 2016) – may lead to a similar result, even in the absence of any labor-saving innovation. In turn, if labor market transitions are mostly affected by what happens in the service sector, we might expect those facing the greater risk of becoming unemployed to be employed in occupations displaying relatively large proportions of routine cognitive tasks. Cognitive tasks characterized by marked repetitiveness (such as tasks carried out by call-center operators or elementary accountancy operations) are in fact likely to be replaced as a consequence of the increasingly widespread use of ICTs in the service sector (Autor and Dorn, 2013).

By focusing exclusively on task-related characteristics (identified using the RTI or its sub-components) as proxies of technology driven unemployment risks, we would risk overlooking crucial elements connected to industry-specific economic and technological features. On the one hand, the risk of becoming unemployed, even for workers performing mostly routine tasks, is expected to be lower in mature sectors characterized by low innovation propensity. On the other hand, fast-growing sectors showing (on average) sustained employment dynamics are also likely to be experiencing compositional changes, with non-routine jobs increasing their share at the expense of routine ones. Sectors are, moreover, heterogeneous in terms of prevalent labor institutions and characteristics of the industrial relations. To account for such heterogeneities explicitly, RQ1 and RQ2 are analyzed, separately for 18 sectors including both manufacturing and services (see the next section for a detailed description). Finally, as a robustness check, RQ1 and RQ2 are tested using individual wages as an additional control. Due to data limitations, this final robustness check is performed on the subsample of employees only (while all the other estimations are run over a full sample of employees and self-employed).

4. Data and descriptive evidence

The empirical analysis is based on an integrated dataset merging the ILFS and ICP data. The ILFS provides quarterly micro-level information on: employment, wages, individual and socio-demographic characteristics, and type of contract. The overall ILFS sample includes more than 250,000 Italian households, corresponding to over 600,000 individuals, distributed across about 1,400 Italian municipalities. Individual level information is gathered using a mixed CAPI-CATI strategy complying with the highest statistical standards in terms of sampling strategy and representativeness (for a detailed description, see also Gualtieri et al. 2018). The ILFS covers all the

Italian industrial sectors (NACE) and occupations at the highest possible level of disaggregation (i.e. 5-digit ISCO codes[4]).

The second component of the adopted database (i.e. the ICP survey) builds conceptually and methodologically on the American O*Net.[5] The survey is based on a representative sample of 16,000 workers covering the whole spectrum of the Italian 5-digit occupations (i.e. 811 occupational codes). For the purposes of this analysis, we use the last wave of the survey carried out in 2012. ICP information is collected by means of 1-hour-long face-to-face interviews (CAPI) with ex-post validation relying on the experts' assessment. The ICP variables provide information regarding: work contents and attitudes, skills and tasks, technological and organizational nature of productive processes. Relying on this data source we characterize our statistical units (workers belonging to a certain 5-digit occupation) according to their relative degree of routine-task intensity (i.e. the relative proportion of repetitive and encodable tasks characterizing each occupation). Following Acemoglu and Autor (2011), we adopt the Routine Task Index (RTI) in order to rank occupations from the least (RTI=0) to the most (RTI=1) routine-intensive. As illustrated above, characterization of occupations in terms of their task content is taken further by distinguishing between manual and cognitive tasks. In what follows, we provide the synthetic formulas of the RTI, RTCI (routine cognitive task index), and RTMI (routine manual task index):

$$RTI_i = RM_i + RC_i - NRM_i - NRMIA_i - NRCI_i - NRCA_i \; (i \in CP2011 - 5digits) \quad (3)$$

$$RTCI_i = RM_i - NRCI_i - NRCA_i \quad (4)$$

$$RTMI_i = RM_i - NRM_i - NRMIA_i \quad (5)$$

where RM stands for Routine Manual; RC for Routine Cognitive; NRCI for Non Routine Cognitive Interpersonal; NRCA for Non Routine Cognitive Analytical; NRM for Non Routine Manual (NRM); and NRMIA for Non Routine Manual Interpersonal Adaptability (see Acemoglu and Autor, 2011 for a detailed discussion). The three indices are standardized over the interval 0-1 and merged with ILFS individual data using 5-digit ISCO codes.

4.1 Employment-unemployment transitions: measuring the risk of becoming unemployed

Building upon ILFS data it is possible to calculate the risk of becoming unemployed providing information on the interviewees' labor market status at t and at t+1. Transitions are estimated on a yearly basis using the longitudinal component of the ILFS.[6] Half of the individuals included in the survey were interviewed for two quarters in year t and the same two quarters in year t+1. For each

[4] To characterize 5-digit occupations in terms of their routine-task intensity we rely on the Italian 'Classificazione delle Professioni' provided by ISTAT. From the 3d to the 1st digit this classification overlaps the ISCO.
[5] The O*NET repertoire represents the major source of information regarding the qualitative characteristics of work, working activities and workplaces' organizational features. An extremely large amount of empirical literature (see Autor et al, 2003 and followers) build upon the O*NET repertoire to study recent trends in the advanced economies' labor markets.
[6] We rely on a calibration estimator in order to reduce attrition and potential selection bias. The auxiliary variables used in the calibration system refer to the Italian demographic and employment structure.

individual in the ILFS we can thus trace annual labor market transitions relying on two different measures. The first measure, *U narrow*, is based on the ILO definition of unemployment whereas the second, *U wide*, also includes individuals that - according to the ILO definition - are inactive (i.e. not actively searching for a job) but willing to work. We focus on all employed persons, including both employees and self-employed. We use data for annual transitions from 2011 to 2017. This period covers the 2011-2013 recession as well as the following recovery, and estimates should therefore not be greatly affected by cyclical dynamics. The total sample size amounts to 484,587 observations. Table 1 provides the full list of variables used in the analysis.

Table 1 - Variables' description and sources

Variable	Description	Source
RTI, RTCI and RTMI indices	Dimensions comprised in the RTI by 4-digit occupation; standardized in the 0-1 interval.	ICP
Labor market status (observed at t and at t+1)	Employed, unemployed and inactive	ILFS
Wage	Log of monthly net wage.	ILFS
Education	Dummies for upper secondary education; bachelor degree; master degree (base category: up to lower secondary education)	ILFS
Type of labor contract	Permanent (base category); fixed; self-employed.	ILFS
Age	10 years dummies: 25-34 years; 35-44 years; 45-54 years; 55-64 years, 65-70 years.	ILFS
Sex	Female=1	ILFS
Family status	Dummies for single (base category); married; widowed/divorced.	ILFS
Sector of employment	Dummies for 18 sectors of activity.	ILFS
Year	Yearly dummies	ILFS
Geographical area	5-area dummies: North-East; North-West; Centre; South; Islands.	ILFS

