Does routinization affect occupation dynamics? Evidence from the 'Italian O*Net' data

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Abstract

Taking advantage of a dataset providing O*Net-type information on the task content of Italian occupations, this work analyses empirically if and to what extent employment patterns are affected by task characteristics in terms of 'relative routinarity'. The investigation focuses on the 2005-2016 period relying on a panel including all Italian 4-digit occupations. Occupations characterized by relatively large shares of routinary tasks are penalized in terms of employment dynamics. This result proves to be robust despite the inclusion of a large number of worker, occupation and industry-level controls. A considerable heterogeneity between manufacturing and services is highlighted. While in services the negative relationship between routine task and employment is verified, in manufacturing the same relationship becomes statistically weak. Moreover, Italian occupations with high level of routinary tasks seems to get 'younger' rather than 'older'. According to our empirical results, in highly routinary occupations youth employment tends to grow rather than shrink. Finally, being in highly routinary occupations seems to be less an issue for workers with college degree given the weaker significance of the RTI coefficient as compared to the whole sample model.

Keywords: polarisation, technological change, occupations

JEL Codes: J21, O33, J24

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1. Introduction

In the last fifty years, the diffusion of Information and Communication Technologies (ICTs, hereafter) has led to a profound transformation of production and employment structures. The 'computerization' of workplaces with the following set of process and organisational innovations are largely recognized as key drivers of polarisation in the relative distribution of employment opportunities and incomes (for a review of the relevant literature, see Vivarelli, 2014). Indeed, classical economists such as Adam Smith, Karl Marx and Joseph Schumpeter had already identified technological change as a fundamental factor explaining changes in terms of division of labour; quality and quantity of labour demand; as well as income structures. By rediscovering precious analyses on the matter as Braverman (1973)'s, it is also possible to crystallise key evolutionary phases of capitalistic development by observing the peculiar way in which technical changes, division of labor (i.e. management and organization), quantity and quality of work tend to mould each other.

As a large body of literature recognized, ICTs unfold with significantly asymmetric effects on jobs and incomes. Occupations characterised by relevant shares of 'routinary' (i.e. codifiable and easily replicable) tasks face a relatively stronger risk of substitution by machines and electronic devices. On the contrary, occupations characterized by tasks entailing a high degree of creativity and/or complex reasoning (i.e. 'strictly human' tasks) tend to face lower risks of substitution. In addition, occupations characterized by a large share of complex tasks might experience an increase in their relative demand given the (potential) complementarity between these tasks and IT tools. A dynamics similar to that of high-skill jobs might also characterize the occupations located at the bottom of the skill distribution: the prevalence of tasks requiring frequent social interaction and/or manual dexterity makes these occupations difficult to replace or relatively more resilient to the risk of technological unemployment.

From the 1990s onwards, a growing number of empirical contribution identified a dynamics of *polarization* in occupational and income structures. A dynamics detected in most - even if not all, as highlighted by Bogliacino and Lucchese, 2015; Fernández-Macías and Hurley, 2016 and, more recently, by Cirillo, 2016 - advanced economies (Spitz-Oener, 2006; Autor and Dorn, 2009, 2013; Goos et al. 2014). Almost all studies focusing on that matter converged in recognizing ICTs (together with the phenomenon of productive delocalization or 'offshoring' mounting since the 1970s) as the major engine of these asymmetric labor market developments. The flourishing of studies investigating employment and wages polarization coincides with the transition from analytical approaches concentrating their attention solely on 'technology vs skills' – the popular 'Skill-Biased Technological Change' (SBTC, hereafter) approach proposed, among the others, by Katz and Murphy (1992) and Katz (1999) - to approaches focusing on the very object of potential substitution by machines and IT devices: tasks. Task-based analysis – whose related literature (see, for example, Autor, 2013 and Autor and Dorn, 2013) is known as 'Routine Biased Technological Change' (RBTC, hereafter) – start distinguishing jobs no longer on the basis of their generic 'skill endowment' but according to the relative share of routinary tasks characterizing each of them. Being the object of coding and replication by intelligent machines, routinary tasks are guilty (or presumed to be so) for human labor crowding-out and inequalities in the labor market.

However, the relationship between technological change, employment and incomes is decisively influenced by a multiplicity of other factors differentiating economies: macroeconomic conditions; heterogeneities in terms of industrial specialization, institutions and technological capabilities; heterogeneous competitive/hierarchical positioning in Global Value Chains (GVCs, hereafter). On the other hand, the conceptualization of tasks concerning their relationship with technological and organizational factors call into question a series of theoretical and methodological criticalities that may give rise to problems concerning interpretation and generalization of the empirical results. In addition, it is important to emphasize that a significant portion of the studies supporting the hypothesis of an ICT-driven polarization are based on general equilibrium frameworks. Such framework relies on strong hypothesis as perfect competition and agents rationality. As a result, the room for considering complex (but crucial) elements characterizing the

technology-employment relationships as institutions, constraints on agents' rational behaviour and technological heterogeneities is substantially reduced (Pianta and Vivarelli, 2003; Gualtieri et al. 2018).
A number of criticalities concerning the conceptualization of routine tasks as well as their operationalization in empirical terms are extensively discussed by Fernández-Macías and Hurley (2016, pp: 3). These authors argue that '*the main problem…is the concept of routine itself, which is one of those commonly used terms which are difficult to define and measure precisely.*' To better clarify this issue[1], they stress that '*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*'. From a different perspective, it is also argued that '*the concept of routine also has strong subjective connotations: routine is often simply understood as 'boring', and a task can be (subjectively) defined as routine even if it does not involve so much repetitiveness and standardization in strict terms*'.
From a strictly empirical standpoint, when it comes to characterize occupations in terms of tasks' characteristics measurement problems are not less relevant. To begin with, occupations are significantly heterogeneous even if analysed at high digits of disaggregation. Therefore, extremely detailed information on tasks and skill referring to occupations at the highest possible level of disaggregation are required so to capture (properly) both between and within-occupation heterogeneities. The second problem relates to the complex and multidimensional nature of tasks (on this point, see the thorough discussion in Fernández-Macías and Hurley, 2016). In order to derive a comprehensive measure of task routinarity, a plurality of data are needed: physical, cognitive and procedural characteristics of tasks; degree of standardization; role of technologies and machineries; managerial, organizational and relational characteristics of the workplace. The absence of a single one of these dimensions exposes to the risk of partial or even distorted measures of task routinarity. Finally, the important role of institutional and structural factors requires an explicit consideration of the latter when the technology-task-labor market nexus is explored. Even in this case, lacking an appropriate account of such factors may bias both measurements and interpretations.
According to Goos et al. (2014), a large majority of European economies have experienced a process of job polarization as the one predicted by the RBTC hypothesis. Looking at OECD data for Italy (our object of analysis), between 1995 and 2015 both high and low skill occupations experienced similar rates of growth: over 4.5%. On the other side, middle skill occupations experienced a decrease of around 10%. Beyond past trends, some recent works have estimated the share of jobs at medium and high risk of automation.[2] Against this background, this work aims at analysing, empirically, the role of tasks' routinarity in explaining the employment dynamics of Italian occupations. The investigation focuses on the 2005-2016 period relying on a panel including all Italian 4-digit occupations. We take advantage of a unique database merging information on: occupations (employment, wages, socio-demographic and institutional characteristics); demand and investment dynamics at the 4-digit industry level; skills and tasks at the 4-digit occupation-level. Task and skill variables stem from the INAPP-ISTAT survey on occupations – Survey on Italian Occupations (*Indagine Campionaria sulle Professioni*, ICP hereafter) - representing the only information repertoire referring to a European economy (i.e. Italy) and overlapping (in terms of methodology and content) the US Occupational Information Network (O*Net, hereafter) database. The ICP provides extremely detailed information on tasks, skills and work contents for the whole spectrum of Italian occupations surveyed at the 5th digit[3]. This type of information allow to build highly precise indicators measure the degree of occupations' relative routinarity overcoming some of the methodological and conceptual problems mentioned before. For this study we adopt the Routine Task Index (RTI) (Autor et al. 2003) testing the

[1] Fernández-Macías and Hurley (2016) provide a review of the various theoretical and methodologial approaches to the concept of routine proposed in the literature.
[2] Relying on PIAAC (Program for the International Assessment of Adult Competencies) data providing information on workers' skills and tasks, Arntz et al. (2016) estimate that the 10% of Italian jobs are at high risk of automation-driven crowding out. This number is slightly higher than the OECD average (9%).
[3] The ICP is realized every five years. Currently, two editions are available referring to the years 2007 and 2012. More details are provided in the methodological section.

contribution of the 'relative routinarity' of tasks in explaining the recent employment dynamics of Italian occupations. We firstly provide an extensive descriptive analysis exploring the evolution of Italian employment in relation to a multiplicity of dimensions (age, gender, educational attainment, macro-occupational categories, industry and time span) vis-a-vis the degree of task routinarity characterizing occupations. We than rely on regression analysis to verify whether their characterization in terms of routinary task affects the employment dynamics of occupations. The empirical investigation is carried out on the whole sample of Italian 4-digit occupations and then replicated exploring the role of industry (manufacturing vs services); and occupation-level heterogeneities (young workers and workers with college degree vs the rest of the workforce).

The key results can be wrapped up as follows. Occupations characterized by relatively large shares of routinary tasks are penalized in terms of employment dynamics. This result proves to be robust despite the inclusion of a large number of worker, occupation and industry-level controls. However, the negative correlation between routine task intensity and employment dynamics turns out to be stronger during the 2011-2016 period (i.e. the post-2008 crisis phase characterized by almost 3 years of recession) as opposed to the 2006-2010 one. Employment in routinary occupations shrinks significantly in services while the same is not true by examining manufacturing. Looking at workers age, the empirical results report a picture rather different to the one emerging from previous analysis. Indeed, the Italian occupations characterized by relatively high share of routinary tasks do not seem to 'get old' as in the US case examined by Autor and Dorn (2009). In fact, young workers employment (15-34 years) tends to grow at the top of the RTI distribution while the opposite occurs for the rest of the age cohorts (35-65 years old). Finally, the relationship between workers educational level (i.e. having or not a college degree) goes in the expected direction displaying a negative and significant correlation between the employment dynamics of workers with college degree and the relative intensity of routinary tasks.

