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Anatomy of the Italian occupational structure: concentrated power and distributed knowledge

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Anatomy of the Italian occupational structure: concentrated power and distributed knowledge[*]

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Abstract

Which type of work do Italians perform? In this contribution we aim at detecting the *anatomy* of the Italian occupational structure by taking stock of a micro-level dataset registering the task content, the execution of procedures, the knowledge embedded in the work itself, called ICP (Indagine Campionaria sulle Professioni), the latter being comparable to the U.S. O*NET dataset. We perform an extensive empirical investigation moving from the micro to the macro level of aggregation. Our results show that the Italian occupational structure is strongly hierarchical, with the locus of power distinct by the locus of knowledge generation. It is also weak in terms of collaborative and worker involvement practices, and possibility to be creative. Our analysis allows to pinpoint the role exerted by hierarchical structures, decision making autonomy, and knowledge as the most relevant attributes characterizing the division of labour.

JEL classification: J2, D2, C38.

Keywords: Occupational structure, power, knowledge, factor analysis.

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1 Introduction

Which type of work do Italians perform? This work aims at detecting the *anatomy* of the Italian occupational structure by taking stock of a unique micro-level dataset - the Indagine Campionaria sulle Professioni (ICP)[1] - providing detailed information on tasks, skills, abilities, knowledge as well as on the technological, organizational and procedural sequences of the activities done at the workplace. In this respect, the ICP constitutes the only European data source closely replicating the US O*Net repertoire by reporting, for all Italian occupations at the finest degree of disaggregation (i.e. 5-digit), a notable amount of data concerning unique characteristics of work.

Departing from the standard approach mainly focusing on individual comparative advantage, in this study we put human agency (Hurley and Fernández-Macías, 2016) and organizations at the centre of the stage by intersecting the capability based theory of the firm, the sociology of work, with particular reference to the labour process theory (Knights and Willmott, 1990), and the organizational theory. We intend work as the outcome of a process of continuous learning and evolving capabilities, involving tacit and codified knowledge, shaped by the coevolution of hierarchical organisational routines, continuously adapting to procedural uncertainty (Dosi et al., 2001). In so doing we enlarge both the material-task approach, which interprets work as the process of transformation upon a given object (Hurley and Fernández-Macías, 2016), and the task-based approach (Autor, 2015) which only focuses on the link between purported technological change and substitutability/complementarity with human activity. Therefore, by explicitly considering power relationships and workplace hierarchies as crucially affecting the technology-knowledge-work nexus, our contribution intends to enlarge the domains of analysis currently established in the literature.

We perform an extensive empirical investigation moving from the micro to the macro level of aggregation, with the aim of detecting the dominant traits of the Italian occupational structure. More specifically, the analysis relies on an ex-ante theoretical categorization of the data-set focusing on technological, organizational and skill dimensions namely, *knowledge and learning*; *work organization*, including *degrees of autonomy, routinariety, automation, control and social interactions*; and finally *digital skills*. Against this theoretical classification, we run a factor component analysis to detect the presence of some latent factors. Five factors allow to explain the variance among our variables, with the factor collecting attributes of *power* explaining most of the variability. Other relevant factors are *dexterity and cognitive manual work, digital, creativity and team work*, according to our definitions. After having identified the factors behind the variability, we move from the micro 4-digit occupations to the macro 1-digit ones in order to understand how the latter factors distribute at different levels of aggregation. Finally, we link the occupational categories with the employment framework. In so doing, we intend to isolate any compositional effect due to employment status (i.e. being employee or self–employed), highlighting the role of inter-status heterogeneity, or alternatively how robust our results are, independently from the employment status under observation.

We find some rather striking results militating in favour of a strongly hierarchical occupational structure, whose locus of power is detached from the one of knowledge generation. In this respect, contrarily to what the human capital theory would predict, being endowed by the authority of defining and organizing the division of labour is by far more relevant (to explain inter-occupation variability) than being endowed by high-level knowledge. On the contrary, knowledge attributes are widespread distributed both across factors and occupations. A companion result is that the Italian occupational structure turns out to be weak in terms of team-work and collaborative organizational practices. A similar weakness characterizes creative activities and workers' involvement in them. Our conclusions are resilient with respect to the employment status, i.e., no significant difference emerges in the order and magnitude of

[1]The ICP is realized by the National Institute for Public Policy Analysis (INAPP) jointly with the Italian National Statistical Institute (ISTAT).

the factors when splitting the analysis between autonomous and dependent workers, although the two categories present some specificities in the distributional dynamics of the 1-digit level occupations.