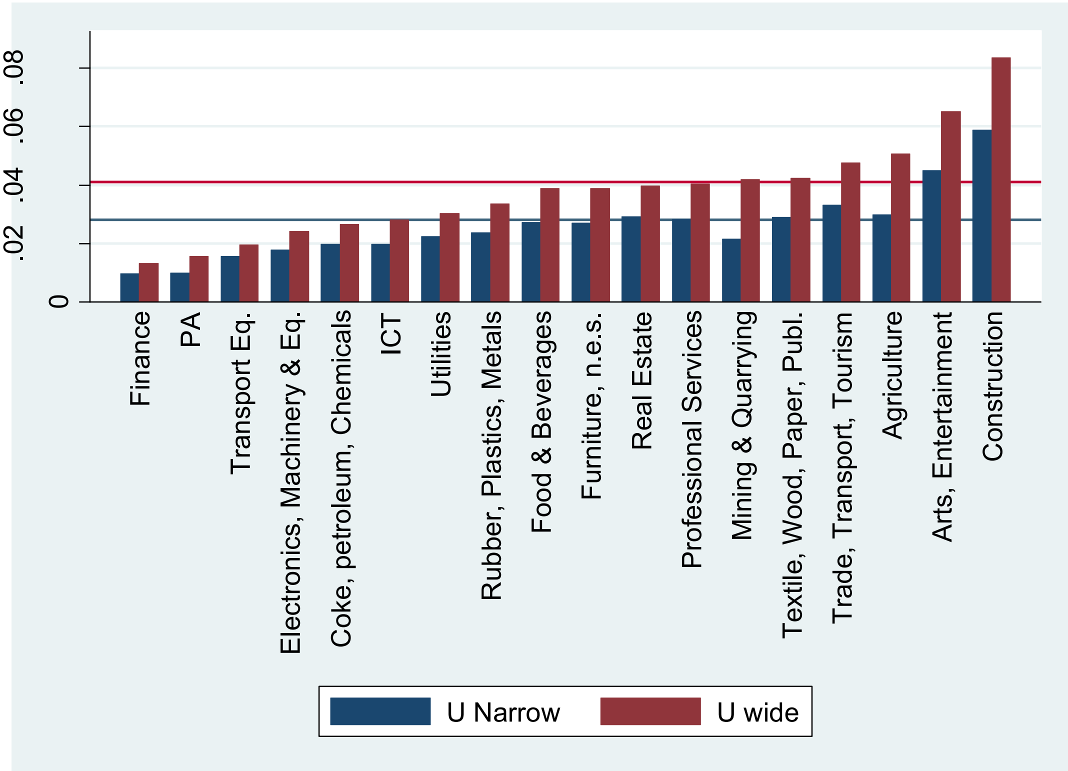
4.2 Descriptive evidence

In this section, we provide some descriptive evidence on the distribution of unemployment risks across sectors and occupations. We then turn attention jointly to unemployment risks and occupation routine-task intensity. We begin by looking at employment-unemployment transitions for the total economy and for 18 sectors of activity (Figure 1). Overall, the risk of becoming unemployed between t and t+1, (measured using the *U-narrow* definition (see above)), comes to 2.8%, but it rises to 4.1% if the *U-wide* definition is applied. Turning to sectoral heterogeneity, higher unemployment risks are detected in sectors such as: Agriculture Construction; Arts and Entertainment; Trade, Tourism and Transport; and the Textile Industry. In turn, relatively lower unemployment risk is detected in sectors such as: Public Administration; Finance; Transport Equipment; Machinery and Electronic Components. To complete the picture, we provide data on unemployment risk together with transition rates from unemployment to employment (entries), net balances (difference between entry and exit rates) and total turnover (sum of entry and exit rates) - see Table A2 in the Appendix. Viewing the economy as a whole, entry and exit rates are seen to be significantly aligned, irrespective of the definition of employment-unemployment transition adopted. Total turnover - i.e. the sum of entries and exits over total employment - amounts to 5.7% using the narrow indicator while it is about 8.4% if the wide indicator is adopted. This evidence shows that there is little difference between the transition rates (from unemployment to employment) characterizing inactive individuals and unemployed individuals. It is therefore worth considering both groups when the relation between transition and task characteristics is analyzed. The exit rates, moreover, are higher than the entry rates in sectors like Mining, Construction and in some manufacturing industries such as Textile, Rubber, Plastics and Metals, and Furniture; while the opposite is true in the rest of the manufacturing and service sectors. This evidence is consistent with the underlying GDP sectoral dynamics (see Table A1 in the Appendix). In fact, the largest drop in employment is observable in sectors that were worst hit by the 2008 crisis (such as the Construction sector) and that are still struggling to recover.

Unemployment risks can be heterogeneously distributed across age cohorts (see Figure A1 in the Appendix) and educational attainment (see Figure A2 in the Appendix). In the case of the age cohorts, a negative correlation emerges between the probability of becoming unemployed and age. In other words, young workers display a higher probability of becoming unemployed than the rest of the workforce. As documented in studies analyzing the recent evolution of the Italian labor market (see, among the others, Cirillo et al. 2017), this might be at least partly the result of the reduction of legal protections against layoffs that have mostly affected young 'outsiders' (i.e. young people entering the labor market for the first time or at the early stage in their career). As for educational attainment, it turns out that workers with a Master degree face a substantially lower unemployment risk. This evidence is confirmed not only with respect to workers having primary and secondary education, but even for those qualified with a Bachelor degree.

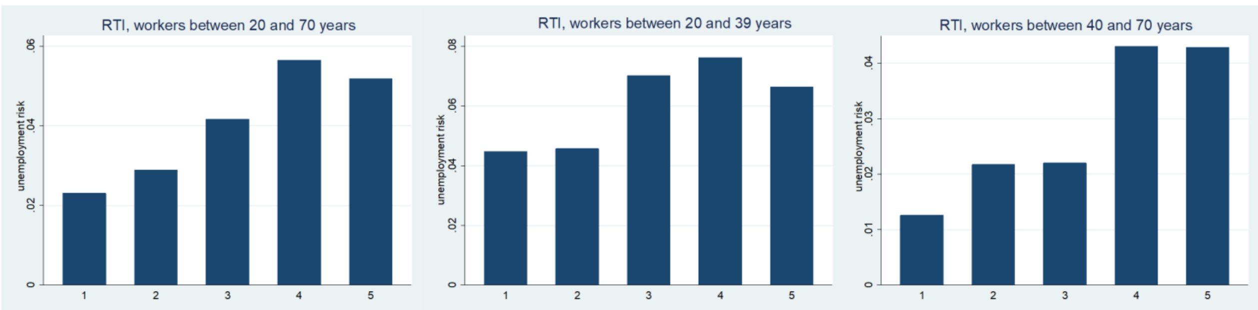
Moving to the relationship between unemployment risk and task characteristics (degree of routineness), Figure 2 displays a positive association: the larger the proportion of repetitive and encodable tasks (i.e. high RTI levels), the greater is the risk of becoming unemployed. However, the correlation becomes less clear when age cohorts are taken into account. The data show that the positive correlation between unemployment risk and routine-task intensity is relatively stronger for workers over 40 (in fact the probability of becoming unemployed increases by a factor of four moving from the first to the last quintile); while it is less marked for those under 40. Figure 3 and Figure 4 show the relationship between unemployment risk and routineness but focusing, respectively, on cognitive (RTCI) and manual tasks (RTMI). The positive relation between unemployment risk and routineness seems to be mostly driven by occupations entailing cognitive tasks, especially in the case of workers over 40. In general, when routineness is measured focusing on manual tasks only (RTMI), the relationship between unemployment risk and routine-task intensity seems to be less clear. Similarly, no clear patterns emerge when the analysis is restricted to the 20-39 age cohort.

Figure 1 - Unemployment risk by sector of activity



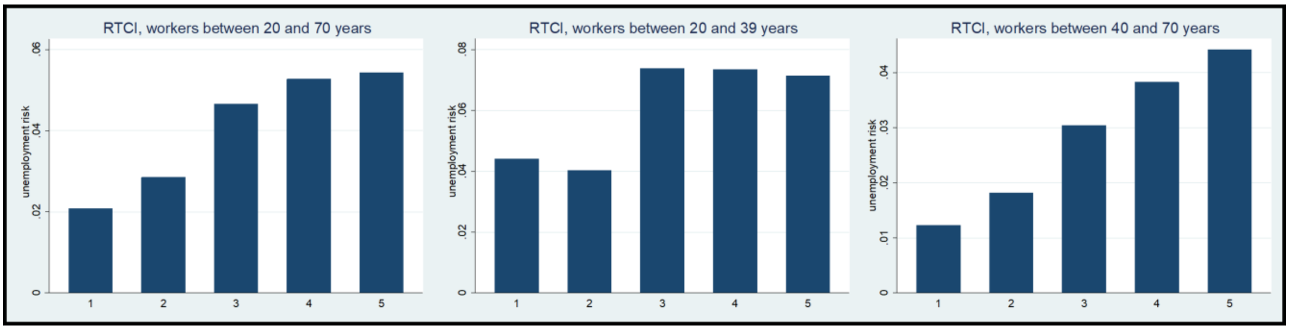
Source: own elaboration on IFLS. Note: horizontal lines indicate the average value for the total economy (blue line for U Narrow and red line for U Wide).

Figure 2 - Unemployment risk by RTI quintiles



Source: own elaboration on INAPP-ICP, ILFS.