The reminder of the paper is the following. The next section reports a brief review of the literature studying the relationships between technological change, task characteristics and labor market dynamics. Section 3 provides a thorough descriptive exploration of the dynamics of Italian employment adopting an occupation-level perspective and focusing on skills, degree of tasks routinarity (distinguishing between manual and cognitive tasks), sectors, workers' age and educational attainment. Research questions, econometric strategy and results are reported in section 4 while section 5 concludes providing some final remarks.

2. Technology, tasks and labor markets

Identifying the elements explaining employment and wages polarization has been the key goal of many influential contributions in economics. The first group of studies looks at the US labor market and focuses on skills. Building upon the SBTC hypothesis, this stream of works (for a comprehensive review, see Bound and Johnson, 1992 and Acemoglu, 2002) moves from the consideration that new technologies, particularly those related to ICTs, are complementary to high skills (mostly those cognitive skills related to the use of computers and IT devices) while might penalize medium-skilled jobs since the latter are more easily replicable and made redundant by machines. A second strand of literature focuses on the increasing degree of international economic integration among countries with differentiated factor endowments. The offshoring of the more labor and low-skill intensive parts of production is identified as a relevant driver of changes in employment demand and structure across both advanced and less advanced economies. Subsequent studies take on board both explanations – i.e. the SBTC and the offshoring hypothesis – stressing also the significant interactions between availability of ICTs and opportunity to offshore and manage fragmented and internationalized productions. In an attempt to interpret empirical regularities difficult to explain within the standard SBTC framework, Autor et al. (2003) and, later on, Acemoglu and Autor (2010) propose a *task-based model of technological change*. The key advancement of this approach concerns the switch from the skills workers use to the tasks they actually perform. Autor et al. (2003) put forth the hypothesis that as a consequence of the decline in ICTs' relative price the demand for jobs characterized by routine task shrinks as well due to the increasing number of standardized human operations that are realizable (at low cost) by computers and machines. This is the base of the RBTC intuition according to which, in contrast to what is expected to happen to rotuinary occupations, jobs characterized by creative and complex task are increasingly demanded also due to their comparative advantage in computer usage.

Moving along these lines, Autor et al. (2006) and Goos and Manning (2007) find a linkage between the heterogeneous routinarity of jobs and the polarization of employment and wage structures in the US and the UK. According to these analyses, employment growth concentrates in low and high skill occupations, while jobs in the middle of the skill distribution experience a contraction (i.e. polarization). In short, creative high-skill jobs as well as low skilled ones implying lots of manual dexterity and/or intensive social interactions are less likely to be crowded out by computers and, thus, of being in shortage of demand. The RBTC have been extensively tested from an empirical point of view. Autor et al. (2003) rely on the American Dictionary of Occupation Titles (DOT) to derive detailed information on tasks' characteristics. The latter are than matched with industry-level information on employment dynamics and, note less relevantly, on investment in computer and IT capital. In line with the RBTC hypothesis, it emerges that the increase in IT investments induces a parallel increase in analytical and interactive non-routine task inputs favouring, in turn, a contraction of routine task inputs decrease. Similar patterns are reported by Michaels et al. (2014) analysing the relation between wages (distinguishing workers by education level) and ICT capital in 11 economies (including United States, Japan and nine European countries) investigated over the 1980-2004 period. Their result show that in industries where a relatively faster ICT growth is detected labor demand shifts from middle-educated to highly educated workers. They report that the introduction of ICTs accounts for more than a quarter of the growth in demand for highly educated workers.

The relation between introduction of ICTs and changes in labor demand is also at the core of Autor et al. (2013 pp: 1590)'s work. Exploiting spatial data on 722 Commuting Zones (CZ) proxing local labor markets and observed between 1980 and 2005, they show that computerization in the US has crowded out low-skill workers performing routine tasks while '*complementing the abstract, creative, problem-solving, and coordination tasks performed by highly-educated workers*' (again in line with the RBTC predictions). From a theoretical standpoint (Autor et al. 2013 pp: 1559), the analysis relies on a general equilibrium model of '*routine-task*' replacing technological change. In this model, technological progress is completely reflected in the declining cost of '*computerizing routine tasks which can be performed both by computer capital and low-skill ("noncollege") workers in the production of goods. The adoption of computers substitutes for low-skill workers performing routine tasks—such as bookkeeping, clerical work, and repetitive production and monitoring activities—which are readily computerized because they follow precise, well-defined procedures*'.[4] An important implication of the Autor et al. (2013 pp: 1559)'s general equilibrium model concerns the ratio between the elasticity of substitution in production (between computer capital and routine tasks); and the elasticity of substitution in consumption between goods and services. As a consequence of the fall in computers' price '*wages for low-skill labor performing routine tasks to fall relative to wages for low-skill labor performing manual tasks*.' This is the crucial element leading to polarization: '*low-skill labor flows accordingly from goods to services, while high-skill labor remains in goods production*'.

One of the first contributions of this field focusing on Europe is the one by Spitz-Oener (2006). Focusing on changing occupational skill requirements in West Germany between 1979 and 1999, she identifies a shift toward analytical and interactive activities moving away from cognitive and manual routine tasks. These results hold within occupations, within occupation-education groups as well as within occupation-age

[4] Making more explicit the key assumptions of their model, Autor et al. (2013 pp: 1559) stress that '*the falling price of accomplishing routine tasks using computer capital complements the "abstract" reative, problem-solving, and coordination tasks performed by highly-educated workers such as professionals and managers, for whom data analysis is an input into production. Critically, automation of routine tasks neither directly substitutes for nor complements the core jobs tasks of loweducation occupations—service occupations in particular—that rely heavily on "manual" tasks such as physical dexterity and flexible interpersonal communication. Consequently, as computerization erodes the wage paid to routine tasks in the model, low-skill workers reallocate their labor supply to service occupations*'.

groups. Goos et al. (2014) provided further evidence of a RBTC-type process of polarization unfolding in most of the European economies. The authors rely on a 1993-2010 series of European Union Labour Force Survey (ELFS) providing employment data at the 2-digit International Standard Occupational Classification (ISCO) and 1-digit industry-level codes.[5] Regarding the measurement of routine task, Goos et al. (2014) adopt the same approach we put forth here relying on the Autor and Dorn (2013)'s RTI.[6] Summing up their findings, Goos et al. (2014, pp: 2524) emphasize that '*the employment structure in Western Europe has been polarizing with rising employment shares for high-paid professionals and managers as well as low-paid personal service workers and falling employment shares of manufacturing and routine office workers…job polarization is pervasive across European economies in the period 1993–2010 and has within-industry and between-industry components that are both important*'.

A more complex European picture emerges by looking at findings in Fernández-Macías and Hurley (2016) and Cirillo (2016). These works adopt a partially different conceptual and empirical approach as compared to Goos et al. (2014)'s one putting in question the reliability of task indexes used by the RBTC literature (Fernández-Macías and Hurley, 2016); and emphasizing the role of industry-level technological trajectories, country-level heterogeneities, institutional and demand factors (Cirillo, 2016). As for the former, the empirical test of the RBTC predictions display no pervasive pattern of job polarization in Europe along the time span taken into account (1995–2007). Stressing the country-level heterogeneity they detect, the authors underline that in some cases (Germany, France, Netherlands and to a lower extent the UK) is possible to identify job polarization but in many others not (Finland and Spain). When polarization is not detected, a process of skill upgrading seems instead to emerge more in line with the SBTC's predictions. Cirillo (2016) studies job polarization by clustering ISCO categories into four major groups: managers, clerks, craft workers and manual workers. Using a mixed sectoral-occupation level approach, she finds a clear polarization trend in Europe with relevant differences between manufacturing and services: polarization clearly emerges in services while this is not always the case for manufacturing.

A routine intensity measure – i.e. the Routine Intensity Index (RII) – partially different from the RTI has been recently proposed by Marcolin et al. (2018). This measure is based on individual-level information stemming from the PIAAC OECD survey. The RII focuses on the degree of freedom workers have in organizing their activities building upon four PIAAC questions concerning: degree of freedom in establishing the sequence of tasks; degree of freedom in deciding the type of tasks to be performed on the job; frequency with which workers plan their own activities; frequency with which workers organise their own time.[7] Analysing a panel (2000-2010) of 20 OECD economies, these authors find that employment tend to increase in non-routine occupations with a more significant evidence in services as opposed to manufacturing.

3. Data and descriptive evidence

This work exploits, for the first time, a unique longitudinal database[8] merging 'off-the-shelf' measures (Goos et al. 2014 pp: 2511) of task, skills and work attitudes at the 4-digit occupation-level stemming from the ICP INAPP-ISTAT dataset; information on employment, income, workers' socio-demographic characteristics,

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[5] Goos et al. (2014) rely on data for the following 16 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom.

[6] While we build the 'Italian RTI' taking advantage of O*Net type variables stemming from the INAPP-ISTAT SOI allowing to compute indicators overlapping those proposed by Autor et al. (2003) and Autor et al. (2006), Goos et al. (2014)'s RTI index is mapped European ISCOs categories by imputing DOT values referring to the US occupational categories (Standard Occupations Classification – SOC, hereafter).

[7] The Marcolin et al. (2018)'s RII follows the conceptualization proposed by Oldenski (2012). The latter emphasizes the linkage between *autonomy* and *degree of task routinarity*. According to this view, routine intensive task, due to their replicability and codifiability, imply little autonomy for the employed individual at work.

[8] Previous evidence stemming from a preliminary version of this database are provided by Gualtieri et al. (2018).

contract types at the 4-digit occupation level drawn from the Italian Labor Force Survey; and AIDA Bureau-Van Dyik (AIDA BvD, hereafter) balance-sheet data on revenues, demand, investments and R&D expenditure referring to representative occupation-industry 4-digit cells. Such combination of highly detailed information allows exploring, empirically, the evolution of Italian employment at the occupation-sectoral level accounting simultaneously for the role of supply, demand, structural factors as well as for the whole set of indicators used in the RBTC literature to capture to role of routine tasks. In what follows, we firstly provide a brief description of the INAPP-ISTAT ICP database as well as of the other key variables included in the analysis. Subsequently, we report the outcome of a thorough descriptive inspection of the evolution of Italian employment focusing on occupation, sectors, workers age and educational attainment as well as degree of task routinarity.

