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Digitalization, routineness and employment: An exploration on Italian task-based data

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ABSTRACT

This paper explores the relation between the digitalization of labour processes, the level of routineness of labour tasks and changes in employment in the case of Italy in the period 2011-16. The levels of digitalization and routineness of occupations in more than 500 4-digit ISCO professional groups are measured using data from a unique Italian profession-level survey on skill, tasks and work contents – the INAPP-ISTAT *Survey on Italian Occupations* (ICP), an O*NET-type dataset. Two digitalization indices are used: a *digital use* index, measuring the use of computers and e-mail in the workplace, and a *digital tasks* index, capturing the presence of a set of key digital tasks, such as those related to programming or activities concerning the use of specialized hardware. The same dataset is used to compute a composite *routine task intensity* index. The descriptive evidence presented in the paper shows strong differences across occupations in the level of digitalization and routineness, and the presence of a negative relation between the two in most professional groups. The econometric estimates show that digital-intensive occupations tend to grow more than the rest of the workforce, particularly when digitalization is measured relying on the digital use indicator. The level of routineness, in turn, is negatively or, in some specifications, not significantly associated to employment change. However, occupations that are both digital and routine-intensive turn out to be penalized in terms of employment growth, providing further support to (and further qualifying) the the routine biased technological change (RBTC) hypothesis. In other words, our results show that the impact of digitalization on employment is mediated by the level of routineness characterizing the tasks bundled in each occupation.

1. Introduction

The diffusion of digital technologies is expected to have profound effects on the economy and society. However, there is yet no consensus on whether digitalization is merely an incremental change on previous technological trajectories, or rather a fully-fledged change in the technological paradigm, able to fuel a new long-term cycle of economic growth and a deep process of structural change (Freeman and Louçã, 2001; Brynjolfsson and McAfee, 2014). Such a topic has opened up, among the other things, a lively debate characterised by contrasting views on the consequences of digitalization on work: one envisaging the spectre of mass technological unemployment; another one emphasising the economic (and employment) opportunities brought about by the new technological paradigm (Arntz et al., 2016; Frey and Osborne, 2017; OECD, 2018; Nedelkoska and Quintini, 2018). Indeed, there is a long tradition of scholarly and popular concern about the effects of technological change on employment, dating back at least to Ricardo and Marx. Even then, positions were polarized: there were those, such as Marx, recognizing the direct threat of technological unemployment. While there were others, such as Ricardo, supporting the idea of the existence of intrinsic 'compensation mechanisms' (mostly based on income and price changes) capable to minimize (or to eliminate) the risks of technological unemployment (for a thorough discussion, see Vivarelli, 2014; Calvino and Virgillito, 2018; Van Roy et al., 2018).

This paper is the outcome of research activities carried out in 2018 and 2019 when Dario Guarascio and Valeria Cirillo were affiliated at INAPP (Italian Institute for the Analysis of Public Policies) and Matteo Sostero was a post-doctoral research fellow at the same Institute.

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As with many past technological breakthroughs, assessing the aggregate and long-term effects of digitalization on employment is a rather challenging task. In fact, digitalization is a very difficult phenomenon to conceptualise and measure (McKinsey Global Institute, 2015; Calvino et al., 2018). Moreover, it is likely to have different effects on employment depending on the productive and institutional context in which it takes place: industries and firms characterized by different technological and organizational features; economies characterized by different labour markets structures, policies, industrial relations as well as macroeconomic conditions (Guerrieri and Bentivegna, 2012; Evangelista et al., 2014; Calvino and Virgillito, 2018). The main reason behind the revival of fears of mass technological unemployment is that contemporary digital devices are believed to be far 'smarter' than their analogic forebears. Digital technologies enable machines and operating systems to perform tasks that are cognitively complex for humans, raising the prospect of technology substituting human beings in an increasing number of roles and tasks. From an employee perspective, this means that the threat from digital technologies goes far beyond their traditional boundaries, opening the way to the automation of entire phases of the production processes, or even to increasingly fragment them into micro-tasks, often performed on a global scale (Tubaro and Casilli, 2019).

Some contributions – recalling the 'Taylorist' view of the technology-organization nexus in analysing and measuring the risks of technological unemployment – underline the strong linkage between digitalization and routineness (for a discussion, see Fernández-Macías and Hurley, 2016; Autor, 2015). By defining jobs as 'bundles of tasks', this approach identifies individual tasks as the key units of the analysis: worker's tasks are in fact the fundamental entities which can be reshaped (or substituted) by digital machines (Autor et al., 2003; Fernández-Macías and Hurley, 2016; Fernández-Macías et al., 2016). The analytical shift from skills towards tasks has prompted the transition from the Skill Biased Technical Change (SBTC) approach to models based on the Routine Biased Technical Change (RBTC) hypothesis.[1] The key insight of the RBTC is that occupations featuring a large share of repetitive and encodable tasks (i.e., routine-task) face a relatively higher risk (i.e., possibility and opportunity) of being automated. A significantly lower risk, in turn, affects occupations performing tasks entailing a high degree of creativity or complex reasoning (i.e., 'strictly human' tasks). However, there is relatively little empirical evidence relating digitalization with routineness directly, and examining their joint relation to employment.

This work aims to contribute to the existing literature by defining, measuring and exploring empirically, digitalization and routineness of labour activities in their specific occupational context. We also try to assess how digitalization relates – on its own, or mediated by routineness – to employment dynamics. These research targets will be addressed exploiting the INAPP[2]-ISTAT[3] *Survey on Italian Occupations* (ICP), an O*NET-type dataset, merged with data on employment drawn from the ISTAT Italian Labour Force Survey (ILFS). The combination of the two datasets allows us to measure the levels of digitalization and routineness of more than 500 4-digit ISCO professional groups (referring to the year 2011) – and to relate both dimensions of labour processes to the employment dynamics observed in Italy in the same occupations (across 12 NACE 1-digit sectors) in the period 2011-16. The level of digitalization is captured by two main indices: a *digital use* index, measuring the use of computers and e-mails; a *digital tasks* index capturing the relevance of a selected set of digital tasks, such as software programming or database administration. The level of routineness is measured using an index composed of the task-related dimensions considered by Autor et al. (2003) and by other relevant contributions following this seminal work.

The key takeaways of the empirical analysis are the following. The use of digital technologies is more intense and concentrated among high-skilled occupations (e.g., scientists, engineers, software developers) while it is significantly less intense and more dispersed among low-skilled occupations (e.g., couriers, waiters, construction workers). Only a minority of occupations is characterized by primarily carrying out digital tasks. These are found in highly skilled professional groups (e.g., software developers, software or network technicians, designers). The situation is reversed when it comes to the degree of routineness: low-skilled occupations (e.g., textile workers, machine operators, cashiers) display the highest level of routine-tasks while the opposite is true for high-skilled occupations (e.g., school superintendents or inspectors, executives, university professors). The evidence presented shows that digitally intensive occupations show better employment performances than the least digitalized professional groups. However, the occupations characterized by the joint presence of high levels of routineness and digitalization are also those that experience the worst employment performances, compared to occupations where such combination is not found. This result provides some additional support to the RBTC hypothesis.

The paper is organized in seven main sections. The next section locates this contribution within the existing empirical literature dealing with the employment effects of digitalization and routineness. Section 3 sets the key research questions investigated in the empirical sections. Section 4 describes the data set and the indicators used in the empirical analysis. Section 5 describes the relationships between digitalization and routineness, and how both elements are related to the dynamics of employment. Section 6 explores econometrically the relationship between the levels of digitalization and routineness of occupations, on one side, and the dynamics of employment, on the other. Section 7 summarises the main results of this study and presents avenues for future research.

2. Digitalization, routineness and employment: a review of the literature

In what follows, we briefly review the main literature dealing with: i) the relation between digitalization and employment; ii) the role of tasks in shaping the technology-employment nexus. The section ends by discussing some notable features of the Italian economy – the empirical focus of this paper – in terms of employment, technology, and digitalization.

2.1. Digitalization and employment

Over the last three decades, the spread of digital technology has been investigated by a massive amount of theoretical and empirical research. A first stream of literature has tried to assess the economic impact of Information and Communication Technologies (ICT) on key performance variables such as output and productivity growth, at any possible level of aggregation (firms, sectors, regions and countries). Results and methodologies, as well as strengths and limitations, of this first group of contributions have been effectively summarized by several reviews (OECD, 2004; Van Reenen et al., 2007).

More recent developments have revived the scientific interest on this topic by shifting the focus on the long-term economic effects of digitalization. Following the influential book by Brynjolfsson and McAfee (2014), a growing number of contributions (see, for a thorough review, Arntz et al., 2016) have tried to answer the following question: Is this

[1] For an in-depth discussion see, among the others, Acemoglu and Autor (2011) and the literature review contained in section 2.

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time different?[4] This question refers to the potentially massive employment impact of digitalization. The major difference, as compared to the previous technological waves, concerns both the pervasiveness as well as the number of tasks that digital devices and digital equipped machines are now apt to perform, some of which were previously believed to be an exclusive prerogative of humans. A key empirical issue at stake, in the studies investigating the relevance and impact of digitalization, has to do with the very definition and measurement of this phenomenon. Most of the literature defines digitalization as the mere acquisition or deployment of specific ICT technologies (computers, software, internet, robots). Autor and Dorn (2013) and Michaels et al. (2014), for instance, take into account the role of investment in computer and information technology capital. Acemoglu and Restrepo (2018), Graetz and Michaels (2018) and Dauth et al. (2017) assess the employment effects of the use of robots. An aggregated employment-based approach to the measurement of digitalization, on the other hand, has been proposed by Marcolin et al. (2016). As an industry-level digitalization proxy, they use the share of workers employed in the business functions related to "ICT services" and "Engineering and related technical services" over total employment. It is worth noticing that the use of these proxies of digitalization has been most of the times dictated by data constraints. In fact, finding a comprehensive and coherent set of indicators able to grasp the essential features of a multifaceted phenomenon such as digitalization continues to be a very challenging task.[5] Some efforts in such direction have nonetheless been done both by international organizations and through specific research projects. Over the last 15 years, Eurostat, through its "Community survey on ICT usage and e-commerce in enterprises", has been collecting data on a rather broad array of ICT related activities carried out by firms and households. These data potentially represent a very rich information source to assess the relevance and the economic impact of digital technology at a macro, sectoral and even at a micro level. Unfortunately, the actual usability of these data for empirical research is limited. In fact, the access to microdata is severely restricted and the sectoral (and country) coverage of the data made publicly available by Eurostat is far from complete. Other studies have tried to map the digital intensity of industries and countries combining internationally available data sources on ICT and digital activities (Guerrieri and Bentivegna, 2012; Calvino et al., 2018; McKinsey, 2015). A study coordinated by Guerrieri and Bentivegna (2012) has collected and merged data from the most relevant international data-sets on ICT and summarised them into three composite indicators of digitalization broadly referring to the level of ICT infrastructure, the actual usage of internet services and the impact of these technologies and services in key socio-economic domains and the associated process of digital empowerment. Following a similar methodology, Calvino at al. (2018) have proposed a taxonomy of sectors according to the extent to which they have "gone digital", combining data on tangible and intangible investment in digital technology (i.e., hardware and software), the purchases of relevant intermediate goods and services, the stock of robots, the number of specialists and the share of turnover from online sales and also presenting an overall composite indicator of digitalization.

The empirical evidence on the employment effects of digitalization is mixed. This is largely the result of a marked heterogeneity of the existing studies in terms of the level of aggregation of the analysis, the type of indicator of digitalization used and the economic context (countries and sectors) in which these effects have been investigated. However, the majority of studies seems to converge in highlighting (although with different caveats) the presence of a beneficial effect of digitalization on employment. A first set of contributions has investigated the employment effects of the access to the broadband (the latter used as a proxy for ICT intensity). Kolko (2012) and Atasoy (2013), relying on US data, find that the access to broadband is significantly and positively associated to employment dynamics. The study by Jayakar and Park (2013), investigating the ICT-unemployment relationship in the US context, confirms the results of Kolko and Atasoy: countries with better broadband availability display lower unemployment rates as compared to the other countries. Biagi and Falk (2017), focussing on Europe, address a similar research question, finding that the increase in ICT and e-commerce activities has not led to a decline of jobs. Restricting their analysis to enterprise resource planning (ERP) systems as an ICT proxy, Biagi and Falk (2017) detect a positive impact of digital technologies on employment. Further evidence on Europe is provided by Balsmeier and Woerter (2019). They exploit Swiss firm-level information on investment in digital technologies – such as ERP, supply chain management, robots, 3D printing, autonomous vehicles, Internet of Things (IOT). Overall, the authors find that digitalization stimulates the growth of high-skilled jobs. The study also finds a negative relationship with medium- and low-skill employment. Autor and Solomons (2018) investigate the effect of technological innovation on productivity, employment and the labour share of value added, in different industries in a panel of advanced economies. In terms of employment, they distinguish between the negative direct effect of innovation in each industry, with the positive (and ultimately countervailing) indirect effects across all other industries. However, they also note that the overall effect of technological change on the labour share of value added has been negative.

Finally, the large literature on *digital divide* provides additional indirect evidence on the employment impact of digitalization, highlighting the emergence of new forms of economic and social exclusion, negatively affecting old generations and digitally unskilled labour (Codagnone, 2009). More generally, this literature shows that the access to – and ability to use – ICT affects employability conditions along the entire life cycle of individuals, influencing the decision to enter the labour market (the labour participation decision), the likelihood of getting a job (the transition from unemployment to employment) (Codagnone, 2009), the likelihood of losing a job (the transition from employment to unemployment) (Friedberg, 2003; Aubert et al., 2006) as well as decisions of early retirement (Schleife, 2006), job duration (Silva and Lima, 2017) and work contract (Aubert-Tarby et al., 2018).