The paper is organized as follows: in Section 2 we discuss the notion of labour process inside organizations, distinguishing among alternative interpretations, and positioning our own work vis-a'-vis the extant literature, in Section 3 we present our dataset, the variables selection and validation, and the empirical analysis carried out, in Section 4 we discuss our findings, and we conclude, highlighting potential avenues of future research.

2 Different perspectives on labour and organizations

In the following we shall provide a fresco of some alternative notions of labour deriving from the socio-economic literature. The discussion will allow the reader to get acquainted with the theoretical framework which informed our empirical investigation.

Historically, two main notions of labour can be distinguished. From the one hand, according to Marx, the ownership of the means of production allows to identify the boundary of social classes: labour is defined with respect to its own antinomy with capital and it is the mean of production that needs to be sold to ensure its internal reproduction. Those owning exclusively their physical and mental capacities (i.e. the workers, or "proletariats") will sell their performative counterpart to survive, while those owning the means to exploit and organize labour (i.e. the capitalists) will set the conditions according to which labour activities have to be performed and paid. Labour is the fundamental element out of which *value* is generated by leveraging on workers knowledge and on internal division of power. Capitalists are therefore able to appropriate and accumulate the generated value while workers are excluded, and *alienated* from the decision-making process. According to this perspective, the notions of property, class and power are crucial in defining the conceptual borders of labour. From the other hand, the Marginalist perspective framed labour as an input of the production function, which might have alternative degrees of substitutability with capital, but whose nature was clearly independent from any power relation vis-a'-vis capital. With the marginalist approach, the problem of power relations disappears while the problem of optimal allocation becomes dominant: each factor should be rewarded according to its marginal contribution to the production process. As a consequence, elements such as property of the means of production, labour-value, surplus, and class get out of the picture.

The current debate on the impact of automation upon the quantity and the composition of jobs has spurred new attention on the relationship between "human and machines", already there since Ricardo. The dominant discourse has conflated the notion of labour as a *bundle of tasks* which are executed by each worker. Indeed, the nowdays popular task-based approach envisages some limits to the canonical production function framework, regarding its static description of the nature and scope of capital and labour. Consequently, it adopts "job tasks" as unit of analysis, whose supply can derive from domestic, foreign workers or by capital itself, and whose distribution can vary over time, together with the evolution of technologies. The division of tasks between capital and labor utlimately rests upon technological and economic conditions (i.e. labour cost), that jointly determine in a dynamic way the "comparative advantage" between factors, tasks and skills (Autor, 2013, p.5-7). According to this approach, workers can be defined in terms of the skills required to execute the bundle of tasks they are assigned to and, depending on the degree of repetitive activities performed, they are more or less likely to be substituted by machines. This theory, initially under the heading of skilled-bias technical change (SBTC) and later routine-bias technical change (RBTC) has produced a long series of contributions (Autor et al., 2006; Goos et al., 2009, among the others) all trying to document wage polarization via the relationship between the declining price of computers (technology) and the increasing labour demand for skilled labour.[2] Conceptually, two main critiques have been advanced even by its main proponents: according to Autor and Handel (2013), the relation between tasks (intended as jobs' characteristics) and human capital (intended as workers' specific features) remains blurred and there might be a significant unaccounted heterogeneity in types and intensity of tasks performed within the same occupation by different workers; on the other hand social tasks are usually not accounted in this framework, despite they are increasingly demanded as complement to cognitive skills (Deming, 2017). However, these types of criticisms still move within the same theoretical framework, without digging into the nature of work and toward the construction of its actual anatomy. More radical criticisms have come by alternative strands of literature. A comprehensive discussion on pros and cons of the task-based approach is provided in Fernández-Macías et al. (2016) who emphasize as limitations the dismissal of the social and institutional reasons behind the technical attribution of tasks in the production process; on a parallel perspective Pfeiffer (2018), focusing on the manufacturing sector, contests the demarcation between cognitive and manual tasks, highlighting the role of knowledge accumulation and subjective experience in the execution of the work activity.