3.1 The dataset

As argued, the analysis carried out here relies on an extremely rich combination of information sources. Skills and tasks variables stem from the INAPP-ISTAT ICP. The ICP survey has been realized twice (2007 and 2012) involving a representative sample of 16.000 workers covering the whole spectrum of the Italian 5-digit occupations (i.e. 811 occupational codes) building, conceptually and methodologically, on the American O*Net.[9] Relying on about 1-hour long face-to-face interviews, the ICP is capable to provide more than 400 variables on skill, work contents, attitudes, tasks and many other subjective and objective information on occupations.[10]

The two waves of the ICP adopt two different occupation classification due to a change in such classification operated by ISTAT in 2011. The 2007 wave relies on the 'Classificazione delle Professioni 2001' (CP2001, hereafter) while the 2012 one on the 'Classificazione delle Professioni 2011' (CP2011, hereafter).[11] Both classifications cluster occupations into eight macro-professional groups (the so-called 'Grandi Gruppi Professionali') as follows: *1st group* - Lawyers, Entrepreneur, top managers; *2nd group* – Intellectual and academics, Scientific and high-specialization occupations; *3d group* - Technical occupations; *4th group* - Executive and Administrative Occupations; *5th group* – Qualified personnel in sales, services and related occupations; *6th group* - Farmers, crafts and specialized occupations; *7th group* - Blue Collar and machinery operators; *8th group* - Non-qualified occupations. The *9th group* includes the Armed forces which are not accounted for in this analysis. The ICP offers a massive amount of information concerning work contents and attitudes, skills and tasks, technological and organizational nature of productive processes in which

[9] The O*Net database builds upon the Dictionary of Occupational Titles (DOT, hereafter) which since 1939 reported information on occupations with a specific focus on the skills required in the public employment service. The O*Net is based on the SOC providing for each elementary occupation variables on knowledge, skills, abilities and tasks. The key dimensions included in the O*Net are the following: *worker characteristics* – permanent characteristics affecting workers performance as well as their propensity to acquire knowledge and skills; *worker requirements* – workers characteristics matured by means of experience and education; *experience* - characteristics mostly related to past work experience; occupation – a large set of variables referring to requirements and specific features of the various occupations.

[10] The major difference between SOI and O*Net regards the source of information on which the two survey rely. The SOI is based entirely on face-to-face interviews to job incumbents while the O*Net relies on a mixed pool of job incumbents and labor analysts. It should be noted, however, that both SOI's waves has been followed by a continuous set of qualitative analysis (focus groups involving labor market experts and practitioners) aimed, among the other things, at periodically validate and maintain information stemming from job incumbents interviews. The SOI sample stratification strategy has two steps. First, a large number of companies is randomly selected (the public administration is not included). Once the company-level sample is selected, questionnaires are submitted via Computer Assisted Personal Interviewing (CAPI) techniques to workers.

[11] In 2011, there has been a revision of the Italian occupation classification. Such break in the classification do not allow a one-to-one matching at the 4th digit while a crosswalk based on conversion matrices is possible at the 3d digit. To exploit the SOI's information at their maximum level of detail, this work relies on variables the 4th digit. As a consequence, the both descriptive and econometric analysis focus on two distinct time period: 2005-2010 (relying on the CP2001 occupation classification) and 2011-2016 (relying on the CP2011 classification).

interviewed workers are involved, degree of standardization and control of workers operations, importance and nature of social interactions. For the sake of this study we focus exclusively on the set of dimensions considered by Autor et al. (2003) and subsequent contributions to compute the RTI index (see table 2 below). The richness of information provided by the ICP, however, might represent a valuable starting point to put the research forth and to test new measures of task routinarity. This can help overcoming, at least in the Italian case, some of the measurement and conceptual issues signalled by Fernández-Macías and Hurley (2016). The ICP variables used in this analysis are collected at the 5th digit of the Italian occupation classification and then aggregated at the 4th digit (using employment weights stemming from the ISTAT RCFL) to realize the ICP-RCFL-AIDA matching.

Data on employment, wages, workers socio-demographic characteristics (age, gender, educational status), labor market institutions (share of workers with temporary contract) at the 4-digit occupation level are drawn from the ISTAT RCFL.[12] Every year a sample of more than 250.000 families resident in Italy is interviewed (for a total of about 600.000 individuals) distributed in about 1.400 Italian municipalities. Interviews are based on a mixed CAPI-CATI strategy. The individual questionnaire is composed of a *general section* (reporting personal and family information) and 12 sections, from A to N, each characterized by a specific information objective: A) respondents detail; B) employment status in the reference week; C) main job; D) secondary job; E) previous work experience; F) job search; G) employment services and employment agencies; H) vocational education and training; I) self-perceived condition; L) detailed information on the family of the respondent; M) information provided by the interviewer; N) pending codings. The quality of RCFL information is particularly high due to large sample size, refined sampling strategy as well as to the regulatory provisions according to which respondents are obliged to reply.

The economic variables are taken from the AIDA-BvD archive. The latter provides balance-sheet information for the whole population of Italian corporations.[13] The AIDA-BvD variables included in the analysis are the following: total revenues (proxing the evolution of aggregate demand), capital stock, and total R&D expenditure. To be used as controls in the econometric analysis[14], the company-level economic and structural variables stemming from the AIDA-BvD archive are aggregated at the 4-digit industry-level. We first reconstructed the employment distribution of each 4-digit occupation into the 4-digit ATECO sectors. For each (4-digit occupation – 1-digit sector) cell, balance-sheet information referring to 4-digit sectors are than summed up and weighted by the number of employees belonging to that specific 4-digit occupation. The distribution of employment by 4-digit occupation over all 4-digit industries has been calculated using ISTAT RCFL data (for the details, see Gualtieri et al. 2018).

As a result, we end up with an integrated database having 4-digit occuation-1-digit sector cells as relevant statistical unit and matching information on employment, wages, workers and labor market characteristics (RCFL variables); task related variables stemming from the ICP[15]; variables on revenues, capital stock and R&D expenditure (AIDA-BvD variables computed as weighted averages). Table 1 provides the list of variables included in the analysis reporting details on measurement units and sources.

[12] The ISTAT RCFL represents the main official source of statistical information on the Italian labour market. The RCFL information is the basis for the official employment and unemployment estimates (on both quarterly and annual basis) as well as information on the main aggregates of labour supply - occupation, sector of economic activity, hours worked, type and duration of contracts, training.

[13] The AIDA-BvD archive do not provide information on micro and small enterprises as the non-limited companies. In this way, a not so insignificant part of the Italian companies is excluded from the analysis. However, the amount of information that can be drawn from AIDA constitute an absolutely significant share of the Italian economy.

[14] In the econometric analysis, the relevant unit of analysis is the occupation (CP2001 and CP2011 4-digit) – sector (ATECO, 1-digit) cell for which RCFL representative labor market variables are available while. Similarly, the match with the RTI is guided by the 4-digit occupation codes.

[15] Note that the indicators computed building on ICP variables vary by occupation only.

Table 1. Variables – description and sources

Variables	Description	Source
Labor market variables		*RCFL*
• Total employment • Women (%) • Young workers (%) • College degree • Temporary employment • Median wage	• # employees by 4-digit occupation/1-digit ATECO sector • Share of women (employees) over the total by 4-digit occupation/1-digit ATECO sector • Share of 15-34 years old employees over the total by 4-digit occupation/1-digit ATECO sector • Share of employees with college degree over the total by 4-digit occupation/1-digit ATECO sector • Share of employees with temporary contract over the total by 4-digit occupation/1-digit ATECO sector • Median wage reported by the RCFL respondents by 4-digit occupation/1-digit ATECO sector (data available for the 2011-2016 period only)	
Task-related variables		*ICP*
• RTI index and subcomponents	• Dimensions comprised in the RTI by 4-digit occupation (see table 2 for details)	
Economic variables		*AIDA-BvD*
• Total revenues • Capital stock • R&D investments	• Weighted average of the median revenues as reported by companies' balance sheet at the 4-digit ATECO level. The adopted weight is the log of total employment at the ATECO 4-digit. • Weighted average of companies' capital stock as reported by companies' balance sheet at the 4-digit ATECO level. The adopted weight is the log of total employment at the ATECO 4-digit. • Weighted average of the median R&D expenditure as reported by companies' balance sheet at the 4-digit ATECO level. The adopted weight is the log of total employment at the ATECO 4-digit.	

The ICP Routine Task Index

In line with Goos et al. (2014), we measure the degree of task routinarity relying on the RTI index. Taking advantage of the ICP's questionnaire, we are able to account for the same task-related dimensions considered by Autor et al. (2003) and followers in their empirical analysis. In our case, however, we are able to go a step further than Goos et al. (2014) since our task and skill variables are directly referable to the Italian economy. In fact, the availability of ICP variables shields us from potential methodological problems arising when information referring to the American occupational structure (i.e. stemming from the US O*Net repertoire) are matched (i.e. by means of the SOC-ISCO crosswalk) to labor market data referring to significantly different economies as the European ones. As in Autor et al. (2003 pp: 1298), we build upon five dimensions allowing to qualify jobs according to their relative routinarity. The RTI includes three dimensions (two referring to the degree of manual and cognitive task routinarity, the other to the degree of 'non-routinarity' of tasks) resulting from the combination of the five DOT dimensions considered by Autor et al. (2003). The detailed component of the RTI we use in this analysis are reported in table 2 The RTI adopted here is significantly close to the one in Autor and Dorn (2013) and Goos et al. (2014) and can be formalized as follows:

$$RTI_{k,t} = RC_{k,t} + RM_{k,t} - (NRCA_{k,t} + NRCI_{k,t} + NRM_{k,t} + NRMIA_{k,t}) \quad (1)$$

Where for each 5-digit occupation *k* (k = 1,…,811) and ICP wave *t* (t=2007, 2012) 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 proxing the degree of repetitiveness and of pre-determination 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. The indicator in (1) rises with the importance of routine task in each 4-digit occupation while declines with the importance of abstract and non routinary tasks.