Summing up, the existing empirical evidence seems to support the hypothesis of a labour-friendly impact of digitalization, at least at an aggregate level. However, the results supporting this interpretation may be affected by a (largely omitted and under-investigated) technological-competitiveness effect (Mastrostefano and Pianta, 2009; Vivarelli, 2014). In other words, firms and industries going digital might increase employment as the result of a "technological competitive strategy", characterized by an intensive and effective use of digital technologies associated to the introduction of new products and business models. Putting tasks at the centre of the analysis – and accounting for the internal heterogeneity of the occupational structure – allows to better assess the employment impact of digitalization (Autor, 2015).

2.2. SBTC, RBTC and beyond

The Skill-Biased Technical Change (SBTC) hypothesis (for a comprehensive review, see Acemoglu, 2002) resumes and further qualifies the classical thesis that technologies compete with human beings as production factors or performers of production tasks, and this applies also to digital technologies in the form of a "race" between humans and computers. Furthermore, SBTC assumes that digital technologies have differentiated effects on the marginal productivity of labour depending on the level of skills and qualifications of the labour force. New technologies, particularly those related to ICT, are assumed

[4] This question is posed in the title of a very recent paper (Balsmeier and Woerter, 2019) analysing, empirically, the impact of digitalization on employment.

[5] Data on a broader set of ICT related technologies (including Internet, intranet, broadband, home pages, services offered via home pages, electronic commerce, and electronic data interchange) are used by a study of Böckerman et al. (2019).

to be complementary to high-skill jobs (mostly due to the importance of cognitive skills related to the use of computers and ICT devices) while they are expected to penalize medium and low-skilled jobs. Furthermore, skilled (i.e., more educated) workers are expected to be better at learning how to use new technologies – thus enhancing their productivity – and more flexible in the event of changing job assignment. For this group of workers, digital technologies free their time from repetitive (routine) tasks and, at the same time, provides additional resources for performing abstract and creative tasks.[6] Medium and low-skilled jobs, in turn, are at greater risk of being substituted by the same technologies because their skills are less complementary to ICT. This is the first hypothesis put forth by the literature (Bresnahan et al., 2002; Autor and Dorn, 2009; Kemeny and Rigby, 2012; Michaels et al., 2014) to explain the long-term changes in the composition of employment observed in most industrialized countries from the early 1980s onwards and, in particular, the increasing share of the high-skill component of the workforce.

Being unable to fully explain the employment and wage polarization dynamics emerging from the US data since the 1990s,[7] the SBTC has been more recently superseded by a new approach focusing on the very object of a labour-saving technology-driven process: workers' tasks.[8] Known as Routine Biased Technical Change (RBTC), this approach ranks jobs according to their relative share of routine tasks rather than in terms of their generic skill requirements. The RBTC hypothesis was put forth in the work by Autor et al. (2003) arguing that the unfolding of ICT is biased towards the replacement of routine tasks. Acemoglu and Autor (2011, p. 1076) define routine tasks as "sufficiently well understood [tasks] that can be fully specified as a series of instructions to be executed by a machine". Being repetitive, standardized and easily encodable, these types of tasks – both cognitive and manual – are expected to be more exposed than others to the risk of substitution in case of labour-saving technological change.

The emergence of the RBTC approach has paved the way for the flourishing of a new stream of empirical contributions aiming at testing the underlying hypotheses through the use of different methodologies, datasets and types of indicators (see, among the others, Goos and Manning, 2007; Autor et al., 2006; Spitz-Oener, 2006; Goos et al., 2010; Autor and Handel, 2013). Autor, Katz and Kearney (2006) and Autor and Handel (2013) elaborate on the initial routine-task indicator proposed by Autor et al. (2003) classifying tasks into *abstract, routine* and *manual*. In a subsequent work, Goos et al. (2009) add the concept of service tasks featuring social interaction and close relationship with clients. In both cases, the effort has been to characterize the degree of jobs' routineness in a more precise way.

Particularly relevant for the topic investigated in this article is the potential relation between the level of routineness of labour tasks and the degree of their digitalization. In an influential paper by Autor et al. (2003), it is argued that computerisation (i.e., digitalization) enhances the possibility of automating tasks with a high degree of routineness. This is because routine tasks can be more easily parcelled out and transformed in digitized inputs, more easily parsed by machines. The same process, on the contrary, does not occur if tasks require the accumulation of tacit knowledge, specific experience, or if the organizational context is characterized by rapid and unpredictable changes. Nevertheless, the hypothesis that high levels of routineness lead to increasing opportunities for digitalization of tasks and organisations has been rarely assessed empirically. In fact, only few studies have explicitly assessed the routineness-digitalization nexus relying on indicators able to capture their independent, or combined, effects on employment. Marcolin et al. (2016), relying on the sectoral indicator mentioned above, find a positive correlation between digitalization and the growth of non-routine jobs and a negative correlation when it comes to routine ones.

The RBTC approach has been the object of some criticisms. According to Fernández-Macías and Hurley (2016), most of the RBTC literature neglects the role played by social and institutional factors. In addition, the importance of routinization and digitalization, as a determinant of current processes of polarization, has often been downplayed. Beaudry and Green (2016), referring to the US case, attach more importance to the de-skilling process caused by the financial crisis, while Foster et al. (2016) emphasise the role of business cycles. A critical point concerns also the lack of any reference in the RBTC literature, and in particular in the definition of tasks, to the *human agency* dimension. If human agency is taken into account, in turn, factors such as human adaptability, flexibility and specific experience, make some tasks 'irreplaceable' by machines even if their degree of repetitiveness and standardisation make them technically replaceable. Furthermore, the cross-country and cross-industry heterogeneity in terms of labour market institutions – in particular, the degree of unionization and more in general the level of workers' protection against layoffs – might play a key role in explaining the magnitude and direction of the technology-employment relationship, irrespective of the degree of routineness of tasks (Mishel et al., 2013).

The importance of focusing on tasks has been recognized by the literature studying the implications for employment of the processes of international production fragmentation and the participation in Global Value Chain (GVC) (Grossman and Rossi-Hansberg, 2006, 2008). In this literature, digitalization is identified as one of the key technological infrastructures allowing the fragmentation of production on an international scale and the possibility of coordinating GVC. Moreover, by framing production offshoring in a 'trade in tasks' context, this literature assumes that routine tasks – and more specifically, task requiring *codifiable* rather than *tacit* knowledge – are more easily performable remotely than low routine labour tasks. As a result, jobs characterized by a large share of routine-task are threatened twice: by the risk of substitution by machines as well as by the risk of being offshored (Leamer and Storper, 2001; Levy and Murnane, 2005; Blinder, 2009).

2.3. The Italian case

The focus of our empirical analysis on Italy presents some elements of interest and strength but also requires to take into account some peculiarities of its economic structure that might influence the results of this study and their level of generality. These elements are briefly discussed in this subsection.

According to recent reports by ISTAT (2017, 2018) and MISE (2018), Italian companies are less digitalized than their EU competitors. Such a relative digital backwardness is consistent with the poor innovation performance of Italian firms, in terms both of process and product innovations, as documented by recent empirical analyses (Dosi et al., 2019). Italian companies also rank low in the European International Digital Economy and Society Index, and in particular in terms of the adoption of digital technologies (European Commission, 2018). However, over the last few years digital technologies and practices are starting to spread also among Italian firms and industries. ISTAT reports that in 2019: 16% of Italian companies with more than 10 employees employ at least ten ICT experts; almost 60% of Italian SMEs provide

[6] We are grateful to an anonymous referee for pointing this out.

[7] The dynamics of job polarization has been one of the key elements fuelling the development of the RBTC literature (Spitz-Oener, 2006; Autor and Dorn, 2009, 2013; Oesch and Rodriguez, 2011, Goos et al. 2014; Michaels et al. 2014; Bogliacino and Lucchese, 2015; Fernández-Macías and Hurley, 2016; Cirillo, 2016). However, Fernández-Macías and Hurley (2016), have shown that polarisation does not emerge in a number of European economies. According to these authors, polarization is not detected in some European economies due to the specific institutional set-up characterizing these economies pointing to factors such as the deregulation of employment contracts or the heterogeneity in the minimum wage levels.

[8] Following the RBTC hypothesis, digitalization is interpreted as the possibility to perform a routine task with 'machines/computers' rather than with 'routine workers'.

connected devices to their employees in order to accomplish their tasks; training programs explicitly directed at enhancing ICT skills have been organized by 20% of SMEs and by about 60% of large firms. The overall picture emerging from these data is that the intensity of digitalization among Italian firms is low or moderate but increasing, geographically unbalanced (higher in the central and northern regions) and concentrated in medium-large and large companies.

When it comes to the technology-employment relationship, Italy represents a peculiar case. Italy emerges from the European Innovation Scoreboard as a "moderate innovator". In fact, several studies have shown that a large share of Italian firms pursues a cost-competitive strategy rather than a technological-competitive one based on the presence of R&D activities, qualified human resources and the introduction of product innovations (Guarascio and Pianta, 2017; Bogliacino et al, 2016). This structural feature of the Italian innovation system is likely to influence also the pattern of digitalization of Italian firms and sectors as well as the employment effects of the adoption of digital technologies, an aspect that needs to be taken into account in interpreting the results of our empirical analysis. Furthermore, unlike most European economies where the RBTC hypothesis has been validated (see Spitz-Oener, 2006; Goos and Manning, 2007; Dustmann et al., 2009; Goos et al., 2009, 2014), Italy does not display a clear polarized occupational structure and dynamics (Fernández-Macías and Hurley, 2016). This fact might be explained by several country-specific features, such as the moderate technological intensity of the Italian industrial structure[9], the existence of peculiar supply-side conditions[10], as well as the presence of protected market niches allowing low-tech productions and routine jobs to survive.

A major advantage in considering the Italian economy in this study comes from the high-quality data collected by national research institutes. In particular, the Indagine Campionaria delle Professioni (ICP), carried out jointly by INAPP and ISTAT, is an occupational survey in the mould of O*Net, based on rigorous sampling and data-collection criteria. In fact, most of the previous empirical analysis focusing on jobs and tasks to study the impact of technical change on employment in Europe have relied on O*Net data from the United States, or indicators derived from it. This raises issues of mismeasurement and omitted information, given the significant structural differences between the US and the European economy, and in particular the characteristics of their occupations. This problem is amplified when considering the highly granular qualitative information on occupations contained in O*Net. In our case, such mismeasurement risks are overcome thanks to the availability of Italy-based O*Net data, representative of the whole spectrum of Italian 5-digit occupations.

3. Research questions

In what follows, we spell out the research questions that will be addressed in the following empirical sections. As mentioned in the introduction, our focus is on the relation between digitalization, the routineness of occupations described by their tasks, and the dynamics of employment. We examine this topic both at a descriptive level and by carrying out a regression analysis at the occupation-sector level. To build our key research questions several literature strands are woven together. On the technology side, we first dig into the different forms that the digitalization processes might take (Vivarelli, 2014). Workplace digitalization is thus framed distinguishing between 'digital tasks' – i.e. number of digital tasks comprised within each occupational 'task bundle' (Autor et al. 2003; Fernández-Macías and Hurley, 2016), and 'digital use', i.e. the relative intensity in the use of digital devices in performing tasks. Occupation-sectors displaying a relevant share of digital tasks are expected to be those where analysing, processing, or manipulating data, represent key elements of the labour processes and production goals (i.e., occupations most likely to be involved in the production of digital goods and services). On the other hand, occupations with a high digital use potentially involve a heterogeneous set of activities, including those requiring complex knowledge and technology, as well as more elementary ones in which digital devices have the primary purpose of increasing efficiency without any specific knowledge requirement. Our first research question is accordingly formulated as follows:

RQ1. *Do highly digitalized occupations (characterized by high levels of digital tasks or an intense use of digital devices) grow faster than* low-*digitalized ones?*

The expectations on RQ1 are mixed. Whenever technological-competitiveness strategies prevail, we should expect a positive effect on employment dynamics. Vice-versa, we expect worse employment performances in the case of cost-competitiveness strategies – i.e. strategies aimed at increasing efficiency and gaining market shares by reducing the relative weight of labour and wages (Vivarelli and Pianta, 2000; Bogliacino et al., 2013; Guarascio et al., 2016; Calvino and Virgillito, 2019). In the first case, the quality of products and their technological complexity are the key drivers of market expansion. As a result, employment might be positively affected by: i) sustained demand, attracted by the introduction of new and high quality products and services; ii) a high level of complementarity between technology and workers' competences, reducing the risk of a labour-saving impact of digitalization (Autor, 2015; Cetrulo et al., 2019). Employment, in turn, is expected to be penalized when digitalization is more explicitly directed at reducing labour costs. This is likely to occur in occupations or sectors where the complementarity between workers' competences and technology is low, and where price competition prevails.

The impact of digitalization on employment, however, is fundamentally mediated by the characteristics of the tasks bundled in each occupation (see the discussion above). The resilience of occupations to the threat of technological unemployment, as well as the opportunities of pursuing cost-savings strategies associated to the use of digital technologies, might in fact be contingent upon the share of routine-task characterizing occupations. The larger the share of these type of tasks, the greater the potential for a machine-driven substitution of employees (Goos et al., 2014; Vona and Consoli, 2014; Gualtieri et al., 2018; Autor, 2015).