According to our perspective, the task-based approach disregards two main important aspects in defining what people really do at work: first the role of *knowledge* and second the role of *division of labour inside organizations* seen as hierarchical structures wherein knowledge and power are unevenly distributed. In fact, the very nature of the capitalist organization has always involved the power of organizing labour. In this sense, any analysis on the way jobs are performed and more specifically, on how tasks are distributed among occupational roles should not neglect the "socio-economic forces that created them" (Thompson, 1989).[3] One of this forces is explicitly represented by the continuously evolving mechanisms of control over the workforce to ensure the functioning of the production process under specific rules (Edwards, 1980). Historically this occurred by means of the rationalization of the production process way back since the First Industrial Revolution which entailed a combination of new technological paradigms and organizational innovations. As Adam Smith masterly noticed, the division of labour within organized units dramatically increased productivity, and it did so by transferring knowledge from disorganised artisans and part-time farmers into hierarchical forms of production. In this respect the process of technological change has entailed a secular deskilling tendency whereby the machine is used to make it codifiable what before was tacit (Nuvolari, 2002).

Braverman (1974) analysed such dynamics in contemporary capitalism, detailing the micro-organization of the so called *labour process*: the working class is analysed in its relationship with the machine, the shop floor, its management and the related control. The management structure under capitalism is such that the knowledge embodied into workers should be transferred into machines, exerting at the same time a pervasive coordination of all the production units. This ruling class of top- and middle- managers represents the new trait of modern firms (Chandler Jr, 1993, p.3) and it is meant to embed its authority into the social structure of the workplace, transforming jobs into a list of titles and descriptions. All this turned into a new form of "bureaucratic control" (Edwards, 1980, p.20).[4] Yet, the current organisation of work based on skill levels and task types is still perceived as the natural reflection of a technical division of labour into different occupations, neglecting the role played by social and power structures (Thompson, 1989).

What is more, to understand the relationship between human and machine it is crucial to consider technology as an evolutionary process. Think of a technology as a *recipe* with 'ingredients', associated procedures and "admissible acts" required, e.g. to build an artefact. A recipe always embodies a de-

[2]When looking at the quantity of jobs potentially displaced by automation, this stream of research has offered rather different numbers (Frey and Osborne, 2017; Arntz et al., 2016, for two significantly diverging estimates).

[3]Thompson (1989, p. 24) who is actually citing Freedman (1975).

[4]According to the author, capitalist organizations moved from models of "simple/entrepreneurial control", directly exerted by the employers at the early stages of industrialisation within relatively small companies, to forms of "technical control" and later "bureaucratic control". Technical control was "embedded in the physical structure of the labour process", where the introduction of machinery and automation imposed to workers not only strict rhythms of production but also rigid sequences of tasks.

$$\boxed{\text{CAPITALIST ORGANIZATION}}$$
$$\Downarrow$$
$$\boxed{\text{POWER}}$$
$$\Downarrow$$
$$\boxed{\text{DIVISION OF LABOUR}}$$
$$\Downarrow$$
$$\boxed{\text{CONTROL OVER THE WORK-PROCESS}}$$
$$\Downarrow$$
$$\boxed{\text{CODIFICATION OF KNOWLEDGE}}$$

Figure 1: The relation between capitalist organization, knowledge and power, adapted from (Dosi and Virgillito, 2019).

gree of codified knowledge but also non-codified and tacit one (the non-written procedures). In turn, the procedures are typically collective implying a process of coordination among members of the organisation. The execution of the recipe coordinated among the members of the organisation entails an ensemble of *organisational routines*. Organisational routines constitute therefore a *trait d'union* between technology and organisation, typically nested into hierarchical structures and power relations (Dosi and Marengo, 2015). Figure 1 illustrates the point. Given the tacit nature of knowledge embodied in the execution of complex tasks, a "natural trajectory" in technical progress has involved the progressive mechanization/automation of production processes and a drive to make simple, repetitive, and codified the routines of the recipe. Control over rhythms and movements along the sequences of production, correct execution of tasks, and discipline of the workforce have been and are the necessary conditions for the codification of knowledge.

Taken on board the latter framework, overall the importance attributed by the task-based approach to work organization, and in general organizational routines, as the central element in defining what actually people do at work, is scarce. Therefore in our analysis we devote particular attention in framing the labour process inside the organization of production. Crucial elements entail first, the degree of autonomy in performing activities, whereby autonomy captures the extent to which workers have the possibility to set their own rules; second, the degree of control over the production process, which when full even allows the worker to stop the execution of tasks in case of errors; third, degrees of collective knowledge inside the organization deriving from the existence of learning processes and team working; fourth, degrees of hierarchical power, space of control of the supervisors, space of individual actions and goal setting, and in general the social organization structure (Dosi and Marengo, 2015; Knights and Willmott, 1990). In fact, a related missing element is the understanding of firms as the locus of the division and organization of labour. All in all, firms are hierarchical entities wherein knowledge is differently distributed among organisational units and individuals, and the introduction of technological innovation entails processes of uneven learning and adaptation of the different hierarchical layers, in tune with the capability-based theory of the firm (c.f. Winter, 1997; Coriat and Dosi, 1998). If this is so, attention should be devoted to understand the type of learning regimes to which workers are solicited, e.g., the degree of updating their own knowledge, the degree of attention they should devote in executing their own work, the possibility to think creatively and to cumulate experience. Finally, complementary elements of our analysis vis-a'-vis the task-based approach are the degrees of execution of repetitive tasks and automation, such as the use of ICT tools at work, also in line with the PIAAC classification. In the empirical analysis which follows we explicitly intend to uncover the existing gap in the literature by identifying the role of the above mentioned dimensions in shaping the Italian occupational structure.