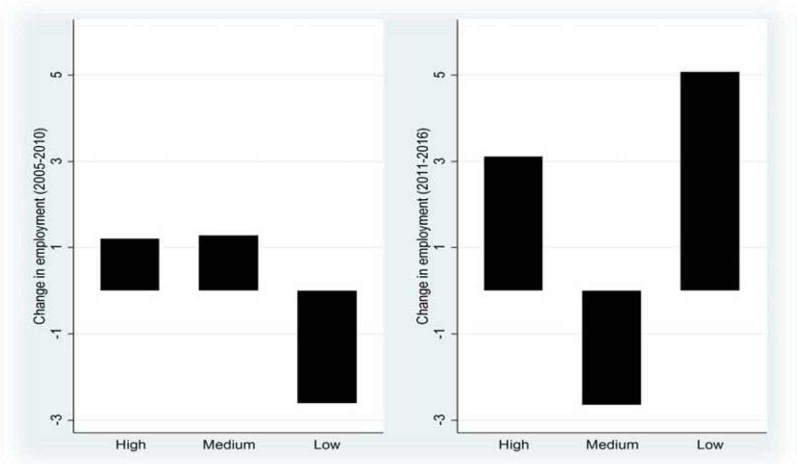
Table 2. The Routine Task Index

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

3.2 Skills, tasks and employment in Italy: descriptive evidence

This section provides a first descriptive glance of the Italian employment (dynamics and structure between 2006 and 2016) looking at occupations, sectors, skills and tasks. The exploration is conducted by looking at total employment as well as focusing on young workers (15-34 years) and employees with college degree. To be in line with the econometric investigation that follows (see above), the descriptive analysis of Italian employment data is carried out over two distinct time periods: 2005-2010 and 2011-2016. As a first step, we inspect the change in total employment by standard skill groups (low, medium and high-skill). The grouping is based on the 1st digit of the CP2001 and CP2011 classifications (see above for details): high-skilled group includes ‘managers’, scientific professionals’ and ‘tech professionals’ (i.e. the 1st, 2nd, and 3^{d} 1-digit groups); the medium-skilled group includes ‘clericals’, ‘service clericals’ and ‘specialized blue collars’ (i.e. the 4th, 5th, and 6th 1-digit groups); the low-skilled group includes ‘blue collars’ and non-specialized professionals’.

Figure 1. Change in employment by skill levels



Source: authors' elaboration on RCFL data

Two distinct patterns seem to emerge. During the 2005-2010 period, the evolution of total employment by skill groups points to a soft upgrading with a moderate increase of medium and high-skill jobs and a contraction of low skill ones. Moving to the 2011-2016 phase, however, a dynamics of polarization is recognizable with employment growing at the top and at the bottom and shrinking for medium-skilled workers. Nevertheless, the patterns emerging by looking at skills might be affected by the high level of aggregation and the strong within-skill group heterogeneity. The second step concerns the analysis of employment dynamics by quintiles of the RTI distribution (figure 2).[16] Even in this case, two heterogeneous patterns are recognizable. In the first time period, employment grows in the 1st and 3d quintiles of the RTI distribution; while decreases in the 2nd and 5th (high levels of routine task). Between 2011 and 2016, thus, occupations characterized by high level of routine task (4th and 5th quintiles of the RTI distribution) are considerably penalized in terms of employment dynamics. To capture potential heterogeneities between manual and cognitive tasks, the analysis reported in figure 2 is replicated by considering the quintile of the Routine Manual Index.

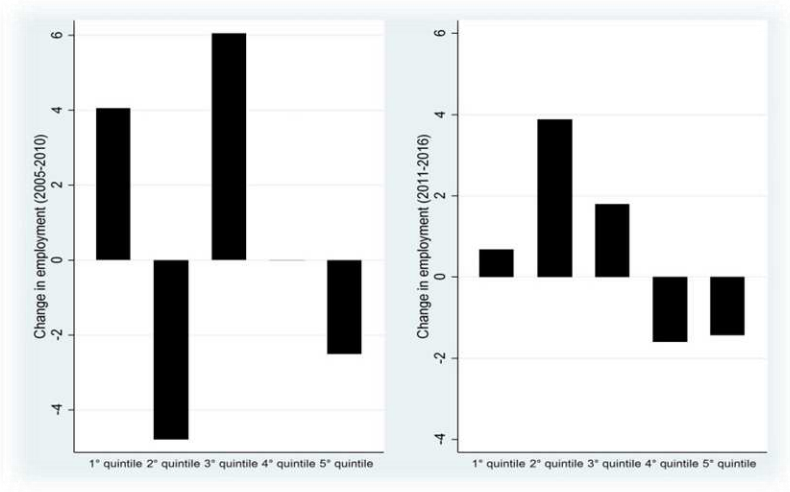
The latter is computed considering only the RTI's components related to manual tasks (2):

$$RMI_{k,t} = RM_{k,t} - (NRM_{k,t} + NRMIA_{k,t}) \quad (2)$$

Interestingly enough, employment seems to shrink everywhere but in the middle of the RMI's distribution. This is particularly true in the first period (2005-2010) while a less clear picture characterizes the second one. Such trend might be linked to the generalized contraction of the manufacturing productive base that interested Italy in the last decade (Cirillo and Guarascio, 2015) given the importance of manual tasks for the processes characterizing that sector. In total, a penalization of occupations featured by significant shares of manual routine tasks is observable all across the considered time span: occupations comprised in the 4th quintile display a contraction between 2005 and 2010 while those in the 5th (highest shares of routine tasks) shrink during both sub-periods.

[16] The change in employment by RTI quintiles is analysed as follows. Occupations (4-digit) are firstly ranked according to their RTI intensity (referring to year 2007 for the first time period (2005-2010) and 2012 for the second (2011-2016)). Than five classes reflecting such ranking are built and total employment by each class calculated (summing up all the employees belonging to each occupations falling in each RTI class/quintile). As higher the quintile of the RTI distribution as more intense the degree of routine task in the considered occupation. Such reading holds for all the task-based indicators analysed in this descriptive section.

Figure 2. Change in employment by RTI's quintiles



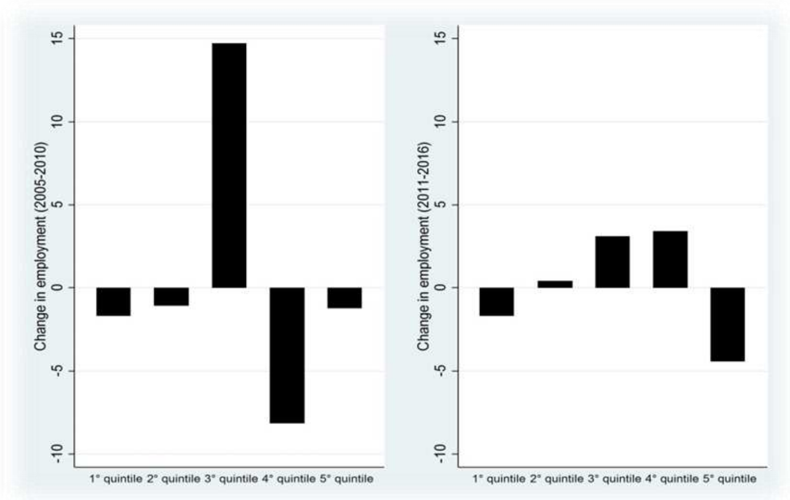
Source: authors' elaboration on RCFL-ICP data

The change in employment during the selected time periods is studied also in relation to the RTI's sub-components more strictly related to cognitive tasks. We define RCI (3) the indicator computed by subtracting to the RC the NRCA and the NRCI components (see table 2).

$$RCI_{k,t} = RC_{k,t} - (NRCA_{k,t} + NRCI_{k,t}) \ (3)$$

Over the RCI's quintiles, Italian employment seems to assume an inversely U-shaped form. This results is particularly evident in the second period (2011-2016) and slightly less during the first (2005-2010). In both cases, however, employment shrinks in correspondence of the 1st and the 5th quintiles of the RCI growing (heterogeneously) in the middle with the largest increase characterizing the 2nd quintile.

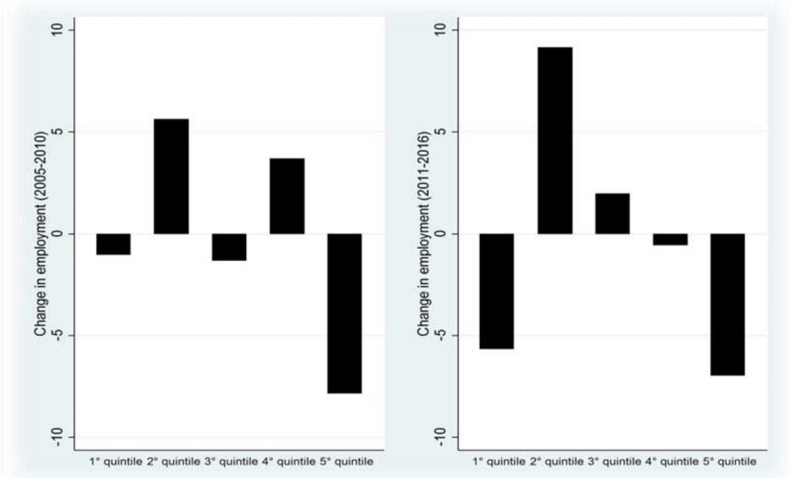
Figure 3. Change in employment by RMI's quintiles



Source: authors' elaboration on RCFL-ICP data

This result is particularly relevant since it suggest an evolution of Italian employment *vis a vis* the relative 'routinization' of cognitive tasks which partly contrasts with the RBTC predictions. In this respect, the negative dynamics of non-routinary occupations (i.e. occupations featured by the prevalence of creative and complex cognitive tasks) signalled by the drop in correspondence if the 1st quintile might be explained (again) by the weakening of the Italian industrial structure which exacerbates after 2008 resulting in a contraction of many high-tech/high-skill intensive industries.[17]

Figure 4. Change in employment by RCI's quintiles

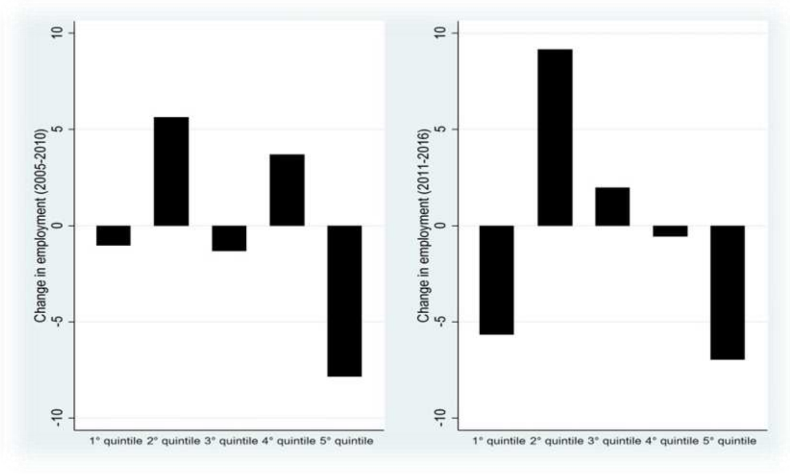


Source: authors' elaboration on RCFL-ICP data

Occupations and industries

The descriptive investigation of Italian employment by tasks' characteristics is put one step forward by exploring the routine task intensity over occupational categories (CP2001 and CP2011 occupation macro-groups or 'Grandi Gruppi Professionali', see above); and industries (1-digit).