Figure 3 - Unemployment risk by RTCI quintiles



Source: own elaboration on INAPP-ICP, ILFS.

Figure 4 - Unemployment risk by RTMI quintiles

Source: own elaboration on INAPP-ICP, ILFS.

The previous evidence suggests, albeit only descriptively, that the unemployment risk increases with the degree of routineness. Table 2 provides further evidence on the relation between labor market status (entry, exit or remaining), on the one hand, and routine-task intensity, on the other.[7] Workers are classified according to age cohort, educational attainment, type of contract and sector of activity.

Workers becoming unemployed display substantially higher RTI values than those retaining their employee status. Remarkably, also entries show relatively high RTI values compared to continued presences in the labor market. It is worth noticing that this evidence is at odd with the findings of Cortes at al. (2020) for the US economy. This might be accounted for by the amply documented (see, for a recent and thorough analysis, Dosi et al. 2019) backwardness of many Italian companies in terms of innovation and investment in workers' skills. Many small and micro firms tend, in fact, to rely on cost competitiveness strategies (i.e. often using employment contracts that allow them to make the most of external flexibility, see Cirillo et al. 2017 and Cetrulo et al. 2019) rather than innovating and strengthening their skills base by introducing efficiency enhancing innovations and recruiting high-skilled workers. This - together with the relative growth, observed in Italy after the 2008 crisis, of low-technology- and low-knowledge-intensive sectors (see, for example, Antonin et al. 2019) – might to some extent account for the entry of low-skilled and high-routine workers into the Italian labor market. Another part of the explanation might be linked to what the OECD (2017)

[7] The same evidence with specific reference to cognitive (RTCI) and manual (RTMI) tasks is reported in the Appendix (Table A4).

has repeatedly documented concerning the inadequate skill supply (in particular regarding technical and high-level skills) characterizing the Italian labor market.

Some support for these arguments can be found on observing the distribution of the RTI by employment sectors and contractual arrangement. On the one hand, low-tech industries, such as production of Food and Beverages or Textiles, show the highest RTI values, irrespective of the employment status. Low-knowledge-intensive services like (retail) Trade, Tourism and Transport are also characterized by above-average RTI values for entries, exits and continued presence in the labor market. On the other hand, workers with fixed-term contracts show higher RTI values and smaller differences between the RTI of entries and exits. This is in line with the idea that employers use fixed-term contracts to fill vacancies for routine-intensive jobs.

Table 2 - Average RTI by transition and main characteristics 2011-2017

		Continued presence	Exits	Entries
	Total	49.6	54.0	53.0
Age	15-24	55.3	55.5	54.6
	25-34	51	52.5	50.9
	35-44	50.2	54.2	53.4
	45-54	49.4	55.1	54.5
	55-64	47.1	54.3	54
	65-74	47.7	51	51.4
Education	Prim/low sec	58.1	59.1	58.5
	Upper Sec.	49.2	52.7	52.9
	Bachelor degree	39.4	41.5	43.3
	Master/Ph.D	36.5	40.3	39.1
Contract	Permanent	49.2	55.1	53.7
	Fixed	51.1	54.3	53.7
	Self-employed	50.2	51.2	50.1
Sector	Agriculture	56.3	56	56.4
	Mining and Quarrying	52.9	54.6	61.4
	Food and Beverages	61.5	66.3	62.9
	Textiles, Wood, Paper, Publ.	61.1	62.3	62.1
	Coke, Petroleum, Chemicals	51.8	55.7	55.4
	Rubber, Plastic, Metals	60.2	62.4	61.8
	Electronics, Machinery and Eq.	54	56.1	58.4
	Transport Eq.	56.6	62.5	60.8
	Furniture, n.e.s.	56.8	57.1	57.6
	Utilities	50.1	52.8	52.2
	Construction	57.2	61.9	61.6
	Trade, Tourism, Transport	54.8	56.5	57
	ICT	44.6	44.4	46.4
	Finance	44	38.9	43.2
	Real Estate	47.3	47.4	46.7
	Professional Services	48.3	50.3	50.9
	PA	34.7	36.3	35.4
	Arts, Entertainment	47.7	47.1	47.4

Source: own elaboration on INAPP-ICP and ILFS.

We can summarize the evidence provided so far in three major points. First, routine-intensive jobs are associated with higher unemployment risks. Second, the exit of aged workers employed in routine-intensive jobs contributes to the overall reduction of the Italian workforce's routineness (see Table A2 in the Appendix – this is partly in line with the arguments presented in Autor and Dorn, 2013). Third, the evolution of the Italian labor market seems to be significantly influenced by two (opposite) forces: the first (partly consistent with the RBTC hypothesis) deriving from the generalized exit of workers performing routine-intensive jobs; the second (of a more structural nature) related to the creation of routine-intensive jobs as a consequence of the growth of low-tech sectors wherein cost competitiveness strategies tend to prevail (in line with the evidence recently provided by Dosi et al. 2019). Relying on regression analysis, the following section explores, econometrically, the relevance of task characteristics in explaining employment-unemployment transitions in the Italian labor market.

5. Econometric strategy and results.

Building upon a longitudinal micro-level sample reporting information on labor market transitions observed between 2011 and 2017, we econometrically test the RQs introduced in section 3. The analysis is based on a standard Probit model with clustered standard errors. We do not follow the standard practice of estimating employment transitions using multinomial regressions (Fabrizi and Mussida, 2009; Constant and Zimmermann, 2011; Ward-Warmedinger and Macchiarelli, 2013) as our focus is on outflows and our definition of unemployment includes a large proportion of transitions toward inactivity.

As pointed out above, a large number of individual level controls is included (see Table 1) to account for idiosyncratic and structural factors likely to affect the relationship under investigation. Standard errors are clustered in 5-digit occupational categories to verify for within-occupation heterogeneity. In fact, routineness could have different 'meanings' according to the specific occupation a worker belongs to. In the case of standardized jobs in manufacturing (as in the case of repetitive work along the assembly line) or service (as in the case of call-center or customer care services), routineness can be considered the organizational precondition that could encourage the introduction of machines or ICT devices able to perform repetitive tasks more efficiently than humans. On the other hand, as Fernandez Macias and Hurley (2017 pp: 565) underline, '*repetitiveness and standardization can also be a component of skills and dexterity: as illustrated by musicians or artisans, the endless repetition of a particular task is often necessary to develop excellence in the performance*'. In the first case, one should expect a positive correlation between routine-task intensity and unemployment risk while the opposite should hold in the second case. Even within the same occupation, however, routineness may go along with repetitiveness and serious risk of substitution as also with precision accuracy and adoption of organizational patterns aimed at maximizing efficiency. Unemployment risk is modeled relying on the two indicators illustrated in the previous section: U-narrow and U-wide. Routine-task intensity, in turn, is accounted for by relying on the RTI and by distinguishing between cognitive (RTCI) and manual tasks (RTMI).

Estimates are performed adopting the following procedure. First, the relationship between probability of becoming unemployed and routineness (RQ1) is tested for the whole economy using the RTI as a measure of routine-task intensity. The results (Table 6, columns 1-4) are further distinguished among age groups and according to the two definitions of unemployment risk illustrated above. The first age group comprises all individuals between 20 and 70 years old, while the second includes those between 20 and 40. In this way, we aim to verify to what extent young workers – expected, on average, to be better equipped in terms of skills and less involved in routine occupations as opposed to older workers (see the discussion in Autor and Dorn, 2013) – behave differently to the rest of the workforce. Second, we test RQ2 by regressing unemployment risk (narrow and wide) against RTCI and RTMI, and by distinguishing, again, between young workers and the rest of the workforce (Table 6, columns 5-8).