Against this background, our second research question accounts for both the degree of occupation-sectors digitalization and the relative intensity of routine-task (explained in the following section). In line with the theoretical considerations dating back to Frederick Taylor, and subsequently consolidated by the RBTC literature, we assume that when tasks are highly repetitive there is a strong case for labour-saving technical change. Therefore, intense digitalization in presence of routine tasks is expected to result in a decrease (or slower increase) in employment, in line with the RBTC assumptions. On the contrary, if digitalization occurs in occupations or sectors that are mostly characterized by complex and knowledge intensive tasks, an increase (or a slower decrease) of employment is likely to occur.

The second research question is thus the following:

RQ2. *In presence of digitalization, does employment in routine-task intensive occupations follow a different dynamics, as compared to the rest of the professional groups?*

There are additional factors that may influence the dynamics of employment in case of digitalization and routineness of tasks (see Fernández-Macías et al., 2016 for a thorough discussion on the RBTC

[9] This is in turn related to the Italian industrial specialization characterized by an extremely large number of small and micro firms as well as by an important share of medium and medium-low tech manufacturing industries, populated by medium-low and low skill workers, that are highly exposed to the competition of low-income low-wage economies (for an in-depth analysis of the Italian industrial structure and of its evolution over time see Celi et al., 2018).

[10] One of the relevant factors is the large supply of highly flexible low-wage labour which might reduce the incentive for technological upgrading and digitalization (Cirillo and Guarascio, 2015).

approach and its limitations). Although we are unable to account for all of them with the data at our disposal, they are nonetheless worth to be mentioned.

First, digitalization might not necessarily induce a decrease in employment, even in occupations characterized by a significant share of routine tasks. This could occur in specific economic and institutional settings: in the case of uncompetitive product markets, in labour markets with a high level of protection against layoffs, or in sectors and markets characterized by a high internal organizational flexibility. In all these cases, the opportunities for digitalization might be relatively lower than in other settings, and their labour-saving effects more limited.

Second, as already discussed in Section 2.3, analysing the relation between digitalization and employment in Italy requires taking into account the characteristics of its productive and occupational structure. Given the relevance of medium-technology sectors in the Italian manufacturing industry, digitalization may threaten the non-negligible share of routine jobs employed in these sectors. A similar risk may affect repetitive and low-complexity jobs in services (accountancy and customer care are often cited as examples). Nevertheless, the same features of the Italian production system described above might lead to less penalizing effects on employment. First, the limited share of innovative firms and the dominance of small enterprises might go hand in hand with moderate digitalization processes, which may also result in a limited impact on employment. Second, wage stagnation and the availability of a large supply of flexible (and cheap) labour may reduce companies' propensity towards labour-saving innovations.[11] Third, the rapidly ageing Italian population may increase the demand for jobs in health and social care services. This would increase the overall demand of non-routine jobs that, by the very nature of their human-centred tasks, are not easily automatable.[12] This element as well may counterbalance, in terms of net employment effects, the reduction of routine jobs occurring in other service sectors.

Overall, the answers to the questions raised in RQ1 and RQ2 are given by the complex interaction of a multitude of factors, and namely: the degree and type of digitalization; the routine task intensity of occupations; the competitive strategy of firms; the structural and institutional shape of the economy and its labour market. As already mentioned, our empirical exercise will not be able to assess the relevance of (or control for) all these factors. Nevertheless, it still provides fresh evidence and relevant insights concerning the digitalization routine-task-employment relation.

4. Data and indicators

Our empirical analysis draws from two major Italian labour market surveys, combined to provide data on employment dynamics, labour market variables, occupational tasks, skills, work attitudes, routine-task intensity, digital tasks and usage of digital tools.

The first source is the Italian Labour Force Survey (ILFS) carried out by ISTAT. As the largest survey conducted in Italy to monitor the quarterly dynamics of the labour market, the ILFS provides data on employment, wages, workforce socio-demographic characteristics and labour market institutional variables. The sample includes more than 250.000 Italian households, or around 600.000 individuals, distributed across about 1.400 Italian municipalities. The ILFS is based on 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). Among its major strengths, there is its large sample size, the refined sampling strategy as well as the regulatory provisions according to which respondents are obliged to reply. The combination of these elements guarantees both data quality and representativeness. Moreover, the continuous reiteration of the ILFS survey allows ISTAT to periodically improve, wave-by-wave, the quality of variables collected. The ILFS covers all Italian industrial sectors and occupations at the highest possible level of disaggregation (i.e., 5-digit *Ateco* code). We rely on it for data on employment status, socio-demographic characteristics (including age, gender and educational attainment), and contract type (open-ended or temporary).

The second source is the INAPP-ISTAT *Indagine Campionaria sulle Professioni* (ICP). The ICP is a rather rich source of information on tasks, skills, work attitudes, routine-task intensity, digital tasks and usage of digital tools. It is the only European survey replicating extensively the American O*Net,[13] the latter being the most comprehensive repertoire reporting qualitative-quantitative information on tasks, work context, organizational features of workplaces at a very granular level. Both the American O*Net and the ICP focus on occupations. Occupation-level variables are built relying on both survey-based worker-level information as well as on post-survey validation by experts' focus groups. The ICP survey has been so far carried out twice (in 2007 and 2012) covering the whole spectrum of the Italian 5-digit occupations (i.e. 811 occupational codes).[14] The interviews are administered to 16.000 Italian workers ensuring representativeness with respect to sector, occupation, firm size and geographical domain (macro-regions). ICP information are collected relying on a 1-hour long CAPI interview administered at the workplace. On average, 20 workers per each Italian occupation are interviewed providing representative information at the 5th digit. The survey includes more than 400 variables on skills, work contents, attitudes, tasks and many other subjective and objective information on occupations.[15]

We join these two datasets by statistical units combining occupation (measured at 4-digit Classificazione delle Professioni or CP, comparable to ISCO[16]) with sector (1-digit Ateco, comparable to NACE). This allows

[11] See Cetrulo at al. (2019) for an analysis of the interaction between the introduction of external flexibility in the Italian labour market, on the one hand, and the degree of companies and industries' innovativeness, on the other.

[12] The majority of the contributions following the RBTC approach – e.g., Autor and Dorn (2013) – have recognized the lower risk of automation faced by low-skill services jobs and jobs requiring manual dexterity, empathy and social skills. Typical examples are jobs in the health and social care services.

[13] 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 their task and skill content. The O*Net is based on the US Standard Occupational Classification (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.

[14] The two waves of the ICP, referring to 2007 and 2012, are not fully comparable due to a break in the occupational taxonomy that does not allow us to compare sufficiently granular occupations over time.

[15] The major difference between ICP and O*Net regards the source of information on which the two surveys rely. The ICP is based entirely on face-to-face interviews to job holders while the O*Net relies on interviews carried out with a mixed pool of job holders and labour analysts. It should be noted, however, that both waves of ICP have been followed by a continuous set of qualitative analyses (focus groups involving labour market experts and practitioners) aiming, among the other things, at periodically validating and maintaining information from job holders interviews. The ICP sample stratification strategy is carried out through two steps. First, a large number of companies is randomly selected (excluding the public administration sector). Once the company-level sample is selected, questionnaires are submitted via Computer Assisted Personal Interviewing (CAPI) techniques to workers.

[16] The most visible difference between ISCO and CP is that two major groups in ISCO (VI *Skilled agricultural, forestry and fishery workers* and VII *Craft and related trades workers*) are grouped together in CP under the heading *Skilled workers in commerce and services.*

to measure changes in employment levels over time between 2011 and 2016.[17] The distribution of occupations across sectors stems from the ILFS micro data. To ensure representativeness of employment variables we opted for a broad sectoral classification: the resulting statistical units are cells of 4-digit occupations by 1-digit sector. The employment and labour market variables are computed by summing up ILFS individual-level employment data for each Italian 4 digit occupation. For each 4-digit occupation we computed the total number of employees and the total number of employees by gender, age, educational attainment, type of contract.

The occupation-level variables on routine-tasks, digital tasks, use of digital tools and innovation (i.e. use of new products), are drawn from the last ICP wave (i.e. 2012), observed at the 5-digit level, and aggregated at 4-digit level by population-weighted averages. In the next three subsections, we describe how these occupational indices are computed.

4.1. The Digital Use Index

We develop the *digital use* index to measure how often and how well workers in any professional group interact with digital technology. Digital technology may take very different forms depending on firm or industry. In order to measure the "use" of digitalization across occupations consistently, we focus on two rather broad and generic items taken into account by the ICP survey: "working with computers" and "Using e-mail as part of one's occupation".

1. (Q. G19) "Working with computers": described as "Using computers and information systems (software and hardware) to program, write software, manage functions, input data, or process information."
   Responses are reported on a 1–7 Likert scale, with the following benchmarks of complexity levels:
   - 2: Input employee data on a digital database
   - 4: Develop an inventory management software
   - 6: Develop an IT system for a large multinational
2. (Q. H2) Using e-mail as part of one's occupation

The first question (Q.G19), stemming from the section of the survey devoted to "General workplace activities" measures the proficiency of respondents in using computers. The benchmarks are meant to be contextualised by the interviewer based on the relevant profession and industry of the interviewee. The question refers to the use of technology by workers themselves, and ranges between using software applications and developing them. The second question (Q. H2), stemming from the section of "Working conditions", asks respondents about how often they use e-mail as part of their work. As a ubiquitous mean of communication – but by no means universally adopted – it serves as a useful signal of digitalization of the workplace, beyond the activities of the individual employee.

Both these questions act as informative indicators (proxies) of different aspects of digitalization of work, in its organisational context. For each occupation, we construct the *digital use* index by averaging the replies expressed in a [0-1] scale. We then normalize the index into a [0-100] linear scale in the range between the minimum and the maximum observed value.

4.2. The digital tasks index

To better capture the different ways work tasks are digitilized, we develop an ad-hoc index based on the precise tasks that characterize each occupation. The ICP survey contains a free-form section where a panel of respondents from 796 5-digit occupational groups describes – using their own words in a lightly coordinated manner – up to 15 work activities (or tasks) characterizing their occupation. For each of these tasks, the respondents report a score indicating its importance.

Table 1
The routine task intensity 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 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 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

This section of the ICP survey thus describes over 6.200 distinct tasks across all professions – after accounting for some identical tasks practiced by different occupations. By examining individually all the nearly 5.700 individual Italian words used to describe tasks found in the survey, we flagged 51 of them that either expressly denote digital technology, e.g., *Informatics (IT), Network, Database, Computer,* or that describe it in a specific context, such as *programming, information, recording, network.*[18] We then individually validated the tasks descriptions that used those keywords in their formulation, to assess them in their context, and rule out false positives.[19] At the end of the process, we identified 131 activities that explicitly involve digital technologies and thus define a highly-digital occupation. These are reported in Table A1 in the Appendix.

We use the list of digital tasks identified to derive an index of *digital tasks* for each occupation: among the different tasks enumerated by each occupation, we compute the weighted average importance score of the digital tasks – those in Table A1 – compared to all tasks used to describe the occupation. This allows to distinguish occupations along the extensive margin of digital tasks – i.e. whether digital task are carried out at all, and the intensive margin – i.e. how important they are relative to the other tasks in that occupation.

Compared to the digital use index, describing occupations by their digital tasks is more restrictive. By construction, it considers only those tasks that explicitly mention digital technology, and thus overlooks cases where technology is unmentioned, incidental, or optional. For example, the task "writing articles or reviews" does not qualify as a digital task, because it does not mention the medium of writing – though that may well be a computer. By contrast, "writing programming code" does qualify, because it involves a computer. Therefore, only 99 out of a total of 796 5-digit occupations have positive values of the digital tasks index, and can thus be considered "highly digital" occupations. Their distribution is further discussed in Section 5.

[17] The 2012 ICP wave collects data referred to 2011, for this reason we compute employment changes between 2011 and 2016, instead of 2012-2016.

[18] The list includes variants of keywords in singular or plural forms, or as adjectives, nouns or adverbs.

[19] For instance, in Italian the keyword *Programmare* ("to program") can refer either to writing software or to more general activities such as planning/scheduling. We only selected tasks that clearly mean the former.