Figure 5. Routine task intensity (RTI) by macro-professional categories



Source: authors' elaboration on RCFL-ICP data

Figure 5 reports the average RTI intensity[18] by occupational macro-group highlighting a pattern in line with the expectations: occupations lying at the top of the skill distribution (i.e. managers, high technical and intellectual professions) are characterized by significantly low RTI values. The RTI increases as we go down

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[17] For a detailed empirical analysis of the recent structural developments of the Italian economy, see Lucchese et al. (2016).

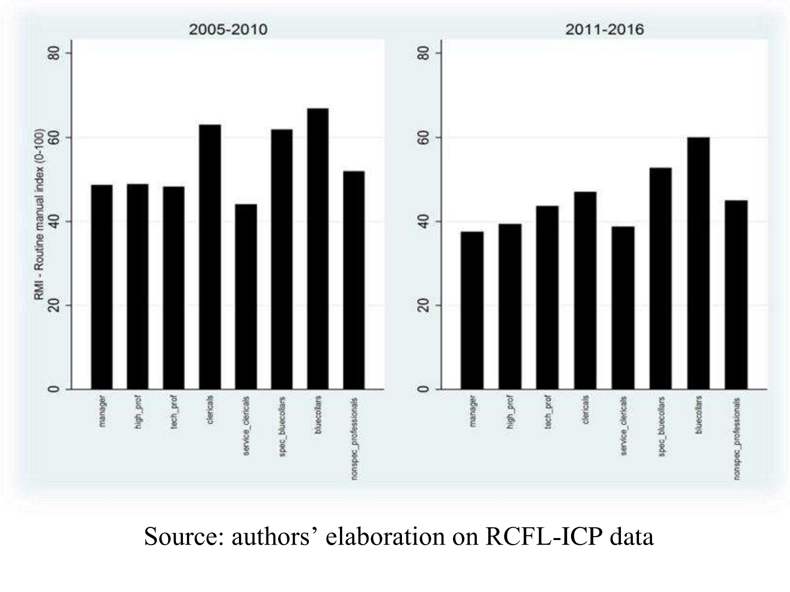
[18] For each 1-digit macro occupational group we computed the average RTI values by averaging over all 5-digit occupations comprised in such group.

along the skill distribution with clericals and bluecollars (both specialized and non-specialized) reporting values that are more than double those of managers and top level professionals. This pattern turns out to be substantially homogeneous across time periods. An analogous analysis is carried out for the RMI and RCI indicators (figures 6 and 7). This breakdown might be of some interest due to the differentiated relevance of manual and routine tasks in occupations as clericals and blue collars. In the clericals' case, significant risk of substitution by machines derives from the prevalence of standardized, repetitive and easily encodable cognitive tasks. A typical example is that of accounting and low-level administrative tasks which are now largely performed by computers and IT devices (for an historical reflection on the pattern of machine-driven task substitution, see Autor 2015). On the other hand, blue collars (particularly those operating in automated production chains) are generally more characterized by the prevalence of manual tasks which, in turn, are easily performable by means of intelligent machines and robots (on this point, see the recent contribution by Acemoglu and Restrepo, 2018).

With respect to routine manual task, macro-occupational groups do not show a strong heterogeneity as the one emerging by examining the RTI distribution. Between 2005 and 2010, the occupations displaying the highest RMI levels are clericals and blue-collars (both specialized and non-specialized). All other occupations, however, show rather homogeneous RMI values with those at the top of the distribution (i.e. managers and high professionals) staying in line with the rest of the occupational structure. A pattern more similar to the one reported in figure 4 is detected in the second sub-period. Here, the RMI increases going down along the skill distribution with clericals (with the exception of service clericals) and blue collars displaying the highest degrees of (manual) task routinarity.

The strongest heterogeneity among occupational categories concerns the relative degree of (cognitive) routine task. As expected, un-structured and complex cognitive tasks characterize in a relevant way occupations at the top as managers, intellectual and high-tech professionals. Contrarily, high level of standardization and repetitiveness of cognitive tasks as well as low levels of creative/adaptive thinking (see table 1) seems to feature the occupations laying in the mid-bottom of the skill distribution: clericals, service clericals and blue-collars.

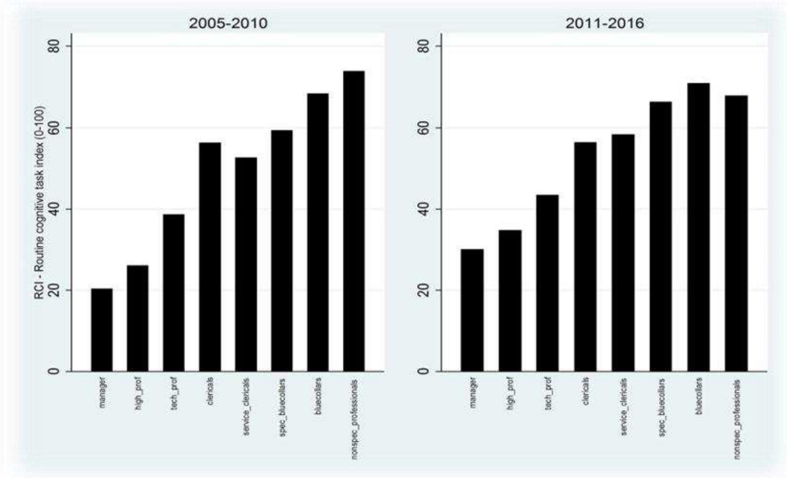
Figure 6. Routine manual task intensity (RMI) by macro-professional categories



Source: authors' elaboration on RCFL-ICP data

To dig further into the Italian occupational structure, we report the ranking of 4-digit occupations by RTI intensity (table 3). The 2005-2010 top-ten shows that occupations characterized by the highest degree of routine task are almost all belonging to the blue-collar macro group (mostly manufacturing operators): *navy machineries operators, electrical and ICT equipment assemblers, unqualified personnel in manufacturing, assembly line operators*.

Figure 7. Routine cognitive task intensity (RCI) by macro-professional categories



Source: authors' elaboration on RCFL data

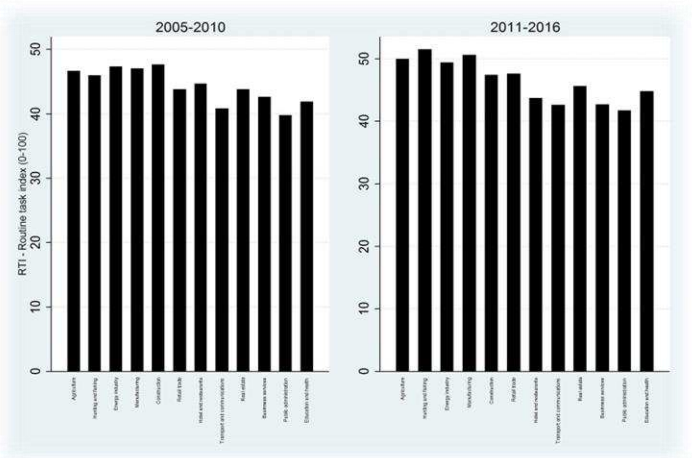
The only services occupation included in the 2005-2010 RTI top-ten, however, is a very paradigmatic one. Bank tellers rank 6th reflecting the significant share of predetermined and encodable tasks that are more and more performed by ATMs and computers via online-banking.

Table 3. Italian occupations (4-digit) ranked by RTI

Top ten 'routinary' occupations (RTI ranking - 2005-2010)
Navy machineries operators
Electrical and ICT equipment assemblers
Spinning and winding machinery operators
Petroleoum-related machineries operators
Unqualified personnel in manufacturing
Bank tellers
Manufacturing assembly line operators
Mining and quarrying plant operators
Mass wood production operators
Mass production of chemical products operators
Top ten 'routinary' occupations (RTI ranking - 2011-2016)
Textile industry operators
Operators for the production and refining of non-ferrous metals
Navy machineries operators
Operators for the production of other rubber products
Machinists for the production of other rubber products
Paper and printing industry operators
Operators for the production of bricks and tiles
Drivers of bookbinding and related machinery
Offset printers operators
Precision mechanics

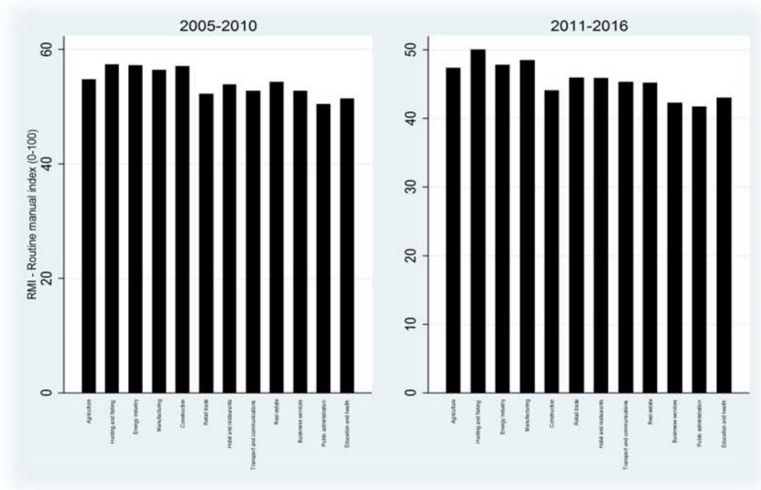
The 2011-2016 top-ten confirms the prevalence of blue collars and manufacturing operators as the more ‘routinized’. Interestingly enough, many occupations related to the ‘paper and printing’ industry are included in the ranking. Even in this case, such evidence goes along with a pronounced trend of labor-saving innovations characterizing these industries. Moving to macro-sectors, a weaker heterogeneity in terms of routine task indicators emerges (figures 8, 9 and 10). The highest RTI levels are detected in the manufacturing, construction and agricultural sectors while lower levels characterize sectors as real estate, hotel and restaurants, transports and education and health. This trend is rather homogeneous over time. However, it is worth noticing that manufacturing sectors show higher RTI, RMI and RCI levels irrespective of the considered time period. Overall, this subdivision in 1-digit macro sectoral groups does not allow appreciating marked heterogeneities as the ones emerged by looking at occupational clusters. Nevertheless, a deeper exploration entailing higher disaggregation levels as well as the usage of sector-occupation cells may unravel significant heterogeneities related to sectoral specificities.[19]