Overall, routine-task intensity has no significant impact on transitions towards unemployment. This finding holds for both age groups and unemployment risk indicators. On the other hand, unemployment risk is negatively correlated with educational attainment (i.e. those holding a master degree, a secondary and, to a lesser extent, a bachelor degree faces a lower risk than individuals with no more than primary education), confirming the usual expectations regarding employment-unemployment determinants. Women are again found to be a relatively more fragile component of the Italian labor market, displaying a greater unemployment risk than males, while married people appear less exposed to the risk than singles. The well-known Italian territorial dualism also emerges from the results in Table 3: people living in the central and southern regions show a significantly higher probability of finding themselves unemployed than those located in the North. Contractual status matters, too: workers on fixed-term contracts and the self-employed up to 40 years are more likely to move from employment to unemployment than workers on open-ended ones. Observing the time dummies, we can clearly detect the effect of the business cycle: above-average unemployment risk in the years 2011-2013 (i.e. the toughest years of the post-2008 recession in Italy) and below-average during the 2014-2017 period (i.e. recovery phase).

Moving on to RQ2, some remarkable evidence emerges. Individuals employed in occupations characterized by a large proportion of routine cognitive activities – such as the standard tasks performed by cashiers, accountants, call-center operators, etc. – face significantly higher unemployment risks than the rest of the workforce. By contrast, those employed in occupations wherein routine manual tasks are prevalent (i.e. identified by the RTMI indicator) seem to face a comparatively lower risk. As before, this result holds for both age groups and irrespective of the unemployment risk indicator adopted. The evidence concerning the positive association between RTCI and unemployment risk is in line with what emerged from the descriptive inspection reported above (see section 4). It also lends support to one of the strongest stylized facts in the RBTC literature: routine occupations in the service sector are relatively more exposed to unemployment risks related to (among other things) labor-saving technological change. As for the negative relationship between RTMI and unemployment risk, take, for example, the case of workers engaged in assistance and care activities, people employed in services like cleaning or maintenance of public facilities, or workers employed in small handicraft manufacturing activities such as carpentries. All these occupations tend to display low complexity in terms of the numbers and the characteristics of the tasks they perform, in some cases resulting in high RTI and RTMI values. However, these occupations are hardly likely to be replaced with machines, given the often unstructured nature of circumstances in which they perform their work, while being at the same time in great demand in the Italian labor market. As for controls, no major differences arise with respect to the results reported in columns 1-4.

In order to account for sectoral-level heterogeneity, RQ1 and RQ2 are now tested separately for each of the following 18 sectors: Agriculture; Mining and Quarrying; Food and Beverages; Textiles; Wood, Paper and Publishing; Coke and Petroleum; Chemicals; Rubber, Plastic and Metals; Electronics, Machinery and Equipment; Transport Equipment; Furniture (non-electronics); Utilities; Construction; Trade, Tourism and Transport; ICT; Finance; Real Estate; Professional Services; Public Administration; Arts and Entertainment. With this test it is possible to account for crucial elements of economic (i.e. qualitatively and quantitatively heterogeneous demand flows, differences in terms of capital and investment intensity, different degrees of internationalization), technological (i.e. sectoral differences in terms of technological regimes and trajectories) and institutional (i.e. heterogeneities in terms of labor market discipline) heterogeneity that could substantially affect the relationship under investigation. First, sectors are exposed to demand flows that are heterogeneous in terms of intensity and volatility with an obviously heterogeneous impact on employment and unemployment risks. Second, as documented by a large body of theoretical and empirical literature (see, among others, Dosi, 1982; 1988), sectors differ in terms of technological trajectories and opportunities. In this case, technological heterogeneity matters with respect to the differentiated intensity that sectors may display regarding process and labor-saving innovation (i.e. those more closely subject to unemployment risk). The results, divided among age groups and restricted to the U-wide indicator, are shown in Table 4. The upper panel shows the results for the sample of workers between 20 and 70 years whereas the lower panel shows the results for workers between 20 and 40 years. Since the aim of this test is cross-sectoral comparison of the coefficients associated with RTI, RTCI and RTMI, we do not provide the coefficients associated with the other controls (which are, however, included, with the exception of sectoral dummies, in all the specifications).[8]

Sectoral estimates for the whole sample (i.e. workers aged between 20 and 70) indicate that the RTI has a positive and significant impact on unemployment probability in the entire manufacturing sector, but more specifically in the Food Industry, Coke, Petroleum and Chemicals, Manufacturing of Transport Equipment, Construction, and Utilities. A negative RTI impact is found in Finance. The greatest positive impact is found in Construction, where a 10% increase in the RTI is associated with a 2.2%increase in unemployment probability. The significant RTI impact seem to be driven by the RTCI, which is also significant in Rubber, Plastics and Metals as well as ICT and Professional Services. Marginal RTCI impacts range from 0.038 in Textiles, Wood and Paper to 0.164 in

[8] The results for all the variables and for the narrow definition of unemployment are available upon request.

Construction. As for the RTMI, it is negative in most cases and barely significant only in Agriculture, Rubber, Plastic and Metal, Electronics, ICT, Professional Services, and Arts and Entertainment.

Turning to the sample of workers between 20 and 40 years (lower panel of Table 4), the results show only small differences. In particular, it is worth noting that the marginal impact in the Food industry increased to 0.119, indicating that a 10% increase in the degree of routineness is associated with a 1.2% increase in unemployment risk. In addition, the RTI coefficient proves significant in the Real Estate sector (0.2). Workers performing a considerable amount of cognitive tasks characterized by repetitiveness and encodability (i.e. high RTCI levels) display stronger unemployment risk if employed in sectors as Rubber, Plastics and Metals, Construction, Trade, Real Estate and Professional services. Overall, this finding suggests that the positive relation between unemployment risk and routineness is largely driven by RTCI intensive occupations. On the contrary, the RTMI coefficients turn out to be negative and significant in few sectors: Agriculture, Professional Services, and Arts and Entertainment. In these sectors, the people carrying out manual tasks, even if repetitive, often work in unstructured and rapidly changing environments and so need to adapt to continuously evolving situations. Although characterized by a low endowment of formal skills and required to perform repetitive tasks, these occupations turn out to be crucial to ensure complete implementation of production (e.g. the thousands of farm workers employed in the Italian agricultural sector where traditional manual working practices still play a fundamental role). This might in turn account for the high demand for them and the relatively lower unemployment risk they face. Interestingly enough, we find that high levels of RTMI are positively associated with unemployment risk in the case of young individuals working in the public sector. In this case, the relation can be accounted for with both technology-related and structural factors. On the one hand, the massive use of ICTs may have reduced the need for workers performing repetitive manual tasks. More convincingly, on the other hand, the demand for such occupations may have dropped due to the significant reduction in public spending which followed the 2008 crisis, and to the generalized policy of externalization to private firms followed by the Italian public administration over the last two decades (Argento et al., 2010; Cirillo et al., 2017; Barbieri et al. 2019).

To sum up, the results indicate that unemployment risk is higher for workers performing routine cognitive tasks. This is particularly true in the Construction sector, in some manufacturing industries and in high value-added services like ICT and Professional services. Young workers displaying high RTI levels, in turn, face a higher unemployment risk if employed in the Food industry and in Real Estate activities. These results accord with the descriptive evidence in the previous section. Having controlled for the individual factors, unemployment risk seems to be driven by the intertwining of task characteristics on the one hand, and by the structural dynamics of sectors, on the other.

The results reported so far are based on the entire sample of employed individuals, including both employees and self-employed. In Italy, it is extremely important to give due weight to self-employment to understand the process of job creation and job destruction as these workers often hold positions similar (or overlapping) to those of standard workers. However, using the whole sample exposes our econometric analysis to a major limitation: the impossibility to control for wage dynamics, since the ILFS does not provide information on the earnings of the self-employed. As a robustness check Table 5 and Table 6 provide sectoral estimates restricting attention to employees and adding wages as control. To be even more transparent with regard to the reliability of the results shown in Table 3 and Table 4, we first run the estimation on employees only and without wages as control. In this way, we check whether our main results are driven (or affected) by the exclusion/inclusion of the ILFS' self-employed component. Secondly, we control for wages to see if such a crucial variable has any impact on the unemployment risk-routine task relationship stemming from the baseline analysis.[9] Overall, the results are only slightly affected. The major difference regards the fact that the coefficient associated with the RTI becomes negative and slightly significant in Electronics and Professional Services. Moreover, a positive correlation emerges for workers employed in Construction and, to a lower extent, in the Food Industry and Utilities. The negative correlation between routine task intensity and unemployment is confirmed in the case of Finance. Overall, restricting attention to employees reduces the statistical significance of the RTCI. This may have to do with the fact that a significant proportion of routine cognitive tasks are performed by the self-employed, in particular in the service sector. Once wages are included as additional control, in turn, the significance of the coefficient associated with the RTCI drops in the case of Professional Services and Arts and Entertainment, while the results are broadly confirmed with regard to the RTMI. In a few words, the robustness checks reported in Table 5 and Table 6 confirms the results of the baseline model, for both RQ1 and RQ2. In addition, we have shown that controlling for wages does not alter the main results set out in Table 3 and Table 4.