Table 2
List of variables and sources used in the analysis

Variable	Description
Labour market (ILFS) • Total employment (thousands) • Women (%) • Young workers (%) • Temporary contracts (%) • Part-time workers (%)	Observed by 4-digit occupation/1-digit sector cells • Rate of change of employment (2011-2016) • Share of women (employees) over cell total (2011) • Share of 15–34 years old employees over cell total (2011) • Share of workers with temporary contracts over cell total (2011) • Share of workers with part-time contracts over cell total (2011)
Task-related (ICP, 2012) • Routine indices (0–100)	Observed by 4-digit occupation group • Dimensions comprised in the RTI (see Table 2 for details)
Digital (ICP, 2012) • Digital Use (0 – 100) • Digital Tasks (0 – 100)	Observed by 4-digit occupation group • Dimensions comprised in the Digital Use • Dimensions comprised in the Digital Tasks indicators (see Table A1 for details)
Innovation-related (ICP, 2012) • Process innovation (%)	Observed by 4-digit occupation group • Incidence of process innovation

4.3. The routine task intensity index

In line with Goos et al. (2014), we measure the degree of task routineness relying on the Routine Task Intensity (RTI) index. Based on the ICP questionnaire, we account for the same task-related dimensions considered in the empirical analysis by Autor et al. (2003) and subsequent contributions. In our case, however, the task variables derived from the ICP are measured directly in the context of the Italian occupational structure. This direct measurement avoids issues – such as occupational mis-classification or incomplete mapping – that would arise by imputing values from the US O*Net repertoire onto Italian labour market data, for example by means of a SOC-ISCO crosswalk. We aggregate the six task domains considered by Acemoglu and Autor (2011) into three main task-categories – namely Routine Task, Non-Routine Cognitive and Non-Routine Manual tasks. The detailed component of the RTI we use in our analysis are reported in Table 1. The RTI adopted here is substantially close to the one used in Acemoglu and Autor (2011) and can be formalized as follows:

$$RTI_k = (RC_k + RM_k)_{routine\ component} - (NRM_k)_{non-routine\ manual\ component} - (NRCA_k + NRCI_k)_{non-routine\ cognitive\ component} \quad (1)$$

For each 5-digit occupation k in ICP, the RTI index is computed as the difference between the routine and non-routine dimensions of occupations. The routine component sums 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) with the Routine Manual (RM) indicator (proxying the degree of repetitiveness and of pre-determination of manual operations). The Non Routine Cognitive Analytical (NRCA) term captures the relevance of tasks that imply to think creatively as well as to analyse and interpret data and information; Non-Routine Cognitive Interpersonal (NRCI) refers to the importance of social relationships, interaction, managing and coaching colleagues; Non Routine Manual (NRM) captures the degree of manual dexterity needed to perform operations[20].

The indicator in (1) is increasing in the relative importance of routine task in each 4-digit occupation while decreasing with the importance of abstract and non-routine tasks.

The full set of variables used for the empirical analysis for occupation-sector cells (at 4-digit × 1-digit level respectively) is summarised in Table 2. On the employment side (variables stemming from the ILFS): the rate of change of employment is between 2011 and 2016 (logarithmic difference), the share of female employees, the share of young workers (aged 15–34), the share of workers with tertiary education, the share of workers with temporary contracts refer to 2011. Concerning tasks, digital tasks and use of digital tools (variables stemming from the ICP): Routine Task Index (RTI) and its subcomponents (i.e. Routine Manual (RM), capturing the relative degree of manual routine tasks; and Routine Cognitive (RC), capturing the relative degree of cognitive routine tasks); Digital Use Index and Digital Tasks Index. In addition, we include an ICP variable on the share of workers, by each 4-digit occupation, declaring that a process innovation occurred in their workplace.[21]

5. Descriptive evidence

In this section, we provide descriptive evidence on: a) the levels of digitalization and routineness of occupations; b) the relationship between the level of digitalization and routineness across occupations; c) the dynamics of employment in professions characterized by different levels of digitalization and routineness.

5.1. Digitalization and routineness across occupations

Occupations strongly differ concerning ‘what they do at work’ and ‘how they perform their tasks’. This heterogeneity relates to both the technical characteristics of tasks as well as to the organizational specificities of the workplace. Fig. 1, showing digital and routine-task indices (digital use, digital tasks, routine task) for each 4-digit occupation, confirms that on average, the 1-digit *occupation major groups* (i.e., the most aggregate occupation classes in the ISCO and CP classifications) show significant differences in terms of usage of digital tools and repetitiveness of tasks performed. High-skilled occupations – *Managers, Professionals* and *Technicians* – are characterized by the highest levels of digitalization measured in terms of digital use; conversely, *Plant and machine operators* as well as *Elementary occupations* show the lowest values. Notably, service and skilled craft occupations vary widely in the level of digital use, presumably depending on their sector of activity, type of firm and innovation and competitive strategy. Looking at the middle of the occupational ranking (i.e. *Service workers, Crafts* and, to a lower extent, *Plant and machine operators*) the values of the digital use indicator turns out to be relatively more dispersed. This might be related to the heterogeneity – in terms of technological characteristics and prevalent competitive strategies – characterizing the industries and

[20] Following Acemoglu and Autor (2011), in the empirical evidence presented in the main text, we compute the RTI index excluding the “Non Routine Manual Interpersonal Adaptability” component referring to the degree of social perceptiveness. However, in the Appendix we also provide estimates based on the definition of RTI including the ‘Non routine Manual Interpersonal Adaptability’ (NRMIA) component – see Tables A4 and A5.

[21] The data-set used in this study does not allow us to compute our innovation variable at industry or firm level, nor to estimate its employment impact at these levels of aggregation. However, we can assume that innovations activities affect the different productive and organizational areas of firms with a different intensity and frequency, producing differentiated effects on the different professional groups operating in the same firm and sector. We feel rather confident therefore that our innovation indicator is able to grasp, at least to some extent, the intra-industry intra-organizational effects of innovation (and digitalization) on employment.

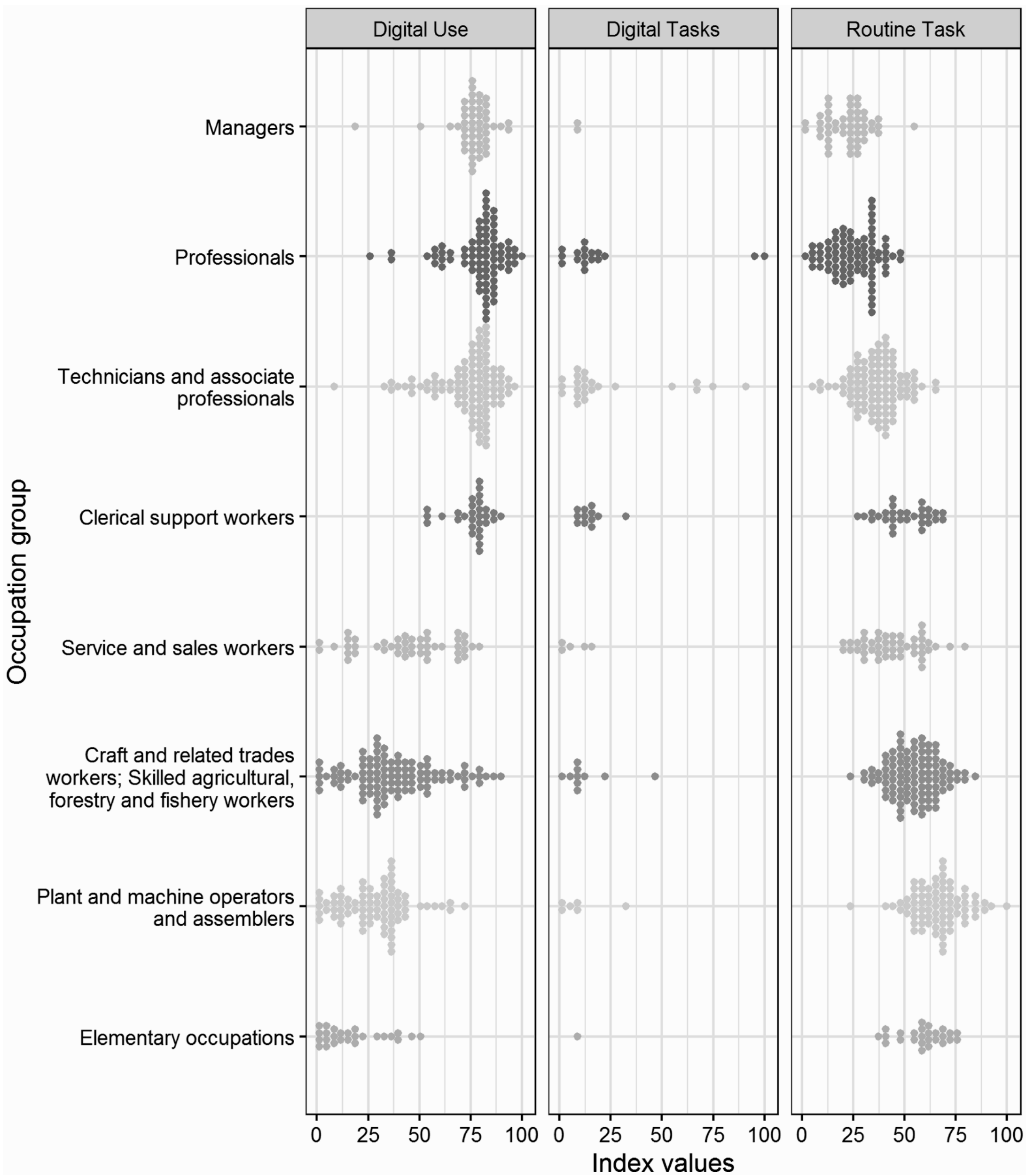

Fig. 1. Digital and routine indices of occupations (4-digits) by occupation major groups (1-digit). Note: Authors' elaboration on ILFS-ICP data. The plot shows the values of the indices of digital use, digital tasks, and routine task across all occupations. Each dot represents a single 5-digit occupation, irrespective of employment, stacked together show the distribution of values, and grouped vertically by one-digit occupation major group. Digital tasks are present only in a minority of occupations; the plot shows only the values greater than zero, to focus effectively on those occupations, and avoid over-plotting the density around zero.

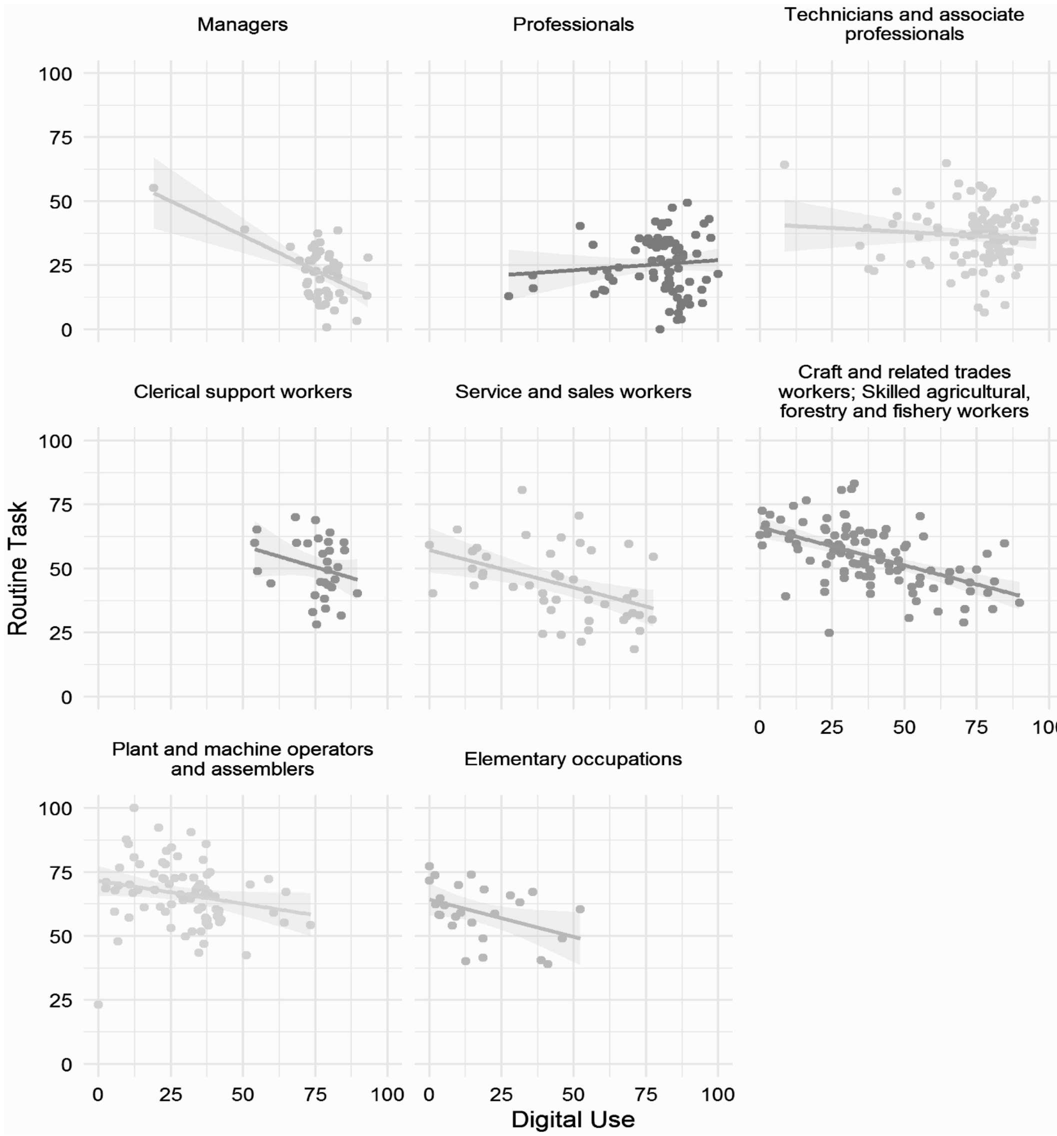

Fig. 2. Levels of digitalization and routineness across single occupations (4-digit), by occupational major groups (1-digit)

firms wherein the 4-digit occupations (belonging to such middle layer 1-digit groups) are employed. A different pattern emerges when we look at the distribution of professions according to the digital tasks indicator. As already mentioned, only a minority of occupations rank high in terms of digital tasks (see Table A1 in the Appendix). Digital tasks tend to be relatively more numerous among professionals and technicians. The joint analysis of the distribution of our two indicators of digitalization, across and within the eight 1-digit macro-occupational groups, shows that digitalization is a process involving mainly high-skilled occupations, although in presence of a high degree of heterogeneity that is consistent with the digitalization patterns of the Italian production structure. The latter is in fact often depicted as clustered in two major groups: a first one made of a relatively limited number of highly innovative and highly digitalized firms; a second one, consisting of a large cluster of slower adopters of digital technologies (European Commission, 2018).