Figure 8. Routine task intensity (RTI) by macro-sector



Source: authors’ elaboration on RCFL-ICP data

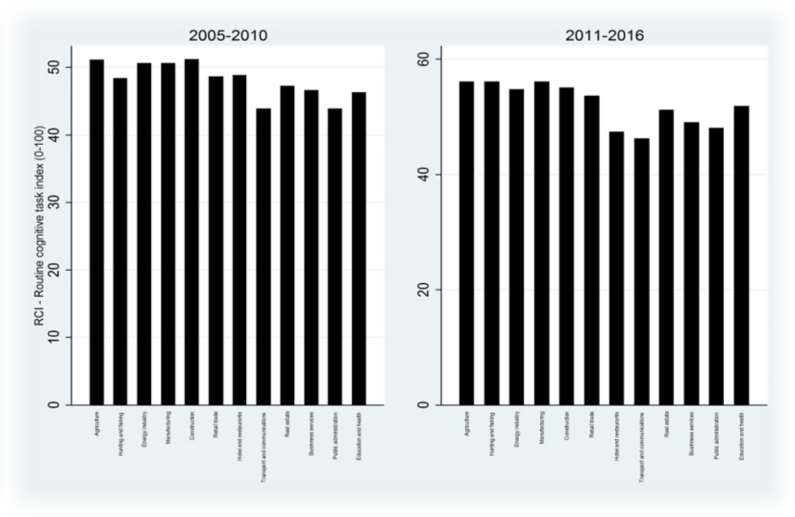
Figure 9. Routine manual task intensity (RMI) by macro-sector



Source: authors’ elaboration on RCFL-ICP data

[19] An extensive analysis of sectoral-occupation cells at the 4-digit level exploring both tasks characteristics as well as the technological characteristics of processes is forthcoming (information stemming from a thorough qualitative analysis of the Italian industrial structure realized by INAPP in 2013 and named ‘Atlante Lavoro’).

Figure 10. Routine cognitive task intensity (RCI) by macro-sector

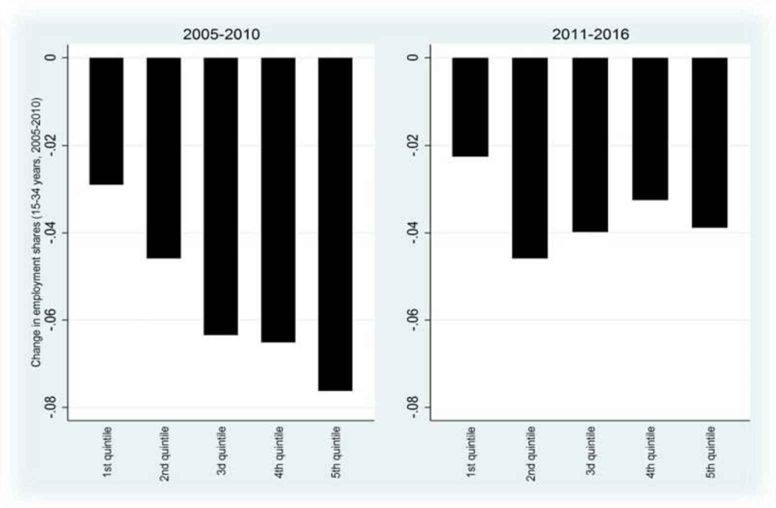


Source: authors' elaboration on RCFL-ICP data

Are Italian jobs getting old?

This descriptive analysis ends by posing a question closer to the one spelled out by Autor and Dorn (2009). That is, we verify descriptively whether occupations characterized by high share of routine task are 'ageing' (i.e. ageing is proxied by the contraction of the share of young workers employed in such occupations). This information is of a certain importance since one should expect that the higher the share of routine task in a certain occupation the lower the inflow of young workers and thus the stronger the relative 'occupation ageing'. Being equipped with 'fresh' skills (i.e. skills expected to be relatively more complementary with new technologies), in fact, young workers are likely to be attracted by sectors and occupations requiring creative and adaptive skills rather than by jobs entailing highly repetitive and standardized tasks. Of course, and in line with the predictions of the RBTC, one should also expect to find a sustained demand devoted to low-skill routine tasks implying, for example, high-levels of manual dexterity or 'social capabilities' as those characterizing operators in the education, health and social-assistance sectors.

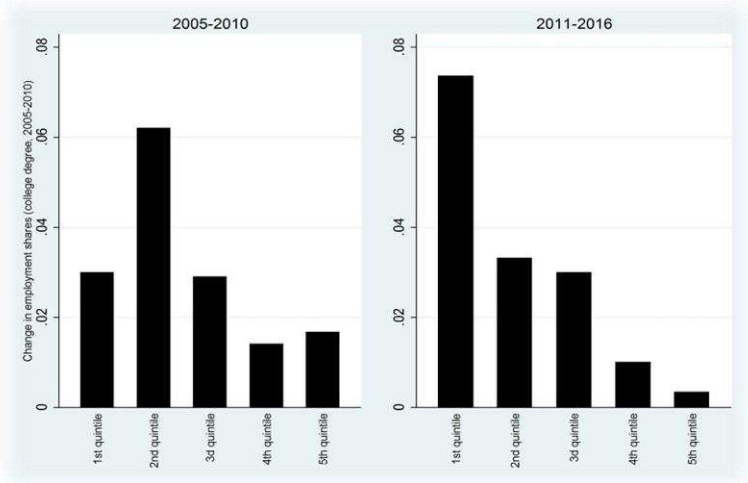
Figure 11. Change in employment (15-34 years) shares by RTI's quintiles



Source: authors' elaboration on RCFL-ICP data

Figure 11 reports the change in shares (simple difference between the employment shares at the end and at the beginning of each period[20]) looking at the ratio 15-34 years workers over the total by RTI's quintiles. The evidence is remarkable. Overall, the whole Italian workforce seems to be affected by an ageing process since all RTI quintiles are characterized by a reduction of young workers' share all across the considered time horizon.[21] Comparing the dynamics across RTI's quintiles, however, some interesing heterogeneities are detectable. The 2005-2010 period displays a pattern significantly in line with the RBTC's expectations: the young workers' share contracts more as higher the RTI level. That is, highly routinary occupations (i.e. those falling in the top quintiles of the RTI distribution) are ageing (or, at least, are ageing relatively more than the other occupation). The 2011-2016 is less clear with an almost homogeneous contraction of the young workers share with the exception of the 1st RTI's quintile.When workers are distinguished by educational attainment (figure 12), the emerging picture is more in line with the standard expectations. The share of workers with college degree tend to increase irrespective the RTI's quintiles. Nevertheless, the stronger increase is registered at the top of the distribution (1st and 2nd quintiles) where occupations characterized by non-routinary and complex tasks are concentrated.

Figure 12. Change in employment (college degree) shares by RTI's quintiles



Source: authors' elaboration on RCFL-ICP data

Such evidence is in line with the well-established hypothesis of complementarity (Autor et al. 2003) between new technologies, non-routinary/creative/abstract tasks and high skill levels (roughly) proxied by college degree. As expected, the share of workers with college degree show almost insignificant upward movements in correspondence of the 4th and 5th RTI's quintiles.

4. Research questions, econometric strategy and results

According to our preliminary descriptive inspection, differentiated degree of task routinarity match with significantly heterogeneous employment patterns at the occupation-level. Some of those patterns are close to what the RBTC literature predicts. Even if the main tenet of such literature is not neatly verified (i.e. a clear

[20] The change in shares is computed as follows. First, we calculate the share of 15-34 employee over the total in each RTI's quintile (2007 ranking for the 2005-2010 period, 2012 for the 2011-2016). Than we simply subtract the first to the last year share. The same procedure is applied to workers with college degree.

[21] This evidence seems to give further support to findings of those (see, among the others, Guarascio and Simonazzi, 2016; Calligaris et al. 2016; Lucchese et al. 2016) reporting a generalized impoverishment of the Italian productive structure resulting, among the other things, in reduced opportunities for high-skilled young workers. This evidence is also in line with the high levels of youth unemployment affecting Italy since the explosion of the 2008 crisis as well with the large numbers of high-skilled young Italians leaving the country due to the lack of relevant job opportunities.

polarization dynamics), our data show that occupations laying at the top of the RTI's distribution (i.e. occupations entailing relevant shares of repetitive and standardized tasks) tend to be penalized in terms of employment as compared to other occupations. This is particularly true for the 2011-2016 period but a similar picture emerges even by looking at the 2005-2010 phase. This negative routine task-employment relationship, however, become less clear when cognitive and manual tasks are distinguished; as well as when young workers (15-34 years) and workers with college degree are separately inspected. Moreover, the relative intensity of routine tasks prove to be highly sensitive to the occupational and sectorial cluster under investigation. Clericals and blue collars (both specialized and non-specialized) are characterized by higher RTI values as opposed to the other macro-groups. From a sectoral point of view, in turn, industries as manufacturing and construction report relatively higher RTI values if compared to the remaining 1-digit sectors. Building on the large body of literature reviewed above, we test econometrically the following set of research questions.

> **RQ1.** Does 'routinization' (i.e. being characterized by a relatively large share of repetitive and codifiable tasks) penalize Italian occupations in terms of employment dynamics?