5. Conclusions

Exploiting a unique worker-level database on labor market transitions, we provided fresh evidence on the relationship between unemployment risk and routineness, controlling for a relevant set of individual factors that are likely to affect the relationship. This work contributes, on the one hand, to the (scant) empirical literature on the determinants of labor market transitions and, on the other hand, to the large body of research investigating the impact of technological change on employment by focusing on routine-task intensity (i.e. the RBTC literature).

The analysis was based on a novel dataset merging the longitudinal component of the Italian LFS for the years 2011-2017 – with indicators derived from the ICP (see Gualtieri et al. 2018; Cetrulo et al. 2019b). This allowed for the use of extremely granular data on labor market transitions and relevant individual characteristics including age, gender and contractual status, together with

[9] In this respect, the introduction of wages causes a problem of endogeneity due to reverse causality. However, since the focus is on RTI coefficients, this issue is of minor importance.

information on the routine intensity of occupations measured by means of the RTI computed as in Acemoglu and Autor (2011).

Overall, we find that workers employed in routine-intensive occupations do not display higher unemployment risk than the rest of the workforce. However, when cognitive and manual tasks are distinguished, it turns out that workers employed in occupations entailing a large proportion of routine cognitive tasks (such as workers employed in service occupations as cashiers or call-center operators) are in fact exposed to a relatively higher risk of becoming unemployed. On the contrary, a relatively lower risk seems to characterize workers employed in occupations entailing a large proportion of routine manual tasks. In this case, the negative relationship between unemployment risk and routineness could be driven by the sustained demand enjoyed by occupations such as professionals working in care or personal assistance activities as well as workers providing essential public services like garbage collection and cleaning services.

An additional finding concerns the relevance of sectoral-level heterogeneity as a driver of labor market transitions and unemployment risk. In manufacturing, the positive association between routine-task intensity and unemployment risk is detected in industries like Food, Metals and Transport, while a somewhat less clear pattern is observed in a labor-intensive industry like Textiles. Turning to services, a stronger association is detected in the case of Retail Trade, Tourism and Restaurants. The results are robust to a series of additional tests including a separate test on employees the main results being based on a sample including both employees and self-employed) and a robustness check with the change in wages added as a control. Moreover, all specifications are tested focusing, separately, on the whole workforce and on young workers (20-40 years old). Finally, the estimates were based on two distinct unemployment risk measures (narrow vs wide). Although some heterogeneity is detected, all the key results are confirmed.

Overall, the evidence provided in this paper offers some interesting insights into the distribution and the determinants of unemployment risks in the Italian labor market. In line with the main literature on the subject (see, among the others, Goos et al. 2009; Autor and Dorn, 2013), workers employed in occupations characterized by large proportions of routine cognitive tasks face significantly higher risks of becoming unemployed. As our descriptive and econometric evidence has shown, however, the distribution of unemployment risks among workers (and occupations) is accounted for by the dynamics of sectors. The greater unemployment risks faced by some specific categories of workers (regardless of the greater or lesser routineness of their tasks) may not only be related to labor-saving technologies expected to 'punish' primarily routine-intensive jobs. Indeed, the risk could also be associated with other sector-specific characteristics including the prevailing arrangement in terms of industrial relations and the intensity of competition (Cetrulo, 2019a; Dosi et al. 2019).

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Tables and Figures

Table 3 - Estimation results for the entire sample

	Equation (1)				Equation (2)			
	20-70 years		20-40 years		20-70 years		20-40 years	
	U narrow	U wide	U narrow	U wide	U narrow	U wide	U narrow	U wide
RTI	0.007	0.013	0.011	0.017				
	[0.006]	[0.008]	[0.010]	[0.012]				
RTMI					-0.024*	-0.025*	-0.027*	-0.026
					[0.010]	[0.013]	[0.013]	[0.016]
RTCI					0.021***	0.028***	0.028***	0.033***
					[0.006]	[0.008]	[0.010]	[0.012]
2012	0.004***	0.006***	0.007***	0.009***	0.004***	0.006***	0.007***	0.009***
	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]
2013	-0.001	0	-0.001	0.001	-0.001	0	-0.001	0.001
	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]
2014	-0.004***	-0.003*	-0.005*	-0.004	-0.004***	-0.003*	-0.005*	-0.004
	[0.001]	[0.002]	[0.002]	[0.003]	[0.001]	[0.002]	[0.002]	[0.003]
2015	-0.004***	-0.006***	-0.004*	-0.006*	-0.004***	-0.006***	-0.004*	-0.007*
	[0.001]	[0.002]	[0.002]	[0.003]	[0.001]	[0.002]	[0.002]	[0.003]
2016	-0.006***	-0.008***	-0.006*	-0.010***	-0.006***	-0.008***	-0.006*	-0.010***
	[0.001]	[0.002]	[0.003]	[0.003]	[0.001]	[0.002]	[0.003]	[0.003]
Age 25-34	0.051***	0.082***	0.015***	0.024***	0.051***	0.082***	0.015***	0.024***
	[0.006]	[0.008]	[0.003]	[0.003]	[0.006]	[0.008]	[0.003]	[0.003]
Age 35-44	0.046***	0.075***	0.008***	0.013***	0.046***	0.075***	0.008***	0.013***
	[0.006]	[0.008]	[0.002]	[0.002]	[0.006]	[0.008]	[0.002]	[0.002]
Age 45-54	0.040***	0.065***			0.040***	0.065***		
	[0.006]	[0.008]			[0.006]	[0.008]		
Age 55-64	0.036***	0.061***			0.036***	0.061***		
	[0.006]	[0.008]			[0.006]	[0.009]		
Age 65-70	0.027***	0.050***			0.027***	0.050***		
	[0.006]	[0.008]			[0.006]	[0.008]		
Female	0.005***	0.009***	0.008***	0.015***	0.004***	0.009***	0.008***	0.014***
	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]
Married	-0.008***	-0.012***	-0.014***	-0.018***	-0.008***	-0.012***	-0.014***	-0.018***
	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]
Widowed	0.002	0.002	0.001	0.001	0.002	0.001	0	0
	[0.002]	[0.002]	[0.003]	[0.004]	[0.002]	[0.002]	[0.003]	[0.004]
North-East	-0.003*	-0.004*	-0.003	-0.004	-0.003*	-0.004*	-0.003	-0.004
	[0.001]	[0.001]	[0.002]	[0.003]	[0.001]	[0.001]	[0.002]	[0.003]
Center	0.005***	0.008***	0.011***	0.017***	0.005***	0.008***	0.010***	0.016***
	[0.001]	[0.002]	[0.002]	[0.003]	[0.001]	[0.002]	[0.002]	[0.003]
South	0.014***	0.028***	0.024***	0.045***	0.014***	0.027***	0.024***	0.044***
	[0.001]	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]
Secondary	-0.007***	-0.011***	-0.012***	-0.016***	-0.006***	-0.010***	-0.011***	-0.015***
	[0.001]	[0.001]	[0.002]	[0.003]	[0.001]	[0.001]	[0.002]	[0.003]
Bachelor	-0.004	-0.007*	-0.010*	-0.014*	-0.003	-0.006	-0.009*	-0.012*