Italian occupations prove to be highly heterogeneous also concerning the level of routineness of labour tasks. The degree of routineness is inversely related to the qualitative and skill content of the eight occupational groups: professions at the top of the occupational ranking display the lowest RTI values; while the opposite holds for middle and low-skill occupations. *Management and professional occupations* are, on average, those with the lowest level of routineness while *Plant and machine operators* appear as the most routinized.

Table 3
Rates of change of employment by (1-digit) occupation major groups (2011-16)

Occupation major group	Total (thousands)		Change
	2011	2016	(%)
Managers	695	624	-10.1%
Professionals	2904	3234	11.4%
Technicians and associate professionals	3936	4005	1.7%
Clerical support workers	2531	2595	2.6%
Service and sales workers	3949	4355	10.3%
Craft and related trades workers; Skilled agricultural, forestry and fishery workers	3953	3375	-14.6%
Plant and machine operators and assemblers	1863	1806	-3.0%
Elementary occupations	2236	2523	12.8%

Source: ILFS.

On average, Fig. 1 shows that high-skilled occupations use digital tools more frequently, carry out a larger share of digital tasks, and have a lower share of routine tasks. The opposite holds for middle- and low-skilled occupations. Occupations with the highest values of the digital

Table 4
Rates of employment change (2011–16) by the levels of RTI and Digital use (in brackets: share of employees over total employment in 2016)

	(Digital Use)							
	DU < 0.25		0.25 < DU < 0.75		DU > 0.75		Total	
RTI<0.25	-1.6%	(7%)	-7.8%	(15%)	5.6%	(6%)	-2.8%	(28%)
0.25 <RTI < 0.75	9.4%	(15%)	9.4%	(11%)	0.5%	(8%)	7.0%	(35%)
RTI >0.75	0.3%	(28%)	-9.6%	(5%)	-29.6%	(4%)	-1.4%	(37%)
Total	2.9%	(50%)	-1.7%	(31%)	1.8%	(19%)	1.2%	(100%)

Table 5
Rates of change of employment (2011-16) by the level of RTI and digital tasks (in brackets: share of employees over total employment in 2016)

	DIGITAL TASKS<0.50		DIGITAL TASKS>0.50		Total	
RTI<0.25	-3.1%	(23%)	-2.1%	(5%)	-2.8%	(28%)
0.25 >RTI < 0.75	9.7%	(29%)	-3.8%	(6%)	7.0%	(35%)
RTI >0.75	-0.5%	(32%)	-15.2%	(5%)	-1.4%	(37%)
Total	2.4%	(84%)	-4.7%	(16%)	1.2%	(100%)

task index are found mainly among the professional and technical occupational groups (2nd and 3rd occupational group in Fig. 1). Some occupations in services and sales (5th occupational group) – as well as craft and related trades (6th row) – also show high levels of digital use, but lower values for digital tasks. This result indicates that although some less-skilled occupations do make frequent use of digital technologies, very few of them perform the type of advanced tasks captured by our digital task index, such as programming or administration.

The overall relation between digitalization and routineness is further explored in Fig. 2, presenting a series of scatterplots showing the levels of the "digital use" and "routine task" indicators of single occupations across different professional groups. Fig. 2 confirms the prevalence of a negative relation between the levels of digitalization and routineness: in most of the 1-digit macro occupational groups, occupations that are less digitalized tend also to be more routine, with the notable exception of *Professional* occupations, where the correlation is not statistically significant. In general, the steepness of the negative digitalization-routineness relation varies strongly across occupations suggesting, even in this case, a significant degree of structural heterogeneity.

5.2. Digitalization, routineness and employment changes

The descriptive evidence presented so far has shown the presence of marked differences in the level of digitalization and routineness across professional groups. But to what extent are the levels of digitalization and routineness associated to the actual dynamics of employment? This question will be addressed in econometric terms in the following section. In what follows, we start exploring this issue in a pure descriptive fashion comparing the employment performances of groups of occupations characterized by different levels of digitalization and routineness.

Table 3 presents the rates of change of employment occurred in 2011-16 in the eight 1-digit macro-ISCO occupational groups. It shows that the employment performances of the eight occupational categories are only loosely correlated to their skill and professional content. Furthermore, when analysed jointly with the evidence emerging from Figs. 1 and 2 the data reported in Table 3 do not reveal any easy correlation between the levels of digitalization and routineness of tasks and the dynamics of employment, at least when digitalization and routineness are taken into account separately one from each other.

We further explore the nexus between digitalization, routineness, and employment by comparing the rates of change in employment between 2011 and 2016 in all 4-digit occupations, grouped on the basis of the two distributions (quantiles, referring to 2011): one referring to the levels of digitalization (i.e., Digital Use and Digital Tasks), and the other one referring to the level of routineness (RTI).[22] Table 4 shows levels and changes of employment for groups of occupations characterized by different levels of routineness and digitalization. Occupations with either the highest or lowest levels of digital use experienced a positive growth of employment (1.8% and 2.9% respectively), while those with a medium level of digital use contracted (-1.7%). Occupations with the lowest or highest levels of routineness (RTI) both shrank (-2.8% and -1.4%). However, the most striking and interesting result is the very strong job contraction (-29.6%) of occupations characterized by both a high level of digitalization and a high level of routineness (although this sub-group of occupations accounts for only 4% of Italian employees).

When we look at the employment performances of occupations grouped according the levels of the digital task and RTI indexes a somewhat different picture emerges (Table 5). Negative employment growth rates are found among professional groups characterized by high levels of the digital task indicator and at the two extremes of the distribution with respect to RTI indicator. However, it should be noticed that also in this case a strong employment reduction (-15,2%) is observed in all occupations characterized by the joint presence of high levels of the Digital task and the RTI index.

6. Econometric analysis

Following the descriptive evidence provided in the previous section and the research questions stated in Section 3, we now move on to investigate econometrically whether the degree of digitalization – measured by the use of digital technology, or the number of digital tasks performed by occupations – is associated with changes in employment at the occupation-industry level. The dynamics of occupations is affected by a wide variety of factors, which also interact in a complex way with the role played by technological change and more specifically with digitalization. In fact, for workplace digitalization to unfold, with its potential consequences on employment dynamics, macroeconomic and structural conditions matter as well, as do business models as value-capture mechanisms (Teece, 2018). Supply-side innovations, like the digitalization of production processes carried out to increase efficiency, are more likely to occur when demand and growth prospects are attractive enough to induce firms to digitalize labour and organizational models. Of course, with the data at our disposal we can only to a limited extent control – through the sectoral fixed-effects – for the role played by demand conditions in the different industries and markets. However, the use of fine-grained data (4-digit level of the ISCO classification of occupations) allow us to capture at least some sectoral specificities. In

[22] Given the distribution of the digital task index skewed right, we divide occupation-sector cells in two groups: occupations with a value of the digital task index below the median (<0.50) and occupations above the median (>0.50).

Table 6
Estimates of changes in occupation-sector employment – digital use index (Weighted Ordinary Least Squares - WLS)

Change in employment 2011–16 (Log difference)	(1)	(2)	(3)	(4)	(5)
Digital Use	0.0500**	0.0168	0.0364	0.0562*	0.0728*
	(2.76)	(0.68)	(1.45)	(2.15)	(2.54)
Routine Task Index (RTI)		-0.0605*	-0.0479	-0.0409	-0.0414
		(-2.13)	(-1.71)	(-1.43)	(-1.43)
RTI × Digital use			-0.0556*	-0.0587*	-0.0594*
			(-2.36)	(-2.52)	(-2.55)
Sector fixed effects (baseline: Agriculture):				0	0
				(.)	(.)
—Mining and manufacturing				-0.234*	-0.209*
				(-2.44)	(-2.21)
—Electricity, gas, steam and waste mgt				-0.436***	-0.422***
				(-3.79)	(-3.68)
—Construction				-0.352***	-0.330**
				(-3.31)	(-3.12)
—Wholesale and retail trade				-0.167	-0.184
				(-1.28)	(-1.40)
—Transportation and storage				-0.259*	-0.241*
				(-2.24)	(-2.11)
—Information and communication				-0.345**	-0.315*
				(-2.75)	(-2.53)
—Finance and insurance				-0.319*	-0.283
				(-2.15)	(-1.93)
—Real estate and administration				-0.102	-0.0874
				(-1.00)	(-0.86)
—Public administration and defence				-0.581***	-0.543***
				(-5.12)	(-4.80)
—Education and social work activities				-0.325**	-0.288**
				(-3.02)	(-2.66)
—Arts, entertainment and other services				-0.205*	-0.183
				(-1.98)	(-1.76)
Process innovations					-0.107
					(-0.74)
Share of young workers					0.154
					(1.64)
Share of female workers					-0.0123
					(-0.18)
Share of temporary employees					0.385**
					(2.95)
Share of part-time workers					0.154
					(1.35)
Constant	-0.202***	-0.198***	-0.231***	0.0406	-0.167
	(-10.91)	(-10.70)	(-9.63)	(0.46)	(-1.14)
N	2293	2293	2293	2293	2293
Adj. R-sq	0.002	0.004	0.006	0.023	0.029

t statistics in parentheses, robust standard errors
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

other words, we are reasonably confident on the fact that the levels of digitalization and routineness of professions also vary by sector.[23] Furthermore, data on employment changes vary at the occupation-sector cell meaning that the same occupation may grow or shrink, depending on the sector.

To test RQ1 – "*Do more digitalized occupations (defined by more digital tasks or higher digital use) grow faster than less digitalized ones?*" and RQ2 – "I*n presence of digitalization, does employment in routine-task intensive occupations follow different dynamics, as compared to the rest of the professional groups?",* we build upon different specifications. Each of them has been tested alternatively on a distinct digital dimension: digital use and digital tasks (see the full description of the two indicators provided in the previous section). We study employment changes at the occupation-industry level in relation to the relative 'digitalization' of occupations (observed in the 2012 edition of ICP, collecting data referring to 2011). We control for the occupation degree of task-routineness as measured by our RTI indicator (Acemoglu and Autor, 2011). We perform: (i) a baseline regression in which we only include separately the digital use and the digital task indices (2); (ii) a regression including alternatively the digital indices and the RTI measure (3); (iii) a regression including digital indices, the RTI measure and an interaction term between digital and RTI measures (4); (iv) a final regression in which we include, in a step-wise fashion, a set of additional regressors aimed at controlling for some of the occupation sector-specific factors potentially affecting employment dynamics[24]. In specifications (4) and (5), the coefficient of major interest is γ – the one associated with the interaction term – since it signals the potentially additional positive (negative) employment effect of digitalization observable given the occupation-specific degree of task routineness, allowing us to explicitly test for RQ2. In all estimations,

[23] For example, the occupation 1.1.1.1 – *Legislators* - differs from 1.1.1.2 – *Senior government officials* - in terms of tasks and place where the job is carried out. These two occupations indeed differ in terms of digitalization and routineness.

[24] First, we include sectoral controls and then occupation-sectoral controls.

Table 7
Estimates of changes in occupation-sector employment – digital tasks index (Weighted Ordinary Least Squares - WLS)

Change in employment 2011–16 (Log difference)	(1)	(2)	(3)	(4)	(5)
Digital Tasks	0.0239*	0.0202	-0.0126	-0.00709	-0.00553
	(2.01)	(1.70)	(-0.73)	(-0.41)	(-0.30)
Routine Task Index (RTI)		-0.0697***	-0.0794***	-0.0844***	-0.0931***
		(-3.34)	(-3.77)	(-3.91)	(-4.22)
RTI × Digital Tasks			-0.0988**	-0.0951**	-0.0905*
			(-2.68)	(-2.62)	(-2.50)
Sector fixed effects (baseline: Agriculture):				0	0
				(.)	(.)
—Mining and manufacturing				-0.207*	-0.180
				(-2.23)	(-1.95)
—Electricity, gas, steam and waste mgt				-0.418***	-0.397***
				(-3.70)	(-3.50)
—Construction				-0.336**	-0.310**
				(-3.21)	(-2.96)
—Wholesale and retail trade				-0.163	-0.178
				(-1.26)	(-1.36)
—Transportation and storage				-0.231*	-0.207
				(-2.06)	(-1.86)
—Information and communication				-0.311*	-0.273*
				(-2.56)	(-2.24)
—Finance and insurance				-0.282	-0.239
				(-1.94)	(-1.64)
—Real estate and administration				-0.0699	-0.0487
				(-0.71)	(-0.49)
—Public administration and defence				-0.547***	-0.508***
				(-4.97)	(-4.58)
—Education and social work activities				-0.296**	-0.261*
				(-2.81)	(-2.44)
—Arts, entertainment and other services				-0.184	-0.158
				(-1.81)	(-1.54)
Process innovations					-0.0400
					(-0.28)
Share of young workers					0.145
					(1.55)
Share of female workers					0.0169
					(0.25)
Share of temporary employees					0.360**
					(2.79)
Share of part-time workers					0.182
					(1.59)
Constant	-0.200***	-0.199***	-0.203***	0.0474	-0.207
	(-10.80)	(-10.79)	(-10.94)	(0.55)	(-1.43)
N	2293	2293	2293	2293	2293
Adj. R-sq	0.001	0.005	0.007	0.024	0.029

t statistics in parentheses, robust standard errors
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the dependent variable refers to changes in employment between 2011 and 2016, while all controls are computed at the initial year (2011).