Hypothesis 1 grounds on the key assumptions of the RBTC literature. As a result of the diffusion of computers and IT devices all across sectors and firms, occupations characterized by significant shares of tasks replicable by such devices are likely to face increasingly sluggish demand flows. Contrarily to what is done in much of the RBTC literature (see, among the others, Autor and Dorn, 2013), however, we do not investigate task-related changes in the employment structure looking at its distribution over wage percentiles. Rather, we analyse the change in employment over the RTI distribution comparing 'highly routinized' with other occupations.

> **RQ2.** Does 'routinization' (i.e. being characterized by a relatively large share of repetitive and codifiable tasks) a relatively stronger negative effect in services rather than in manufacturing?

Services are one of the privileged domains for the adoption of labor-saving/efficiency-increasing ICTs. In this respect, many contributions (see, for example, Autor and Dorn, 2009 and Cirillo, 2016) stress that most of both job-augmenting and job-disruptive developments linked to the introduction of ICTs are detectable in services. Clericals performing typical secretariat, accounting and customer care tasks are among those more exposed to the risk of technological unemployment.
On the other hand, low-skilled professionals employed in service occupations entailing relevant shares of dexterity and social interactions are shield from technological unemployment since their tasks are hardly replicable by machines and computers. Finally, high-skilled professionals performing creative and complex tasks (i.e. a scholastic example might be that of computer scientists hired to develop continuous innovation in Silicon Valley's IT-related firms) face sustained demand flows eventually earning above-the-average wages. In net, it is reasonable to expect a stronger negative impact of routinization on employment in services rather than in manufacturing.

> **RQ3.** Does 'routinization' affect heterogeneously young workers as compared to the rest of the workforce?

The RQ3 builds upon the arguments put forth in Autor and Dorn (2009) testing whether occupations characterized by relatively large share of routine tasks are 'ageing'. That is, we check if the routine task-employment relation changes in shape and magnitude when young workers (15-34 years) are separately analysed. This questions aims at verifying to what extent RBTC's predictions concerning the linkage between technological change and employment age structure (at the occupation-industry level) are verified for the Italian case.

RQ4. Does 'routinization' affect heterogeneously workers with college degree as compared to the rest of the workforce?

The final research question aims at verifying if the relation between routine task and employment is related to workers' educational attainment. Even in this case, we recall one of the basic arguments of both SBTC and RBTC literatures. Workers holding high-skills, proxied by their educational attainment, are less likely (or expected to be so) in occupations exposed to high risks of technological unemployment due to the high skills-new technologies complementarity. As a result, we might expect to find no effect (or a lighter effect) for workers with college degree as opposed to the whole sample test.

Econometric strategy and results

The abovementioned research questions are tested adopting the following econometric strategy. First of all, our relevant statistical unit is an occupation(4-digit)-sector(1-digit) cell reporting information on employment, workers and labor market characteristics, economic dynamics, degree of task routinarity as captured by the RTI plus a set of time, sectoral (1-digit) and occupational dummies (1-digit). As explained above, industry-level information on sectoral economic dynamics are computed as weighted averages and refer to all 4-digit sectors where each 4-digit occupation distributes in each considered year.[22]

Pooled OLS regressions with clustered standard errors are run over two distinct time span: 2005-2010 and 2011-2016. Standard errors are clustered by occupation-sector cell while regressions are carried out relying on the following specification:

$$\Delta N_{i,k,t} = RTI_i + X_{i,k,t-1} + Y_{i,k,t-1} + \varepsilon_{i,k,t} \quad (4)$$

Where, $\Delta N_{i,k,t}$ is the annual change in employment (log difference) by occupation i, sector k and year t. The degree of relative 'routinization' is captured by the RTI dummy assuming value 1 if the occupation-sector falls in the 4th or 5th quintile of the RTI distribution and 0 otherwise. In the first sub-period (2005-2010), occupations are ranked along the RTI distribution with reference to 2007 task-related information while the second period (2011-2016) is analysed with respect to 2012 task-related information. The $X_{i,k,t}$ matrix includes a set of occupation level controls plugged in at their first lag: change in employment, so to control for persistence in the employment dynamics at the occupation level; change in (log) median wages; (over total occupation-sector employment at t-1) of women, young workers (15-34 years), workers with college degree and with temporary contract. The $Y_{i,k,t}$ matrix includes sectoral level controls at their first lag reporting information on the change in revenues (proxing the dynamics of demand at the occupation-sector level), capital stock (which might be substitute or complementary to labor according to sectors' technological characteristics) and R&D expenditure (variable aiming to capture the role of technology and innovation). The latter variables are included to control for potential heterogeneities in terms of economic and innovation dynamics at the industry-level that might contribute to shape magnitude and direction of the RTI-employment relationship. For both sub-periods, equation (4) is estimated adopting a stepwise procedure. We firstly test the simplest specification by regressing the change in employment against the RTI dummy alone. In this way, we can check whether significant difference-in-mean in terms of employment dynamics are detectable comparing highly routinary occupations-sectors *vis a vis* the rest of the sample. As a second step, we include occupation level controls X as well as time, sectoral and occupation-level dummies. In the third specification, we add the industry-level controls Y.

Focusing on the second period of analysis, occupations characterized by high levels of routine task are penalized in terms of employment dynamics; while a weak negative correlation emerges during the first

[22] It is not possible to carry out the analysis relying on 4-digit information for both occupation and industry-level data because at such a combined high-level of disaggregation Italian LFS data lose their statistical relatiability.

period (table 3). Regarding controls, some elements of interest are detectable. Employment displays a negative autocorrelation all across sub-periods pointing to a significant labor market volatility. Between 2011 and 2016, occupations with relatively high share of young workers turn out to be relatively sluggish in employment terms[23] while the opposite is true with regards to occupation-sector cells reporting high shares of employees with temporary contracts. The positive correlation between our dependent variable and the change in wages at t-1 (second sub-period), in turn, might be related to a positive growth pattern at the sectoral-level positively affecting both jobs and wages. Puzzling enough, no correlation emerges between employment dynamics and the economic industry-level controls.

Table 3. Change in employment vs RTI and controls – whole sample
Pooled OLS estimations with clustered std. errors

	2005-2010			2011-2016		
	RTI only	RTI + occ-lev controls	RTI + controls	RTI only	RTI + occ-lev controls	RTI + controls
RTI dummy	-0.0116	-0.0334**	-0.00170	-0.0451**	-0.0530**	-0.0522**
	(0.00654)	(0.0133)	(0.0224)	(0.0143)	(0.0164)	(0.0160)
Δ Emp (1st lag)		-0.265***	-0.239***		-0.271***	-0.276***
		(0.0119)	(0.0204)		(0.00933)	(0.0134)
Women % (1st lag)		0.0130	-0.0207		-0.0351	-0.0424
		(0.0322)	(0.0624)		(0.0283)	(0.0318)
Young % (1st lag)		-0.0177	-0.131*		-0.164***	-0.208***
		(0.0398)	(0.0648)		(0.0409)	(0.0396)
Coll. degree % (1st lag)		-0.0518	-0.00452		0.0366*	0.0245
		(0.0405)	(0.0310)		(0.0189)	(0.0192)
Temp emp. % (1st lag)		0.0244	0.109		0.156**	0.192**
		(0.0500)	(0.0616)		(0.0621)	(0.0782)
Δ Wages (1st lag)			-0.0153			0.114**
			(0.0285)			(0.0391)
Δ Revenues (1st lag)			0.0252			0.00752
			(0.0264)			(0.0160)
Δ Capital stock (1st lag)			0.00330			0.00142
			(0.0128)			(0.00849)
Δ R&D exp (1st lag)			-0.00688			-0.000315
			(0.00719)			(0.00412)
Observations	14467	10518	4233	11997	8680	6933
Standard errors in parentheses						
* p<0.10, ** p<0.05, *** p<0.010						

Manufacturing vs services

The negative relationship between routine task and employment is no longer detected when the sample is restricted at manufacturing industries only (table 4). In turn, employment grows more in occupation-sector cells where a relatively steadier capital stock (first sub-period) and R&D expenditure (second sub-period) growth is observed. Between 2011 and 2016, young workers are penalized as in the full sample model while a positive correlation is registered with respect to workers with college degree.

[23] This result confirms the evidence provided by Cirillo et al. (2017). The authors report a significant penalization of young workers employment in the post-2008 crisis phase.

Table 4. Change in employment vs RTI and controls – manufacturing sector
Pooled OLS estimations with clustered std. errors

	2005-2010			2011-2016		
	RTI only	RTI + occ-lev controls	RTI + controls	RTI only	RTI + occ-lev controls	RTI + controls
RTI dummy	-0.0208**	-0.0195	0.0295	-0.0444**	-0.0333	-0.0333
	(0.00766)	(0.0201)	(0.0407)	(0.0136)	(0.0203)	(0.0207)
Δ Emp (1st lag)		-0.247***	-0.243***		-0.299***	-0.287***
		(0.0169)	(0.0409)		(0.0292)	(0.0323)
Women % (1st lag)		-0.0279	-0.0227		-0.0426	-0.0694
		(0.0665)	(0.0800)		(0.0559)	(0.0571)
Young % (1st lag)		-0.0926	-0.291**		-0.212*	-0.251**
		(0.0884)	(0.111)		(0.0954)	(0.0751)
Coll. degree % (1st lag)		0.0247	0.167**		0.0523	0.0526
		(0.0476)	(0.0668)		(0.0367)	(0.0595)
Temp emp % (1st lag)		0.0524	0.0620		0.105	0.144
		(0.173)	(0.123)		(0.0764)	(0.110)
Δ Wages (1st lag)			-0.0400			0.0811
			(0.0469)			(0.0733)
Δ Revenues (1st lag)			0.0264			0.00282
			(0.0400)			(0.0281)
Δ Capital stock (1st lag)			0.0496**			-0.0268
			(0.0183)			(0.0240)
Δ R&D exp (1st lag)			-0.0107			0.0269**
			(0.0114)			(0.0105)
Observations	3648	2685	1516	3117	2293	2173

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Supporting the arguments spelled out above, services display a rather different behaviour as compared to manufacturing. In this case, occupations with a high degree of routine task are again penalized (the relation is strongly significant during the 2011-2016 phase while weaker between 2005 and 2010). The negative relationship between routinary task and employment registered for the whole sample of Italian occupations (table 3), thus, seems to be significantly driven by the evolution of the service sector.