	[0.003]	[0.004]	[0.004]	[0.006]	[0.003]	[0.004]	[0.004]	[0.006]
Master	-0.014***	-0.022***	-0.025***	-0.035***	-0.012***	-0.020***	-0.022***	-0.033***
	[0.002]	[0.003]	[0.004]	[0.005]	[0.002]	[0.003]	[0.004]	[0.005]
Fixed	0.041***	0.056***	0.054***	0.071***	0.040***	0.056***	0.054***	0.071***
	[0.001]	[0.002]	[0.002]	[0.003]	[0.001]	[0.002]	[0.002]	[0.003]
Self- employed	0	0.001	0.008***	0.012***	0	0.001	0.009***	0.012***
	[0.002]	[0.003]	[0.003]	[0.004]	[0.002]	[0.003]	[0.003]	[0.004]
N	478572	484557	169688	172780	478572	484557	169688	172780

Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01

Table 4 - Estimation results by sector of activity (dependent variable: U wide)

	All workers between 20 and 70 years							
		RTI		RTCI			RTMI	
	coeff	s.e.	N	coeff	s.e.	coeff	s.e.	N
All	0.037***	[0.012]	484557	0.041***	[0.014]	-0.001	[0.018]	484557
Agriculture	0.000	[0.030]	19928	0.052	[0.034]	-0.085*	[0.047]	19928
Mining and Quarrying	-0.026	[0.067]	754	-0.027	[0.067]	0.009	[0.106]	754
Manufacturing	0.017**	[0.009]	95632	0.034***	[0.009]	-0.020*	[0.012]	95632
Food and Beverages	0.067**	[0.029]	10316	0.036	[0.030]	0.046	[0.032]	10316
Textiles, Wood, Paper, Publ.	0.003	[0.016]	16101	0.038*	[0.023]	-0.046	[0.029]	16101
Coke, Petroleum, Chemicals	0.052**	[0.027]	4914	0.074***	[0.025]	-0.022	[0.034]	4914
Rubber, Plastic, Metals	0.019	[0.017]	22887	0.060***	[0.020]	-0.047*	[0.022]	22887
Electronics, Machinery and Eq. etc. (?)	-0.007	[0.014]	16103	0.016	[0.014]	-0.035*	[0.020]	16103
Transport Eq. (?)	0.026*	[0.014]	6683	0.023	[0.020]	0.008	[0.021]	6683
Furniture, n.e.s. (?)	-0.011	[0.022]	10166	-0.007	[0.028]	-0.006	[0.038]	10166
Utilities	0.066**	[0.029]	7861	0.052***	[0.020]	0.017	[0.045]	7861
Construction	0.224***	[0.042]	34130	0.164***	[0.030]	0.070	[0.055]	34130
Trade, Tourism, Transport	0.006	[0.016]	118353	0.01	[0.016]	-0.010	[0.026]	118353
ICT	-0.003	[0.028]	10297	0.042*	[0.025]	-0.066*	[0.036]	10297
Finance	-0.042**	[0.019]	13777	-0.025	[0.018]	-0.030	[0.032]	13777
Real Estate	0.065	[0.045]	2550	0.015	[0.049]	0.082	[0.078]	2550
Professional Services	-0.006	[0.018]	48100	0.038***	[0.014]	-0.077***	[0.027]	48100
PA	0.002	[0.008]	106472	-0.005	[0.009]	0.011	[0.010]	106472
Arts, Entertainment	-0.037	[0.034]	33313	0.051*	[0.023]	-0.127***	[0.043]	33313
	Workers between 20 and 40 years							
	RTI			RTCI		RTMI		N
	coeff	s.e	N	coeff	s.e	coeff	s.e	
All	0.024*	[0.015]	172780	0.044***	[0.015]	-0.021	[0.019]	172780
Agriculture	-0.032	[0.060]	5935	0.075	[0.064]	-0.172*	[0.099]	5935
Mining and Quarrying	0.157	[0.149]	198	0.077	[0.147]	0.141	[0.135]	198
Manufacturing	0.014	[0.012]	36950	0.035*	[0.014]	-0.023	[0.018]	36950
Food and Beverages	0.119***	[0.042]	4222	0.059	[0.061]	0.086	[0.056]	4222
Textiles, Wood, Paper, Publ.	-0.011	[0.028]	6168	0.032	[0.030]	-0.057	[0.044]	6168
Coke, Petroleum, Chemicals	0.065*	[0.037]	1867	0.055	[0.045]	0.023	[0.055]	1867
Rubber, Plastic, Metals	0.027	[0.025]	9200	0.074*	[0.029]	-0.048	[0.033]	9200
Electronics, Machinery and Eq.	-0.015	[0.023]	6618	0.026	[0.021]	-0.060	[0.038]	6618
Transport Eq.	0.043*	[0.018]	2688	0.019	[0.022]	0.036	[0.024]	2688
Furniture, n.e.s.	-0.014	[0.037]	3852	-0.006	[0.053]	-0.014	[0.074]	3852
Utilities	0.062	[0.057]	2335	0.075	[0.050]	-0.032	[0.092]	2335
Construction	0.221***	[0.055]	14059	0.166***	[0.041]	0.057	[0.075]	14059
Trade, Tourism, Transport	0.018	[0.021]	49130	0.038*	[0.023]	-0.038	[0.035]	49130
ICT	0.006	[0.039]	4449	0.037	[0.028]	-0.048	[0.038]	4449
Finance	-0.073*	[0.036]	4653	-0.043	[0.033]	-0.052	[0.059]	4653

Real Estate	0.206*	[0.112]	921	0.263*	[0.152]	-0.087	[0.205]	921
Professional Services	0.000	[0.030]	19478	0.055*	[0.022]	-0.102*	[0.046]	19478
PA	0.001	[0.021]	24759	-0.026	[0.021]	0.041*	[0.022]	24759
Arts, Entertainment	-0.053	[0.044]	12138	0.033	[0.036]	-0.123***	[0.047]	12138

Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01

Table 5 - Estimation results for the specification with wages (employees only)

	RTI		N	RTI		log(wage)		N
All	0.043***	[0.013]	358869	0.031*	[0.012]	-0.033***	[0.003]	358906
Agriculture	0.038	[0.058]	8512	0.026	[0.058]	-0.021***	[0.006]	8582
Mining and Quarrying	-0.03	[0.063]	746	-0.036	[0.062]	-0.017	[0.018]	748
Manufacturing	0.015*	[0.009]	83029	0.001	[0.008]	-0.040***	[0.003]	83031
Food and Beverages	0.060*	[0.028]	8670	0.051*	[0.029]	-0.028***	[0.007]	8647
Textiles, Wood, Paper, Publ.	0.011	[0.019]	13103	-0.017	[0.017]	-0.051***	[0.007]	13131
Coke, Petroleum, Chemicals	0.034	[0.027]	4560	0.026	[0.025]	-0.021*	[0.010]	4666
Rubber, Plastic, Metals	0.011	[0.017]	19700	-0.001	[0.016]	-0.044***	[0.005]	19700
Electronics, Machinery and Eq.	-0.016	[0.014]	15187	-0.024*	[0.014]	-0.026***	[0.005]	15185
Transport Eq.	0.016	[0.013]	6457	0.008	[0.014]	-0.027***	[0.006]	6459
Furniture, n.e.s.	0.005	[0.028]	7668	-0.012	[0.027]	-0.060***	[0.008]	7677
Utilities	0.050*	[0.030]	7463	0.025	[0.025]	-0.042***	[0.011]	7460
Construction	0.232***	[0.054]	19801	0.201***	[0.050]	-0.077***	[0.009]	19772
Trade, Tourism, Transport	0.004	[0.017]	75788	-0.012	[0.016]	-0.036***	[0.003]	75798
ICT	0.009	[0.028]	7860	-0.004	[0.028]	-0.031***	[0.007]	7869
Finance	-0.029*	[0.015]	11270	-0.030*	[0.013]	-0.012***	[0.004]	11274
Real Estate	0.062	[0.056]	1184	-0.008	[0.076]	-0.042***	[0.012]	1187
Professional Services	0.002	[0.021]	26533	-0.038*	[0.023]	-0.035***	[0.007]	26543
PA	0.004	[0.007]	98310	0	[0.006]	-0.015***	[0.001]	98316
Arts, Entertainment	-0.032	[0.038]	24620	-0.06	[0.044]	-0.042***	[0.006]	24642

Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01

Table 6 - Estimation results by sector of activity, specification with wages (employees only, dependent variable: U wide)

	Employess only, no wage					Employees only with wages						
	RTCI		RTMI		N	RTCI		RTMI		log(wage)		N
All	0.046***	[0.015]	0.002	[0.019]	358869	0.023*	[0.012]	0.014	[0.017]	-0.033***	[0.003]	358906
Agriculture	0.083	[0.066]	-0.068	[0.074]	8512	0.067	[0.064]	-0.059	[0.061]	-0.021***	[0.006]	8582
Mining and Quarrying	-0.031	[0.060]	0.01	[0.084]	746	-0.058	[0.054]	0.057	[0.081]	-0.017	[0.018]	748
Manufacturing	0.033***	[0.009]	-0.020*	[0.012]	83029	0.011	[0.009]	-0.013	[0.012]	-0.040***	[0.003]	83031
Food and Beverages	0.029	[0.030]	0.044	[0.034]	8670	0.005	[0.030]	0.055	[0.037]	-0.029***	[0.007]	8647
Textiles, Wood, Paper, Publ.	0.037	[0.023]	-0.033	[0.028]	13103	0.006	[0.021]	-0.032	[0.028]	-0.051***	[0.007]	13131
Coke, Petroleum, Chemicals	0.056*	[0.027]	-0.024	[0.033]	4560	0.042*	[0.025]	-0.016	[0.030]	-0.020*	[0.010]	4666
Rubber, Plastic, Metals	0.057***	[0.020]	-0.052*	[0.022]	19700	0.033*	[0.020]	-0.040*	[0.021]	-0.043***	[0.005]	19700
Electronics, Machinery and Eq.	0.016	[0.013]	-0.048*	[0.021]	15187	0.002	[0.014]	-0.040*	[0.021]	-0.025***	[0.005]	15185
Transport Eq.	0.015	[0.019]	0.003	[0.022]	6457	0.013	[0.017]	-0.005	[0.022]	-0.027***	[0.006]	6459
Furniture, n.e.s.	-0.005	[0.033]	0.015	[0.045]	7668	-0.029	[0.033]	0.025	[0.048]	-0.060***	[0.008]	7677
Utilities	0.038*	[0.019]	0.014	[0.043]	7463	0.013	[0.018]	0.022	[0.036]	-0.042***	[0.011]	7460
Construction	0.168***	[0.043]	0.081	[0.067]	19801	0.143***	[0.040]	0.077	[0.063]	-0.076***	[0.009]	19772
Trade, Tourism, Transport	0.011	[0.021]	-0.014	[0.030]	75788	-0.002	[0.019]	-0.017	[0.025]	-0.036***	[0.003]	75798
ICT	0.008	[0.031]	0.002	[0.046]	7860	-0.013	[0.031]	0.013	[0.047]	-0.031***	[0.008]	7869
Finance	-0.014	[0.013]	-0.03	[0.021]	11270	-0.017	[0.012]	-0.021	[0.019]	-0.012***	[0.004]	11274
Real Estate	0.096	[0.077]	-0.053	[0.058]	1184	0.034	[0.091]	-0.065	[0.068]	-0.042***	[0.012]	1187
Professional Services	0.043***	[0.015]	-0.069*	[0.028]	26533	0.011	[0.017]	-0.080***	[0.029]	-0.034***	[0.006]	26543
PA	0.001	[0.008]	0.005	[0.009]	98310	-0.002	[0.006]	0.002	[0.007]	-0.015***	[0.001]	98316
Arts, Entertainment	0.077***	[0.025]	-0.156***	[0.047]	24620	0.025	[0.030]	-0.120*	[0.056]	-0.038***	[0.005]	24642

Standard errors in brackets. * p<0.10 **, p<0.05, *** p<0.01

Appendix

Figure A1 - Unemployment risk by age cohort

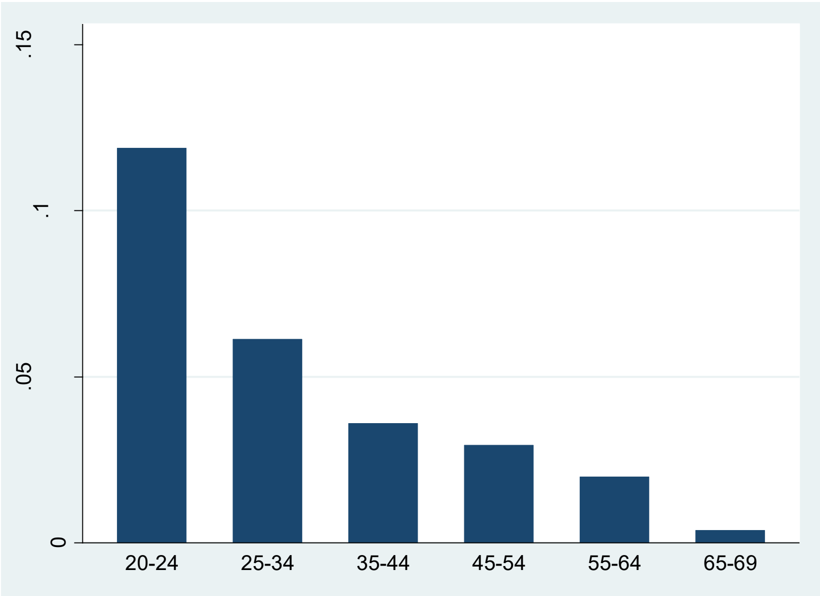


Figure A2 - Unemployment risk by educational attainment

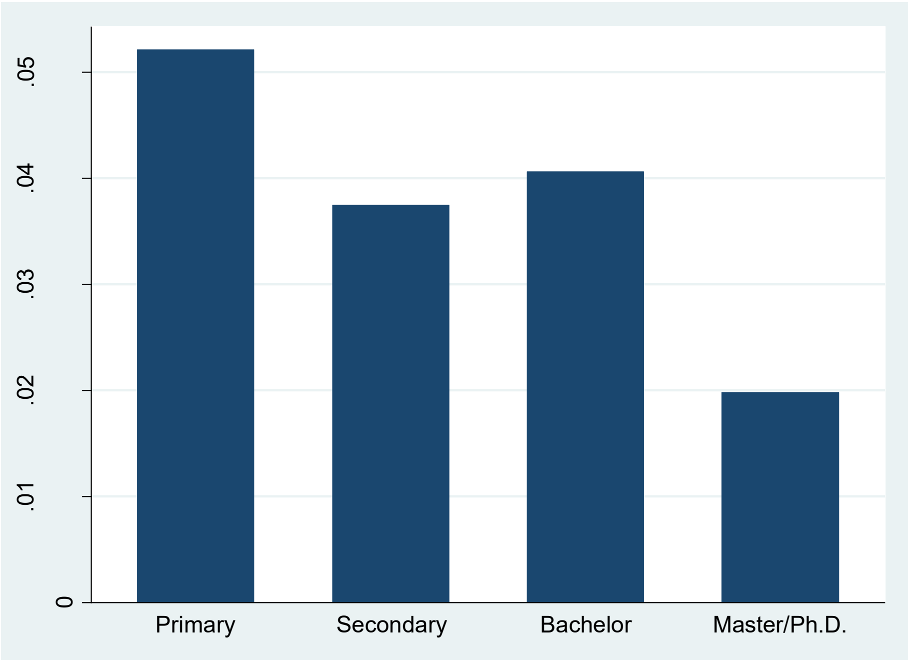
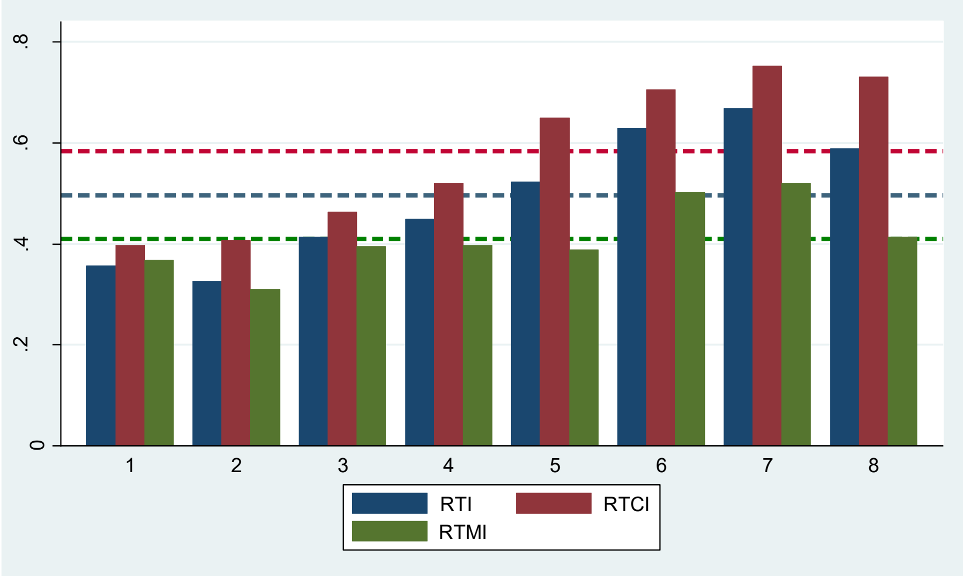