The specifications adopted for the analysis are formalized as follows:

$$\Delta N_{ij} = \alpha + \beta \ DigitalUse_i / DigitalTask_i + \varepsilon_{ij} \tag{2}$$

$$\Delta N_{ij} = \alpha + \beta \ DigitalUse_i / DigitalTask_i + \delta \ RTI_i + \varepsilon_{ij} \tag{3}$$

$$\Delta N_{ij} = \alpha + \beta \ DigitalUse_i / DigitalTask_i + \delta \ RTI_i + \gamma \ Digital \ Use_i / DigitalTask_i * RTI_i + \varepsilon_{ij} \tag{4}$$

$$\Delta N_{ij} = \alpha + \beta \ DigitalUse_i / DigitalTask_i + \delta \ RTI_i + \gamma \ Digital \ Use_i / DigitalTask_i * RTI_i + \theta X_{ij} + \varphi Y_i + Z_j + \varepsilon_{ij} \tag{5}$$

where the *ij* pair corresponds, respectively, to the 4-digit occupation code and to the 1-digit Ateco 2007 (equivalent to NACE Rev. 2) sector. The dependent variable ΔN_{ij} stands for the change in employment between 2011 and 2016 of an occupation-sector cell *ij*, computed as a log difference; *DigitalUse* is the indicator ranging between 0 and 100 and captures the relative importance of digital tools to perform the operations required by each 4-digit occupation included in the analysis; *DigitalTask* ranges between 0 and 100 and refers to the relative importance of 'digital tasks' for each occupation *i*. In order to account for the degree of routineness at the occupation level, we rely on the *RTI* index provided by the ICP for each 4-digit occupation. We then add sectoral fixed effects Z_j in all the estimations allowing to control, at least partly, for structural heterogeneities as well as for sectoral differences in the dynamics of demand.

The X_{ij} matrix includes a set of occupation-sector controls drawn from the Italian Labour Force Survey (ILFS), and namely: the share of young employees (15–34 years old); the share of women; the share of employees with temporary contracts; the share of employees having a part-time contract over the total. Such controls allow to account for important heterogeneities that might affect the employment-digitalization relation. To explicitly account for the role of technical change and innovation we introduce an additional indicator (Y_i), stemming from the ICP, and capturing the relevance of process innovations at the 4-digit occupation level (i.e., share of respondents belonging to a certain occupation reporting that a process innovation has been introduced in their workplace during the last three years). In the Appendix, we show the estimates of specifications (2) - (5) with the inclusion of a different specification of the RTI index – the one computed with the NRMIA component referring to interpersonal adaptability tasks

(Tables A4 and A5). Regressions are estimated relying on the Weighted Ordinary Least Squares (WLS) estimator.[25] Standard errors are adjusted in order to control for heteroscedasticity.[26]

7. Results

The results of all the above-mentioned specifications are reported in Tables 6 and 7. As a first remark, it is worth noticing that occupations displaying a high level of the ‘digital use’ index tend to growth more than the rest of the work force. A one standard deviation increase in digital use is associated to a 5% – 7% employment change. This effect is far from being negligible, as it translates into changes of hundreds or thousands of workers, over a relatively short time. All things being equal, thus, employment in highly-digitalized occupations tend to grow relatively more as compared to the rest of the workforce. This result is in line with other previous studies – see the findings of Van Roy et al. (2018) detecting an employment growth of 5% associated to innovation activities. The same relationship becomes statistically less significant when digitalization is measured relying on the digital task indicator (Table 7). According to our simplest specification (column 1), occupations characterized by highly-digitalized tasks tend to grow faster by about 2% than the rest of the workforce. However, no statistically significant association is detected when other controls are included (columns 2–5).

The picture does not change when the degree of routineness is accounted for by including the RTI index among the regressors (columns 2, 3, 4, 5 in Tables 6 and 7): that is, highly digitalized jobs seem to grow more than the others (columns 4 and 5), partially confirming our RQ1. As already stressed, with the data at our disposal we cannot control for the role that sector specific technological regimes and firms’ strategies might play in explaining the positive association between digitalization and employment found in our estimates. Our results seem however consistent with the hypothesis that professions scoring high with respect to our two digital indexes are likely to be more relevant in sectors where “technological-competitiveness strategies” prevail; this result seems in turn to reject the hypothesis that digitalization as such is driven by strategies aiming at reducing labour costs. This positive effect is detected both when one accounts for the use of digital tools and for performing digital tasks.

Some interesting differences emerge when digitalization and routineness are jointly taken into account introducing interaction terms between the digital indicators and the RTI index (columns 3, 4, 5). The statistically significant negative coefficients of these interacted variables in most of the specifications suggest that the joint presence of high levels of digitalization and routines might have a penalizing effect on employment (compared to occupations that do not present such a combination) (see Figs. A1 and A2 in the Appendix showing the impact of digital use/digital task on employment change for different levels of routines, corresponding to different quantiles of the RTI distribution).[27]

These results lend support to RQ2 (see section 3). The characteristics of the tasks bundled in each occupation (and in particular the level of routineness) may define, on the one hand, the resilience of occupations to the potential labour saving effects of digitalization and, on the other, the opportunity and possibility for firms to obtain substantial efficiency gains and cost savings by substituting human tasks with digital technologies. The higher the proportion of repetitive and encodable tasks characterizing occupations, the higher the probability that these tasks may be substituted by machines leading to direct job losses, or to an overall weak employment growth. These results might reflect also some peculiarities of the Italian production structure, characterized by a high competitive pressure in some segments of its most traditional industries – both in services and manufacturing. In these industries, characterized by the dominance of repetitive tasks, there might be a strong case for labour-saving technological change in order to face a market competition .

As expected, most of the variance in employment change is explained by sectoral dummies capturing major differences in employment growth at occupation-industry level (the inclusion of sectoral controls significantly increases the adjusted R-squared). Among labour market controls, the share of employees having a temporary work contract is positively associated to employment growth. This is in line with much of the empirical literature studying the post-2008 evolution of the Italian labour market, reporting a continuous increase in the share of temporary employment and an intense use by firms of short-term contracts (on this point, see Cirillo et al. 2017; Cirillo and Ricci, 2020).

8. Conclusions

Over the last two decades, the impact of digitalization on employment has been at the centre of a lively debate and has generated a great deal of empirical research. In the most recent literature, digitalization has been associated to the level of routineness of jobs, building on the conceptual framework proposed by Autor et al. (2003) according to which highly routinized professions are those more exposed to job substitution. In that framework, technology is largely seen as a shock affecting labour demand, and subsequently employment, according to the elasticity of substitution between labour and capital. In such a framework, the effect of digital technologies on labour demand depends in turn on the type of task content involved in each profession: in particular, routine tasks that are easier to codify and automate are more likely to be replaced by digital devices and operating systems.

In this work we have provided an empirical contribution in this challenging area of research, by analysing and measuring digitalization and routineness of tasks as distinct phenomena, exploring their relevance across occupations, and assessing econometrically their independent and combined association with the dynamics of employment using as unit of the analysis more than 500 occupational groups across NACE 1 industrial sectors. This was made possible by the detailed occupational data provided by the INAPP-ISTAT survey on Italian occupations (*Indagine Campionaria delle Professioni)*.

The empirical results presented in this paper can be summarized as follows. Digitalization and routineness are indeed distinct phenomena, varying widely across occupations and sectors. A broad relation has emerged between digitalization and routineness, on the one hand, and the skill and professional content of occupations, on the other hand. Namely, high-skilled occupations such as professionals, technicians and managers use digital technologies more intensely than lower-skilled occupations. The same groups of occupations are also more likely to perform digital tasks than less-skilled and more elementary occupations. However, some less-skilled occupations in services – as well as skilled crafts and related trades – are characterized by an intense use of digital tools, though very few of them rank high in terms of digital tasks. The level of routineness of labour tasks emerges, instead, as being negatively associated to the skill content of occupations. We also find a broad negative correlation between digitalization and routineness across most 1-digit ISCO occupational groups.

The econometric analysis has highlighted the existence of a small, positive and significant, relation between digitalization and employment dynamics. That is, occupations using digital technologies more

[25] Regressions have been weighted by the total number of employees in 2011 in each occupation-sector cell.

[26] The main descriptive statistics for the variables used in the regression analysis are reported in Table A3 in the Appendix.

[27] Figures A1 and A2 in the Appendix show that digital use is positively associated to employment change for low and medium levels of the RTI while a slightly negative association is detected for high levels of the RTI. In the case of digital task, a positive employment dynamics is observed with medium-high level of routineness (the marginal effect becomes negative at the median of the RTI distribution) while the opposite holds for above-the median levels of the RTI.

intensely, or performing a larger number of digital tasks, grow faster compared to the others, possibly because they are employed in sectors where technological-competitiveness strategies dominate, with digitalization being a key element associated to the introduction of new products and business models. An additional important insight emerging from both our descriptive and econometric exercises is that the positive association between digitalization and employment turns sign, and becomes negative, in the cases in which digitalization processes take place in productive contexts characterized by highly routinized tasks. Our results suggest that the larger the share of repetitive and encodable tasks characterizing occupations, the greater the potential for the introduction of labour saving digital technologies and, potentially, for the occurrence of job losses. These results are therefore consistent with the idea that in presence of a high concentration of codifiable and repetitive tasks, firms might digitalize labour processes in order to increase efficiency, rationalize and monitor workers' tasks, reducing bottlenecks and tracking errors along the production process, easing knowledge extraction, facilitating communication and favouring cooperation among workers (Braverman, 1974; Fernández-Macías and Hurley, 2016). In this perspective, digitalization – likely to occur when specific technical conditions (i.e., availability of digital technologies and tools) and work-content related conditions (i.e. tasks that are apt to be standardized, encoded and tracked digitally) are verified – might ultimately have relevant employment effects.

In interpreting the results of our empirical analysis, we need to account for some of the distinguishing features of the Italian economic structure. Compared to most of the other Eurozone economies (with the notable exception of Germany) and the United States, manufacturing is still an important component of the Italian economic structure. This means that a non-negligible share of Italian occupations, particularly those involved in the more labour-intensive stages of the production process, is potentially exposed to risk of substitution due to the introduction of labour saving digital technologies.

With the data at our disposal we could not take into consideration the role played by relevant factors affecting the key relationships investigated in this article, such as those connected to the specific strategies pursued by the firms, the different technological and organizational regimes in which they operate, the different demand conditions, and other key sectoral specificities that influence the motivations behind the adoption of digital technologies and their consequences on jobs. This constitutes a major drawback of our analysis but also a promising avenue for future research. It is also worth mentioning that the effects of the 2008–9 economic crisis have probably influenced the phenomena and relationships examined in this study. However, exploring the nature and strength of these effects on the processes and patterns of digitalization, and on their effects on employment, would have required the availability of longer time-series, a "scarce resource" in this area of research. Changes in digitalization strategies pursued by firms over upswings and downswings might represent a further interesting development of the line of research explored in this article.

Credit author statement

This article is the joint research outcome of the four authors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Tables from A1 to A5 and Fig. A1 and A2.

Table A1
List of highly-digital tasks considered to build the digital task index.

Digital tasks
1. Record content (music, video, etc) in digital archives
2. Update archives or databases
3. Update databases
4. Update personnel databases
5. Update software on machinery operation
6. Update or query databases
7. Update or input data and measurements in the computers controlling machinery (check measurements, etc.)
8. Analyse software malfunctions
9. Analyse technical specifications and features of network and telecom equipment
10. Analyse or find client needs (analyse operational problems, define software and hardware requirements, etc.)
11. Analyse or find client needs (feasibility studies, identifying appropriate tools, analyse operational problems, define software and hardware requirements, etc.)
12. Analyse, plan and develop software systems
13. Activating terminals executing plays
14. Equip and program machine tools depending on task
15. Equip and program machinery and robots (turn robots on and off, program tasks, etc.)
16. Equip and program machine tools based on task (milling machine, lathe, sanding machine, etc.)
17. Configure or install IT systems
18. Query databases
19. Contact (also electronically) the customer to receive data to carry out interviews
20. Check the reactor loads by computer
21. Check plays and wins from a terminal
22. Check plays and wins from a terminal, and check sporting results
23. Check operational parameters of robots
24. Check furnace temperature and draw reports on the temperature measured by the computer system
25. Track remotely merchandise shipments
26. Coordinate or carry out lab experiments, computer simulations, observations
27. Coordinate lab activities and prepare exercises (new technologies, network security, etc)
28. Fix or alter digital photos
29. Create and update a supplier database
30. Create, update and manage a database
31. Create, modify or test software and applications
32. Supervise and introduce technological innovations
33. Supervise and introduce technological or product innovation
34. Supervise the digitalisation of services (cataloguing, documentation, bibliographic research, etc.)
35. Supervise the mechanical or digital layout of text, images or other symbols to execute
36. Supervise the preservation and possible recovery of digitized records
37. Supervise the preservation, protection, and possible recovery of digitized records
38. Draw projects on the computer
39. Translate (business, legal, or technical documents, advertisement copy, web content, etc.)
40. Editing digital images
41. Research material for users (library search, on the web, or in other libraries)
42. Image colouring (by paintbrush or by computer)
43. Run computer simulations
44. Calibrate components with computer or similar technologies
45. Perform software tests
46. Extract data from digital archives
47. Advise clients on software or IT systems
48. Manage databases or archives
49. Manage personnel data
50. Manage and update web advertisement copy
51. Manage and update website contents
52. Manage and supervise the sales network
53. Manage the database structure
54. Manage the digital labs and IT equipment
55. Manage IT networks
56. Manage servers
57. Manage IT systems and networks
58. Set the print layout digitally
59. Set the technical specifications for application development
60. Set the technical specifications for application development (ie, develop programs, procedures, interface, etc.)
61. Find and fix software bugs
62. Identify and develop software solutions and procedures