Italian jobs are getting old?

Restricting the analysis to young workers, we end up with quite a different picture as opposed to previous models. Examining jointly results in tables 6 and 7, it turns out that Italian occupations behave rather differently as opposed to the US case reported by Autor and Dorn (2009). Between 2005 and 2010, young workers employment grows relatively more in highly routinary occupations while the opposite holds for the rest of the workforce in line with the whole sample results. During the 2011-2016 phase, the relation between the RTI dummy and the change in young workers employment is almost not significant; while a negative and strongly significant correlation is found with respect to 35-65 years old workers.

Table 5. Change in employment vs RTI and controls – services
Pooled OLS estimations with clustered std. errors

	2005-2010			2011-2016		
	RTI only	RTI + occ-lev controls	RTI + controls	RTI only	RTI + occ-lev controls	RTI + controls
RTI dummy	-0.00770	-0.0345*	-0.0116	-0.0454**	-0.0582**	-0.0587**
	(0.0104)	(0.0167)	(0.0276)	(0.0161)	(0.0193)	(0.0211)
Δ Emp (1st lag)		-0.271***	-0.235***		-0.264***	-0.271***
		(0.0119)	(0.0221)		(0.0103)	(0.0167)
Women % (1st lag)		0.0233	-0.0182		-0.0338	-0.0339
		(0.0294)	(0.0589)		(0.0294)	(0.0325)
Young % (1st lag)		0.00123	-0.0692		-0.149***	-0.193***
		(0.0418)	(0.0865)		(0.0383)	(0.0419)
Coll. degree % (1st lag)		-0.0717	-0.0704		0.0318	0.0134
		(0.0450)	(0.0533)		(0.0242)	(0.0232)
Temp emp. % (1st lag)		0.0166	0.124		0.169**	0.207**
		(0.0678)	(0.0752)		(0.0615)	(0.0780)
Δ Wages (1st lag)			-0.0124			0.123**
			(0.0378)			(0.0446)
Δ Revenues (1st lag)			0.0156			0.00741
			(0.0320)			(0.0179)
Δ Capital stock (1st lag)			-0.00371			0.0106
			(0.0139)			(0.00798)
Δ R&D exp (1st lag)			-0.00533			-0.00775
			(0.00764)			(0.00630)
Observations	10819	7833	2717	8880	6387	4760
Standard errors in parentheses						
* p<0.10, ** p<0.05, *** p<0.010						

Interestingly, employment is negatively correlated with the share of women in both sub-periods while a positive 'college degree premium' is detected. The latter relationship becomes negative for 35-65 years old workers.

Table 6. Change in employment vs RTI and controls – young workers (15-34 years)
Pooled OLS estimations with clustered std. errors

	2005-2010			2011-2016		
	RTI only	RTI + occ-lev controls	RTI + controls	RTI only	RTI + occ-lev controls	RTI + controls
RTI dummy	0.00793	0.0993***	0.104***	-0.0353	0.0464*	0.0488
	(0.00603)	(0.0235)	(0.0282)	(0.0195)	(0.0248)	(0.0268)
Δ Emp (1st lag)		-0.148***	-0.155***		-0.183***	-0.189***
		(0.0197)	(0.0344)		(0.0240)	(0.0242)
Women % (1st lag)		-0.302***	-0.384***		-0.304***	-0.304***
		(0.0437)	(0.106)		(0.0438)	(0.0506)
Young % (1st lag)		0.153**	0.0890		0.0150	0.0160
		(0.0489)	(0.102)		(0.0443)	(0.0526)
Coll. degree % (1st lag)		0.146***	0.206**		0.212***	0.193***
		(0.0274)	(0.0602)		(0.0312)	(0.0322)
Temp emp % (1st lag)		0.0145	0.269**		0.247***	0.252**

		(0.0719)	(0.0979)		(0.0625)	(0.0871)
Δ Wages (1st lag)			0.0175			-0.0411
			(0.0314)			(0.0318)
Δ Revenues (1st lag)			0.0281			0.0281
			(0.0265)			(0.0241)
Capital stock (1st lag)			-0.0129			-0.00386
			(0.0143)			(0.0233)
Δ R&D exp (1st lag)			-0.00896			-0.00811
			(0.00988)			(0.00752)
Dummies						
Observations	8697	6628	2951	7440	5593	4895
Standard errors in parentheses						
* p<0.10, ** p<0.05, *** p<0.010						

Table 7. Change in employment vs RTI and controls – 34-65 years workers

Pooled OLS estimations with clustered std. errors

	2005-2010			2011-2016		
	RTI only	RTI + occ-lev controls	RTI + controls	RTI only	RTI + occ-lev controls	RTI + controls
RTI dummy	0.00384	-0.135***	-0.0835*	-0.0326*	-0.131***	-0.137***
	(0.00867)	(0.0227)	(0.0371)	(0.0154)	(0.0212)	(0.0246)
Δ Emp (1st lag)		-0.210***	-0.195***		-0.225***	-0.231***
		(0.0134)	(0.0202)		(0.0170)	(0.0190)
Women % (1st lag)		-0.121**	-0.122*		-0.148***	-0.165***
		(0.0368)	(0.0632)		(0.0336)	(0.0350)
Young % (1st lag)		0.664***	0.509***		0.597***	0.613***
		(0.0438)	(0.0906)		(0.0546)	(0.0598)
Col degree % (1st lag)		-0.139***	-0.0958**		-0.0213	-0.0286
		(0.0352)	(0.0322)		(0.0239)	(0.0251)
Temp emp % (1st lag)		-0.0275	-0.0521		0.0390	0.0342
		(0.0255)	(0.0628)		(0.0612)	(0.0740)
Δ Wages (1st lag)			-0.0408			0.0178
			(0.0359)			(0.0381)
Δ Revenues (1st lag)			0.0446			-0.00443
			(0.0245)			(0.0320)
Capital stock (1st lag)			0.00373			0.00218
			(0.0188)			(0.0114)
Δ R&D exp (1st lag)			-0.00660			-0.00596
			(0.00686)			(0.00489)
Observations	13117	9737	4060	11219	8259	7153
Standard errors in parentheses						
* p<0.10, ** p<0.05, *** p<0.010						

The role of workers' educational level

The final test regards workers with college degree. The RTI dummy is again negatively (but barely significant) correlated with the change in log employment. As before, a stronger correlation is found in the 2011-2016 period while significance stacks at the 10% level in the 2005-2010 full model. Interestingly, it turns out that the occupations-sectors where college degree employment grows more are those where women and young workers shares are also relatively larger. That is, young workers and women are, as expected, prevalent among growing highly-educated occupations. Such prevalence, however, seem to be not enough to reward those categories with respect to overall employment growth.

Table 8. Change in employment shares vs RTI and controls – workers with college degree
Pooled OLS estimations with clustered std. errors

	2005-2010			2011-2016		
	RTI only	RTI + occ-lev controls	RTI + controls	RTI only	RTI + occ-lev controls	RTI + controls
RTI dummy	0.0246	-0.0370	-0.0504*	0.0193	-0.0353*	-0.0366*
	(0.0350)	(0.0233)	(0.0222)	(0.0178)	(0.0177)	(0.0156)
Δ Emp (1st lag)		-0.113***	-0.131**		-0.182***	-0.169***
		(0.0276)	(0.0393)		(0.0511)	(0.0429)
Women % (1st lag)		0.153*	0.116		0.0940***	0.0789*
		(0.0666)	(0.0924)		(0.0176)	(0.0342)
Young % (1st lag)		0.0769**	0.118*		0.0454	0.0232
		(0.0295)	(0.0586)		(0.0298)	(0.0569)
Coll. degree % (1st lag)		-0.287*	-0.287*		-0.161**	-0.171*
		(0.142)	(0.140)		(0.0621)	(0.0742)
Temp emp sh (1st lag)		0.0175	0.0756		0.0845	0.200
		(0.143)	(0.166)		(0.0582)	(0.127)
Δ Wages (1st lag)			0.0704			-0.0167
			(0.0466)			(0.0261)
Δ Revenues (1st lag)			-0.0354			0.0352
			(0.0335)			(0.0211)
Capital stock (1st lag)			-0.0295			-0.00298
			(0.0226)			(0.0207)
Δ R&D exp (1st lag)			-0.00331			-0.00237
			(0.0191)			(0.00983)
Observations	6329	4946	2369	6153	4676	4019

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010

5. Conclusions

Taking advantage of a dataset providing O*Net-type information on the task content of Italian occupations, this work analysed empirically if and to what extent employment patterns are affected by task characteristics in terms of 'relative routinarity'. The research questions spelled out above have found the following answers. The first one is an affirmative answer pointing to a significant employment penalisation for occupations characterized by relatively high levels of routine tasks. The negative impact of task 'routinarity' on employment is stronger in the second period of analysis (2011-2016) but a similar dynamics (although less robust in statistical terms) is detected also between 2005 and 2010. In this respect, the RBTC's main predictions seems to find a confirmation. Moving to the second research question, a considerable heterogeneity between manufacturing and services is highlighted. While in services the negative relationship between routine task and employment is verified, in manufacturing the same relationship becomes statistically weak. As shown in previous contributions (Autor and Dorn, 2013), thus, services emerge again as the sector where the risk of replacement for routinary occupations is more substantial and widespread. On the contrary, the answer to our third research question is at odd with some key result of the RBTC literature (Autor and Dorn, 2009): Italian occupations with high level of routinary tasks seems to get 'younger' rather than 'older'. According to our empirical results, in highly routinary occupations youth employment tends to grow rather than shrink. This apparently counterintuitive evidence might find an explanation by taking into appropriate consideration some key structural and institutional elements characterizing the Italian economy. The relative industrial and technological weakening of the Italian economy experienced in the last ten years (i.e. the relative contraction of high-tech industries and the contextual growth of low-tech low-value added ones – on this point, see Lucchese et al. 2016) together with the increasing dualism of the Italian labor market (i.e. protected insiders vis a vis new entrants with low protections and temporary contracts) relegates many young Italians to low-quality jobs often precarious in terms of employment protection and wage dynamics (Cirillo et al. 2017). Concerning the fourth research question, being in highly routinary occupations seems to be less an issue for workers with college degree given the weaker significance of the RTI coefficient as compared to the whole sample model.

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