Figure A3 - Routine Task Indexes by ISCO-1digit occupation



Source: own elaboration on INAPP-ICP, ILFS

Table A1 - Growth rates of value added by sector

	2010	2011	2012	2013	2014	2015	2016	2017	2018
Total	1.7	0.6	-2.4	-1.5	0.2	0.9	1.1	1.7	0.9
Agriculture	0.4	1.9	-2.6	1.4	-2.3	4.6	0.2	-3.9	0.9
Industry	6.6	1.1	-2.6	-2.2	-0.1	1.2	2.3	3.6	1.8
Construction	-3.7	-5.2	-6.9	-5.1	-5.7	-0.8	0.4	0.7	1.7
Trade, Tourism, Transport	2.1	1.6	-3.5	-1.6	1.4	2.2	1.7	3.3	2.0
ICT, Finance, Real estate	0.6	1.5	-0.4	-1.5	0.6	0.8	0.8	1.2	0.1
Other svcs	1.6	-0.1	-3.7	-0.8	1.0	0.6	2.5	0.6	0.4
PA	-0.2	-0.2	-1.3	-0.4	0.5	-0.5	-0.9	-0.2	-0.3

Source: ISTAT.

Table A2 - Transition rates from employment (unemployment) to unemployment (employment): average 2011-2017

	U narrow				U wide			
	E to U	U to E	Balance	Turnover	E to U	U to E	Balance	Turnover
Agriculture	3.1	3.4	0.4	6.5	5.3	5.9	0.6	11.2
Mining and Quarrying	2.2	1.0	-1.1	3.2	4.4	1.9	-2.4	6.3
Food and Beverages	2.8	3.2	0.4	6.0	4.0	4.8	0.7	8.8
Textiles, Wood, Paper, Publ.	3.0	2.4	-0.6	5.4	4.4	3.4	-1.0	7.9
Coke, Petroleum, Chemicals	2.0	2.5	0.5	4.5	2.7	3.6	0.8	6.3
Rubber, Plastic, Metals	2.4	1.8	-0.6	4.2	3.5	2.5	-1.0	6.0
Electronics, Machinery and Eq.	1.8	1.6	-0.2	3.4	2.5	2.2	-0.3	4.7
Transport Eq.	1.6	2.0	0.4	3.6	2.0	2.7	0.7	4.7
Furniture, n.e.s.	2.8	2.1	-0.7	4.9	4.0	2.9	-1.1	7.0
Utilities	2.3	2.2	-0.1	4.5	3.1	3.1	0.0	6.2

Construction	6.2	4.5	-1.7	10.7	9.1	6.6	-2.5	15.7
Trade, Tourism, Transport	3.4	3.8	0.3	7.2	5.0	5.4	0.4	10.4
ICT	2.0	2.2	0.2	4.2	2.9	3.0	0.1	5.9
Finance	1.0	1.4	0.5	2.4	1.3	1.9	0.6	3.2
Real Estate	3.0	3.3	0.4	6.3	4.1	4.7	0.6	8.8
Professional Services	2.9	3.4	0.5	6.3	4.2	4.7	0.5	8.9
PA	1.0	1.4	0.4	2.4	1.6	2.3	0.7	3.8
Arts, Entertainment	4.7	5.5	0.8	10.2	7.0	8.2	1.3	15.2
Total	2.8	2.9	0.1	5.7	4.1	4.3	0.2	8.4

Source: own elaboration on LFS data.

Table A3 - The evolution of RTI, RTCI and RTMI between 2011 and 2017

	RTI	RTCI	RTMI
2011	50.01	58.70	41.24
2012	49.95	58.75	41.09
2013	49.86	58.60	41.10
2014	49.77	58.51	41.05
2015	49.76	58.56	40.98
2016	49.66	58.46	40.92
2017	49.55	58.32	40.88
Change 2011-2017	-0.46	-0.38	-0.36

Source: own elaboration on INPP-ICP and LFS. RTI= Routine Task Index; RTMI= Routine Task Manual Index; RTCI= Routine Task Cognitive Index. All indices are standardized over the range 0-100.

Table A4 - RTMI and RTCI by transition and main characteristics, average 2011-2017

		Permanencies		Exits		Entries	
		RTCI	RTMI	RTCI	RTMI	RTCI	RTMI
Age	15-24	64.3	44.3	65.2	43.6	64.2	43.1
	25-34	59.3	42.3	61.9	42	60.5	40.9
	35-44	58.6	41.6	64	42.8	64.1	41.3
	45-54	58.4	40.6	65	43.1	65.7	41.6
	55-64	56.7	38.6	64.9	42.1	65.4	41
	65-74	56.4	39.8	68.4	33.4	66.6	35.8
Education	Prim/low sec	68.2	44.9	69.8	45	70	43.8
	Upper Sec.	57.3	41.3	62	42.3	62.9	41.8
	Bachelor degree	50.7	32.1	51.2	34.9	52.4	36.7
	Master/Ph.D	43.6	34.5	47.8	36.4	46.8	35.4
Contract	Permanent	58	40.6	65.2	43	65.2	40.7
	Fixed	60.6	41.2	64	42.9	63.7	42.3
	Self-employed	58.3	41.9	60.2	41.6	59	41.2
Sector	Agriculture	64.9	45.2	65	44.6	65.2	45
	Mining and Quarrying	59.2	45.3	59.9	47.4	70.9	47.5
	Food and Beverages	65	53.3	69.3	56.8	67.8	52.9
	Textiles, Wood, Paper, Publ.	65.4	52.3	67.3	52.4	68	51.4
	Coke, Petroleum, Chemicals	54.5	48.1	59.9	49.1	60.2	48.4
	Rubber, Plastic, Metals	64.5	51.8	68.1	51.8	67	52
	Electronics, Machinery and Eq.	58	48.2	61.6	48.1	63.5	49.9
	Transport Eq.	61.1	49.4	67.6	52.5	66.3	51.1

Furniture, n.e.s.	62.8	48	63.1	48.2	63.6	48.6
Utilities	57	42.9	61.5	43	60.8	42.6
Construction	65.2	46.5	71	48.2	70.7	47.9
Trade, Tourism, Transport	64.1	43.7	66.3	44.2	67.3	44
ICT	43.9	46.9	46.4	44.2	47.3	46.6
Finance	48.4	41.7	43	38.8	48.8	40.1
Real Estate	54.4	41	54.5	41.1	54.9	39.8
Professional Services	53	44	56.8	43.5	57.2	44.1
PA	48.3	27.1	50.3	27.6	49.7	26.8
Arts, Entertainment	64.2	32.3	65.6	29.9	65.7	30.3
Total	58.3	41	63.8	42.7	63.3	41.6

Source: own elaboration on INAPP-ICP and LFS. RTMI= Routine Task Manual Index; RTCI= Routine Task Cognitive Index. All indices are standardized over the range 0-100.