3 Empirical Analysis

3.1 Data

The anatomy of the Italian occupational structure is dissected by means of the ICP - *Indagine Campionaria delle Professioni* - conducted by the National Institute for Public Policy Analysis (INAPP) in collaboration with the Italian National Statistical Institute (ISTAT). This survey represents the only European source comparable with the American O*Net repertoire (Gallo and Lorè, 2006), being the latter the most comprehensive database reporting qualitative-quantitative information on tasks, skills, work contexts and organizational characteristics at the 5-digit level of observation. The construction of the dataset entails a complex, multi-layer strategy of data collection and information processing allowing for both detailed occupational descriptions and inter-occupation comparability (Peterson et al., 2001).

Currently two waves of the ICP database are available (2007, 2012) with a spectrum covering 797 occupational codes, excluding armed forces.[5] The interviews are administered to 16.000 Italian workers to ensure statistical representativeness with respect to sectorial, occupational, dimensional and geographical heterogeneities. The sampling strategy is articulated as follows. Relying on a matrix – built using the Italian Labour Force Survey (LFS) realized by ISTAT – providing information on the distribution of occupations (in terms of number of employees) across 5-digit sectors, 797 independent samples are generated. Each sample refers to a specific 5-digit occupation and is populated by firms (stratified by region and size class) belonging to the cluster of sectors where the probability of finding such an occupation is above an ex-ante threshold. Firms are randomly extracted from the ISTAT company-level register. The ICP information are then collected according to a two-step procedure. At a first step, firms are contacted by phone to verify the presence of a specific occupational category at 5-digit level. Granted the latter, on average, 20 workers per each occupation are interviewed by means of 1-hour lasting CAPI (computer assisted personal interview).

Both O*NET and ICP questions are organized in six main sections, expressions of a content model that simultaneously provides information from a job-oriented and worker-oriented perspective.[6] The descriptors are: *worker characteristics* (enduring abilities and work style of workers), *worker requirements* (skills and education), *occupational requirements* (organizational and work context), *experience requirements* (training, cross functional skills), *workforce characteristics* (labour market information) and *occupation-specific information* (generalized activities and work context).[7] In so doing, descriptors are formulated by making it possible to distinguish, for instance, inner individual abilities from competences acquired on the job. For each question, two rating scales are generally provided: level and importance. In our analysis, we will pick the level scale only, since it ensures a complete coverage and direct comparability among variables.

3.2 Variables selection and theoretical validation

The empirical stage consists in the factor analysis of 25 ICP variables, gathered in three main domains of analysis: knowledge and learning, work organisation and digital skills, as presented in Table 1.

1. *Knowledge and Learning.* This set of questions collects all variables providing information on both general and specific degrees of knowledge necessary to perform the job. In particular, the ques-

[5] The following analysis is conducted at 4-digit level, considered this level of granularity to be sufficiently appropriate to identify actual job profiles and matchable with other datasets providing additional economic and demographic variables (Guarascio et al., 2018).

[6] For a brief overview on the content model adopted by O*NET consult directly the O*NET website at `https://www.onetcenter.org/content.html.`

[7] Despite the similarities, a significant difference between the ICP and the O*NET databases concerns the set of respondents. In the Italian survey, the information is drawn exclusively from job incumbents - each one compiling the entire questionnaire - , whereas in the American O*NET, different job incumbents do answer to diverse sections for the same occupation and job analysts are also asked to express opinions on the reported tasks.

tions instruct about the importance of e.g., updating knowledge, needs of using critical thinking, and production of new ideas. These types of questions allow to dig inside the actual degree of learning processes involving the worker, distinguishing by types of occupations. Notably, the learning process is inherently nested with the type of work organisation implemented in the workplace. The theoretical foundation of this group stems from the evolutionary perspective on the role of learning within organisations (Stiglitz and Greenwald, 2014; Dosi et al., 2001; Arrow, 1971).