(*continued on next page*)

Table A1 (*continued*)

63. Input data in digital archives
64. Install IT equipment
65. Install automated vending machines
66. Install and update IT networks
67. Install and update network and communication equipment
68. Install or expand telephone networks
69. Install on-board machines or equipment (set up dredges, install electric equipment such as echo-sounders, radar, auto-pilot, etc.)
70. Install programs or applications
71. Install IT networks
72. Install telephone networks
73. Install operating systems and applications
74. Install software
75. Merge data collected with digital databases
76. Submit reports or information electronically
77. Update and optimize IT networks
78. Update and repair network and telecommunication equipment
79. Edit software or other applications
80. Supervise databases
81. Supervise and maintain IT systems and networks
82. Supervise the performance of IT systems and networks
83. Assemble or disassemble components or parts of personal computers
84. Organise and manage inventories, archives and databases
85. Organise the documentation on artwork on microfilm or other digital media
86. Organise or perform laboratory experiment or computer simulation
87. Customise software
88. Design and supervise IT security systems
89. Design and implement solutions for optimising systems
90. Design and implement solutions for optimising network and telecommunication systems
91. Design and develop websites
92. Design and develop systems or telecommunication network apparatus
93. Develop teaching programs (general or customized)
94. Design IT or telecom systems
95. Design, implement and maintain software or IT systems for industrial processes management
96. Design, develop and test database management systems
97. Design, develop and test software for various use cases
98. Develop websites
99. Record date on origin and destination by digital means
100. Repair components or parts of personal computers
101. Reboot machine and robots in case of disruption and intervene in the production line in case of mechanical malfunction
102. Reproduce documents on digital medium
103. Reproduce or print on different media (digital, paper, etc.) documents or images, negatives and photographs (scanning, etc.)
104. Writing program code
105. Study and apply software solutions to solve problems
106. Develop software and other applications
107. Perform ordinary or extraordinary maintenance on systems or programs
108. Test the optimisation of engines
109. Test hardware components, networks, or computing peripherals
110. Send documents electronically to the relevant department
111. Use database or IT systems
112. Use pc and CAD systems to obtain the shape of the artefact
113. Use industry-specific software
114. Use IT systems to query archives or databases
115. Use custom accounting management software
116. Use navigation tools and equipment (cartographic plotter, sounding lead, radar, GPS, navigation computer, etc.)
117. Use digital tools to make technical drawings
118. Use digital tools to make technical drawings, lay out text and images
119. Use digital tools to make videos
120. Inspect and test network equipment
121. Inspect and test network and telecommunication equipment
122. Inspect and check online services
123. Analyse system access and manage profiles
124. Develop and implement security measures for IT systems
125. Inspect IT system efficiency
126. Inspect protection and efficiency of IT systems
127. Manage electronic delivery systems
128. Oversee and service industrial production management systems
129. Design systems and electronic equipment
130. Design, develop and maintain electronic systems
131. Develop electronic equipment and systems

Table A2
Rate of change of employment by macrosectors (2011–16)

Macrosectors	Total (thousands)		Change
	2011	2016	(%)
A Agriculture, Forestry and Fishing	820	884	7.7%
B Mining and Quarrying	34.6	32.4	-6.3%
C Manufacturing	4112	4145	0.8%
D Electricity, Gas, Steam and Air Conditioning Supply	123	125	1.9%
E Water Supply; Sewerage, Waste Management and Remediation Activities	202	235	16.4%
F Construction	1780	1404	-21.1%
G Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	3201	3241	1.2%
H Transportation and Storage	1064	1085	2.0%
I Accommodation and Food Service Activities	1184	1395	17.8%
J Information and Communication	533	562	5.3%
K Finance and insurance	644	649	0.8%
L Real Estate Activities	143	141	-1.5%
M Professional, Scientific and Technical Activities	1377	1459	6.0%
N Administrative and Support Service Activities	834	991	18.9%
O Public Administration and Defence; Compulsory Social Security	1433	1262	-11.9%
P Education	1534	1543	0.6%
Q Human Health and Social Work Activities	1677	1831	9.2%
R Arts, Entertainment and Recreation	257	324	25.7%
S Other Service Activities	715	667	-6.7%
T Activities of Households as Employers	623	763	22.4%
U Activities of Extraterritorial Organisations and Bodies	15.2	15.4	1.3%

Source: ILFS.

Table A3
Descriptive statistics

	Mean	Sd	Min	Max
Employment rate of change	-0.14	1.02	-5.24	3.90
Digital Use Index	58.94	27.03	0	100
Digital Tasks Index	4.44	14.26	0	100
Routine Task Index (RTI)	44.37	16.76	0	100
Routine Task Index (RTI) (without NRMIA)	45.2	16.9	0	100
Process Innovations	0.24	0.14	0	0.80
Share of young employees	0.26	0.26	0	1
Share of female workers	0.36	0.35	0	1
Share of temporary workers	0.11	0.19	0	1
Share of part-time workers	0.85	0.22	0	1
Agriculture	0.05	0.21	0	1
Mining and manufacturing	0.15	0.36	0	1
Electricity, gas, steam and waste management	0.06	0.24	0	1
Construction	0.10	0.30	0	1
Wholesale and retail trade	0.05	0.21	0	1
Transportation and storage	0.08	0.27	0	1
Information and communication	0.05	0.22	0	1
Finance and insurance	0.03	0.18	0	1
Real estate and administration	0.13	0.34	0	1
Public administration and defence	0.09	0.29	0	1
Education and social work activities	0.10	0.30	0	1
Arts, entertainment and other services	0.11	0.31	0	1
Number of observations	2293			

Table A4
Alternative specification of Routine Task Index (RTI) (WLS): RTI with the inclusion of NRMIA component

Change in employment 2011–16 (Log difference)	(1)	(2)	(3)	(4)	(5)
Digital Use	0.0500**	0.0217	0.0424	0.0601*	0.0759**
	(2.76)	(0.91)	(1.69)	(2.32)	(2.68)
Routine Task Index (RTI)		-0.0530	-0.0428	-0.0396	-0.0416
		(-1.96)	(-1.58)	(-1.41)	(-1.47)
RTI × Digital use			-0.0562*	-0.0586*	-0.0592*
			(-2.25)	(-2.39)	(-2.42)
Sector fixed effects (baseline: Agriculture):					
—Mining and manufacturing				-0.231*	-0.206*
				(-2.43)	(-2.20)
—Electricity, gas, steam and waste mgt				-0.432***	-0.419***
				(-3.77)	(-3.67)
—Construction				-0.350***	-0.328**
				(-3.30)	(-3.11)
—Wholesale and retail trade				-0.166	-0.181
				(-1.27)	(-1.38)
—Transportation and storage				-0.258*	-0.240*
				(-2.25)	(-2.11)
—Information and communication				-0.342**	-0.311*
				(-2.74)	(-2.51)
—Finance and insurance				-0.318*	-0.281
				(-2.15)	(-1.92)
—Real estate and administration				-0.0995	-0.0834
				(-0.98)	(-0.83)
—Public administration and defence				-0.582***	-0.543***
				(-5.17)	(-4.84)
—Education and social work activities				-0.326**	-0.286**
				(-3.03)	(-2.64)
—Arts, entertainment and other services				-0.205*	-0.181
				(-1.99)	(-1.75)
Process innovations					-0.106
					(-0.73)
Share of young workers					0.155
					(1.66)
Share of female workers					-0.0216
					(-0.32)
Share of temporary employees					0.384**
					(2.94)
Share of part-time workers					0.156
					(1.37)
Constant	-0.202***	-0.198***	-0.230***	0.0403	-0.167
	(-10.91)	(-10.65)	(-9.39)	(0.46)	(-1.15)
N	2293	2293	2293	2293	2293
Adj. R-sq	0.002	0.004	0.005	0.023	0.029

t statistics in parentheses, robust standard errors
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5
Alternative specification of Routine Task Index (RTI) (WLS): RTI with the inclusion of NRMIA component.

Change in employment 2011–16 (Log difference)	(1)	(2)	(3)	(4)	(5)
Digital Tasks	0.0239*	0.0227	0.0167	0.0216	0.0222
	(2.01)	(1.91)	(1.33)	(1.68)	(1.62)
Routine Task Index (RTI)		-0.0672**	-0.0757***	-0.0836***	-0.0929***
		(-3.29)	(-3.68)	(-3.89)	(-4.22)
RTI × Digital Tasks			-0.0813*	-0.0772*	-0.0716
			(-2.19)	(-2.09)	(-1.96)
Sector fixed effects (baseline: Agriculture):					
—Mining and manufacturing				-0.209*	-0.182*
				(-2.25)	(-1.97)
—Electricity, gas, steam and waste mgt				-0.417***	-0.398***
				(-3.68)	(-3.51)
—Construction				-0.338**	-0.312**
				(-3.22)	(-2.97)
—Wholesale and retail trade				-0.167	-0.177
				(-1.28)	(-1.36)
—Transportation and storage				-0.238*	-0.216
				(-2.11)	(-1.93)
—Information and communication				-0.319**	-0.279*
				(-2.62)	(-2.29)
—Finance and insurance				-0.292*	-0.247
				(-2.00)	(-1.69)
—Real estate and administration				-0.0755	-0.0521
				(-0.76)	(-0.53)
—Public administration and defence				-0.558***	-0.518***
				(-5.04)	(-4.66)
—Education and social work activities				-0.308**	-0.269*
				(-2.89)	(-2.50)
—Arts, entertainment and other services				-0.195	-0.166
				(-1.90)	(-1.61)
Process innovations					-0.0482
					(-0.34)
Share of young workers					0.143
					(1.53)
Share of female workers					-0.00185
					(-0.03)
Share of temporary employees					0.361**
					(2.79)
Share of part-time workers					0.189
					(1.66)
Constant	-0.200***	-0.199***	-0.200***	0.0563	-0.196
	(-10.80)	(-10.76)	(-10.83)	(0.65)	(-1.35)
N	2293	2293	2293	2293	2293
Adj. R-sq	0.001	0.004	0.006	0.023	0.028

t statistics in parentheses, robust standard errors
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

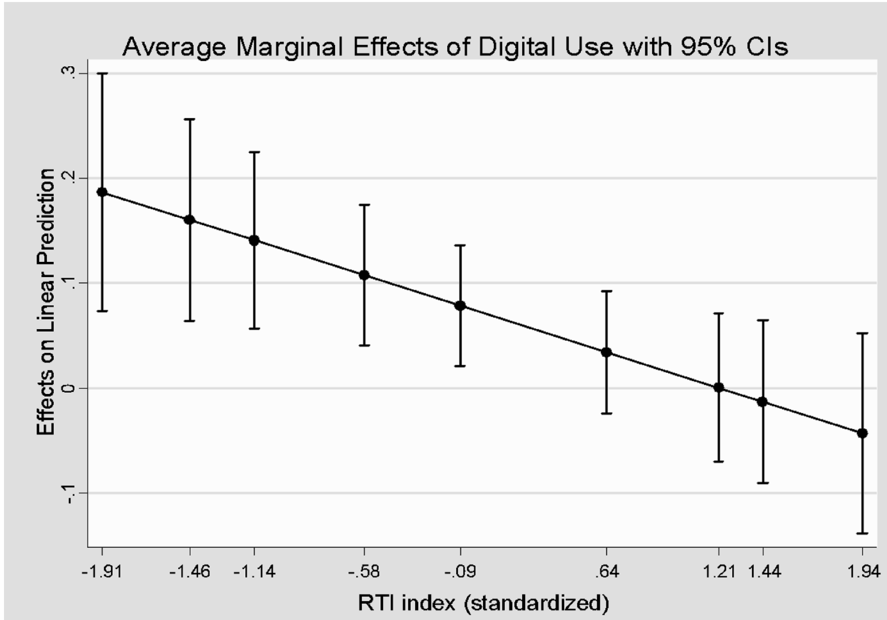

Fig. A1. Average marginal effects of Digital Use with respect to percentiles of RTI index

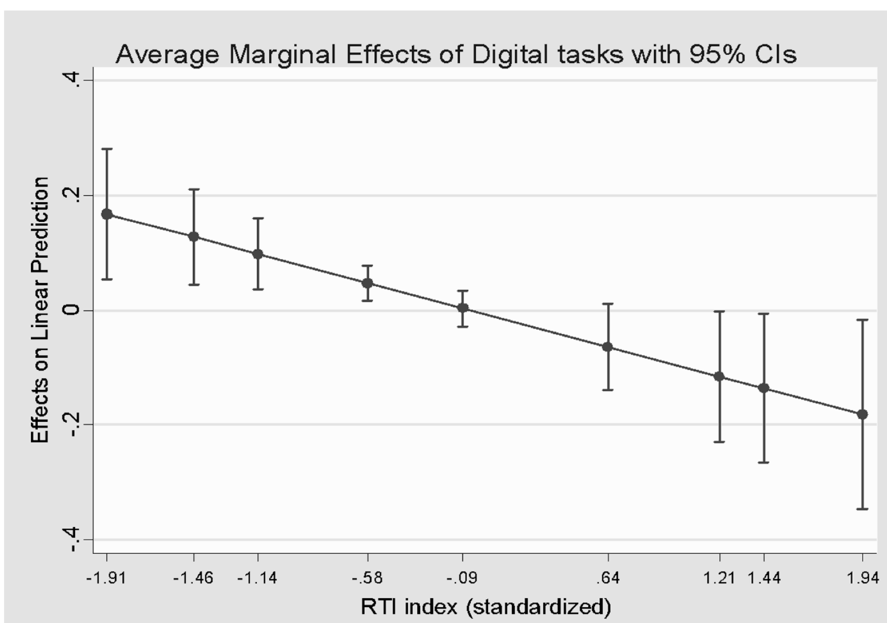

Fig. A2. Average marginal effects of Digital Task with respect to percentiles of RTI index

References

Acemoglu, D., 2002. Technical change, inequality, and the labor market. J. Econ. Lit. 40 (1), 7–72.

Acemoglu, D., Autor, D., 2011. Skills, tasks and technologies: implications for employment and earnings. In: Handbook of Labor Economics, 4. Elsevier, pp. 1043–1171.

Acemoglu, D., Restrepo, P., 2018. The race between man and machine: implications of technology for growth, factor shares, and employment. Am. Econ. Rev. 108 (6), 1488–1542.

Arntz, M., Gregory, T., Zierahn, U., 2016. The Risk of Automation for Jobs in OECD Countries: a Comparative Analysis. OECD Social, Employment, and Migration Working PapersnDELSA/ELSA/WD/SEM(2016)15.

Atasoy, H., 2013. Effects of broadband internet expansion on labor market outcomes. Ind. Labor. Relat. Rev. 66 (2), 315–345.

Aubert, P., Caroli, E., Roger, M., 2006. New technologies, organization and age: firm level evidence. Econ.J. 116, 73–93.

Aubert-Tarby, C., Escobar, O.R., Rayna, T., 2018. The impact of technological change on employment: the case of press digitisation. Technol. Forecast. Soc. Change 128, 36–45.

Autor, D., 2015. Why are there still so many jobs? The history and future of workplace automation. J. Econ. Perspect. 29 (3), 3–30.

Autor, D.H., Katz, L.F., Kearney, M.S., 2006. The polarization of the US labor market. Am. Econ. Rev. 96 (2), 189–194.

Autor, D., Dorn, D., 2009. The skill content of jobs and the evolution of the wage structure-this job is “getting old”: measuring changes in job opportunities using occupational age structure. Am. Econ. Rev. 99 (2), 45–51.

Autor, D., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. Am. Econ. Rev. 103 (5), 1553–1597.

Autor, D.H., Handel, M.J., 2013. Putting tasks to the test: human capital, job tasks, and wages. J.Labor Econ. 31 (S1), S59–S96.

Autor, D., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. TheQ. J. Econ. 118 (4), 1279–1333.

Autor, D., Salomons, A., 2018. Is automation labor share–displacing? Productivity growth, employment, and the labor share. Brook. Papers Econ.Act. 2018, 1–87.

Balsmeier, B., Woerter, M., 2019. Is this time different? How digitalization influences job creation and destruction. Res. Policy 48 (2019), 1–10.
Beaudry, P., Green, D.A., Sand, B.M., 2016. The great reversal in the demand for skill and cognitive tasks. J. Labor Econ. 34 (S1), S199–S247.
Biagi, F., Falk, M., 2017. The impact of ICT and e-commerce on employment in Europe. J. Policy Model. 39 (1), 1–18.
Blinder, A.S., 2009. How many US jobs might be offshorable? World Econ. 10 (2), 41–78.
Böckerman, P., Laaksonen, S., Vainiomäki, J., 2019. Does ICT usage erode routine occupations at the firm level? Labour 33 (1), 26–47.
Bogliacino, F., Lucchese, M., 2015. Endogenous skill-biased technical change: testing for demand-pull effect. Ind. Corp. Change 25 (2), 227–243.
Bogliacino, F., Lucchese, M., Nascia, L., Pianta, M., 2016. Modelling the virtuous circle of innovation. A test on Italian firms. Ind. Corp. Change 26 (3), 467–484.
Bogliacino, F., Lucchese, M., Pianta, M., 2013. Job creation in business services: Innovation, demand, and polarisation. Struct. Change Econ. Dyn. 25, 95–109.
Braverman, H., 1974. Labor and Monopoly Capital. Monthly Review, New York.
Bresnahan, T.F., Brynjolfsson, E., Hitt, L.M., 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. The Quarterly Journal of Economics 117, 339–376.
Brynjolfsson, E., McAfee, A., 2014. The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. WW Norton & Company.
Calvino, F., Criscuolo, C., Marcolin, L., Squicciarini, M., 2018. A Taxonomy of Digital Intensive Sectors, OECD Science. Technology and Industry Working Papers. 2018/14.
Calvino, F., Virgillito, M.E., 2018. The innovation-employment nexus: a critical survey of theory and empirics. J. Econ. Surv. 32 (1), 83–117.
Celi, G., Ginzburg, A., Guarascio, D., Simonazzi, A., 2018. Crisis in the European Monetary Union. A Core-Periphery Perspective. Routledge Studies in the European Economy, London.
Cetrulo, A., Cirillo, V., Guarascio, D., 2019. Weaker jobs, weaker innovation. Exploring the effects of temporary employment on new products. Appl. Econ. 51 (59), 6350–6375.
Cirillo, V., 2016. Employment polarisation in European industries. Int. Labour Rev. 157 (1), 39–63.
Cirillo, V., Fana, M., Guarascio, D., 2017. Labour market reforms in Italy: evaluating the effects of the Jobs Act. Economia Politica 34 (2), 211–232.
Cirillo, V., Guarascio, D., 2015. Jobs and competitiveness in a polarised Europe. Intereconomics 50 (3), 156–160.
Cirillo, V., Ricci, A., 2020. Heterogeneous Effects of Temporary Employment on Productivity and Wages in the Italian Business Firms. ASTRIL Working Paper n° 50/2020 ISSN 2280 – 6229 -Working Papers - on line.
Codagnone, C., 2009. Study on Inclusive Innovation for Growth and Cohesion: Modelling and Demonstrating the Impact of eInclusion. DG Information Society and Media, ICT for Inclusion Unit.
Dauth, W., Findeisen, S., Südekum, J., Wößner, N., 2017. German robots - the Impact of Industrial Robots on Workers. IAB-Discussion Paper, 30/2017.
Dustmann, C., Ludsteck, J., Schönberg, U., 2009. Revisiting the German wage structure. Q. J. Econ. 124 (2), 843–881.
Dosi, G., Guarascio, D., Ricci, A., Virgillito, M.E., 2019. Neodualism in the Italian business firms: training, organizational capabilities, and productivity distributions. Small Bus. Econ. 1–23.
European Commission, 2018. International Digital Economy and Society Index. Publications Office of the European Union, Luxembourg.
Evangelista, R., Guerrieri, P., Meliciani, V., 2014. The economic impact of digital technologies in Europe. Econ. Innov. New Technol. 23 (8), 802–824.
Fernández-Macías, E., Hurley, J., 2016. Routine-biased technical change and job polarization in Europe. Soc.-Econ. Rev. 15 (3), 563–585.
Fernández-Macías, E., Hurley, J., Bisello, M., 2016. What Do Europeans Do at Work?: A Task-based Analysis. Publication Office of the European Union, Paris.
Foster, L., Grim, L., Haltiwanger, L., 2016. Reallocation in the great recession: cleansing or not? J. Labor Econ. 34, 293–331.
Freeman, C., Louçã, F., 2001. As Time Goes By: From the Industrial Revolutions to the Information Revolution. Oxford University Press, Oxford.
Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to comput-erisation? Technol. Forecast. Soc. Change 114, 254–280.
Friedberg, L., 2003. The impact of technological change on older workers: evidence from data on computer Use. Ind. Labor. Relat. Rev. 56 (3), 511–529.
Goos, M., Manning, A., 2007. Lousy and lovely jobs: the rising polarization of work in Britain. Rev. Econ. Stat. 89, 118–133.
Goos, M., Manning, A., Salomons, A., 2009. Job polarisation in Europe. Am. Econ. Rev. 99 (2), 58–63.
Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. 104 (8), 2509–2526.
Graetz, G., Michaels, G., 2018. Robots at work. Rev. Econ. Stat. 100 (5), 753–768.
Grossman, G., Rossi-Hansberg, E., 2006. The rise of offshoring: it's not wine for cloth anymore. In: Paper presented at Kansas Fed's Jackson Hole Conference for Central Bankers.
Grossman, G.M., Rossi-Hansberg, E., 2008. Trading tasks: a simple theory of offshoring. Am. Econ. Rev. 98 (5), 1978–1997.
Gualtieri, V., Guarascio, D., Quaranta, R.2018. Routine tasks and the dynamics of Italian employment. INAPP Policy brief, 7/2018.
Guarascio, D., Pianta, M., 2017. The gains from technology: new products, exports and profits. Econ. Innov. New Technol. 26 (8), 779–804.
Guerrieri, P., Bentivegna, S. (Eds.), 2012. The Economic Impact of Digital Technologies. Edward Elgar, Cheltenham, UK.
Istat, 2017. Rapporto sulla competitività dei settori produttivi. Capitolo 3 "Innovazione, nuove tecnologie e occupazione". ISBN 978-88-458-1924-7.
Istat, 2018. Rapporto sulla competitività dei settori produttivi. Capitolo 3 "Innovazione, nuove tecnologie e occupazione". ISBN 978-88-458-1950-6.
Jayakar, K., Park, E.A., 2013. Broadband availability and employment: an analysis of county-level data from the National Broadband Map. J. Inf. Policy 3, 181–200.
Kemeny, T., Rigby, D., 2012. Trading away which kind of jobs? Review of world economics/weltwirtschaftliches. Archiv 148 (1), 1–16.
Kolko, J., 2012. Broadband and local growth. J. Urban Econ. 71 (1), 100–113.
Leamer, E.E., Storper, M., 2001. The economic geography of the internet age. J. Int. Bus. Stud. 32, 641–665.
Levy, F., Murnane, R.M, 2005. The New Division of Labor: How Computers Are Creating the Next Job Market. Princeton University Press, Princeton.
Marcolin, L., Miroudot, S., Squicciarini, M., 2016. Routine jobs, employment and technological innovation in global value chains. OECD Science, Technology and Industry Working Papers. 2016/01. OECD Publishing, Paris.
Mastrostefano, V., Pianta, M., 2009. Technology and jobs. Econ. Innov. New Technol. 18 (8), 729–741.
McKinsey Global Institute. 2015. Digital America: a tale of the haves and have-mores.
Michaels, G., Natraj, A., Van Reenen, J., 2014. Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. Rev. Econ. Stat. 96 (1), 60–77.
Mishel, L., Shierholz, H., Schmitt, J., 2013. Don't blame the robots. Assessing the Job Polarization Explanation of Growing Wage Inequality. EPI-CEPR working paper (November 19, 2013).
MISE (Ministero dello Sviluppo Economico). 2018. The Diffusion of Industry 4.0 Companies and Policies: 2017 Evidence, Report available at: https://d2uo11xsaedulq.cloudfront.net/wp-content/uploads/2018/07/08232244/Rapporto-MiSE-MetI40.pdf.
Nedelkoska, L., Quintini, G.2018. Automation, skills use and training, Social Employment and Migration Working Papers, No. 202.
OECD, 2004. The economic impact of ICT: measurement. Evidence and Implications. OECD, Paris.
OECD, 2018. Job Creation and Local Economic Development 2018: Preparing for the Future of Work. OECD, Paris.
Oesch, D., Rodriguez, Jorge, 2011. Upgrading or polarisation? Occupational change in Britain. Spain and Switzerland, 1990–2008 Soc.-Econ. Rev. 9 (3), 503–531.
Schleife, K., 2006. Computer use and employment status of older workers. An analysis based on individual data. Labour 20 (2), 325–348.
Silva, H.C., Lima, F., 2017. Technology, employment and skills: a look into job duration. Res. Policy 46 (8), 1519–1530.
Spitz-Oener, A., 2006. Technical change, job tasks and rising educational demands: looking outside the wage structure. J. Labour Econ. 24 (2), 235–270.
Teece, D., 2018. Profiting from innovation in the digital economy: enabling technologies, standards, and licensing models in the wireless world. Res. Policy 47 (8), 1367–1387.
Tubaro, P., Casilli, A.A., 2019. Micro-work, artificial intelligence and the automotive industry. J. Ind. Bus. Econ. 46 (3), 333–345.
R Van Reenen, J., Draca, M, Sadun, M, 2007. Productivity and ICTs: a review of the evidence. In: Mansell, R., Avgerou, C., Quah, D., Silverstone, R. (Eds.), The Oxford Handbook of Information and Communication Technologies. Oxford University Press.
Van Roy, V., Vértesy, D., Vivarelli, M., 2018. Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms. Res. Policy 47 (9), 1762–1776.
Vivarelli, M., 2014. Innovation, employment and skills in advanced and developing countries: a survey of economic literature. J. Econ. Issues 48 (1), 123–154.
Vivarelli, M., Pianta, M., 2000. The Employment Impact of Innovation: Evidence and Policy. Routledge, London.
Vona, F., Consoli, D., 2014. Innovation and skill dynamics: a life-cycle approach. Ind. Corp. Change 24 (6), 1393–1415.