2. *Work Organization*. This set of questions collects information on the forms of work organisation that can be elicited from workers interviews. In fact, in order to characterise what actually people do at work it is necessary to understand e.g., the degree of autonomy in performing specific tasks and in decision-making, the possibility of solving complex problems, the control over the process, the control and influence on other people, the degree of automation and repetitiveness of the performed task. In this respect, this set allows to infer information upon the hierarchical position of workers inside organisations. The theoretical references are multiple, coming from Lorenz and Valeyre (2005); Fernández-Macías (2012); Dosi and Marengo (2015).

3. *Digital Skills*. This set of questions allows to gather information on the level of digital skills required by each occupation, where digital skills are mainly constructed allowing the distinction between basic users and more advanced ones, in line with the DESI approach followed by the European Commission.[8] Indeed, ICT technologies represent a tool affecting not only the way and the type of tasks performed, but also jobs quality (Rubery and Grimshaw, 2001), workers' autonomy (Mazmanian et al., 2013) and the entire organization structure (Orlikowski, 2000). For this reason, it is important to account for different degrees of intensity in technology usage, from e-mail correspondence to more advanced knowledge of ICT.

The procedure of variables selection has followed several steps. The first step consisted in a qualitative scrutiny of the four-hundreds questions of the ICP. Among the full list of questions, we initially focused on a subset of almost one-hundred questions covering the three main domains defined above. The subsequent step was to eliminate uninformative questions for our purposes (i.e. knowledge of Italian/foreign language); more complex topics (i.e. types of innovation occurred in each occupation) which may need a separate analysis; questions based on different scales (years of tenure or weekly working hours rather than the level of importance) and those that were already well represented in the subset (training others, monitoring, etc.). This second-round scrutiny resulted into a final set of seventy questions, grouped into the three main domains and related sub-indicators in the case of Work Organisation, where we distinguish for Autonomy, Routinariety, Control and Social organisation structure. The entire set of variables covering the domains under analysis is presented in Table 5 in the Appendix.

Being the ICP an extremely rich and detailed source of data on occupations, several questions might present a high degree of similarity. Therefore, a careful preliminary analysis on the seventy questions has been necessary in order to clean our dataset from superfluous repetitions and over specifications. After performing a descriptive and statistical analysis (mean, standard deviation, pairwise correlation) for each sub-indicator, we excluded similar variables showing a very strong correlation (equal or higher than 0,9) since we assumed they were capturing the same object.[9] Moreover, we excluded those variables showing a very low degree of variation across occupational groups, signalling in this case a variable

[8] https://ec.europa.eu/digital-single-market/en/news/new-comprehensive-digital-skills-indicator.

[9] Take the case of the variables "Quality evaluation" and "Evaluation of conformity to standards" or alternatively "Planning the work" and "Organising priorities": those variables display very high degree of correlation, driving us to select in both cases only one of the two. Nonetheless, in some other cases, similar questions may present relevant differences. In that case, we opted for that variable providing neater information. For instance, the two variables "Team work importance" and "Coordinating with others" show a high level of correlation (0.83), but we identified some ambiguity in the text of the former question, where interacting with others and being part of a team are put on the same level. For this reason, we selected "Coordinating with others" as a cleaner proxy of team work and, more generally, of coordination with other workers. Analogously, the variables "Guiding others" and "Leadership" present a high level of correlation (above 0.8), even if they are capturing two different traits of control over people.

strictly related to a specific set of occupations[10] or rather, a bias or misunderstanding of the exact content of the questions.[11]

Table 2 compares some of our adopted variables (first column) with those one presenting similar contents in the extant literature, therefore external validating our choices but also highlighting the specificities. We intentionally distinguish between the task-based approach and other relevant socio-economic contributions. Indeed, some of the chosen variables are frequently used by the former literature, such as "Control over the process" and "Controlling machines" adopted to capture manual routine activities, the variables "Leadership" and "Creative thinking" usually used to capture non-routine cognitive interpersonal tasks, and the variable "Coordinating with" capturing social interactions (Spitz-Oener, 2006; Acemoglu and Autor, 2011; Autor and Handel, 2013; Deming, 2017).

Vis-a'-vis the task-based approach, this study enlarges the sphere of the covered domains by including variables intended to capture elements of the organizational models behind, which might range from more Tayloristic towards more "lean-smart-agile" ones, and of the ensuing learning systems (Arundel et al., 2007; Lundvall and Lorenz, 2012). In fact, different organizational models might influence the degree of workers intervention authority in the process. Therefore we adopt variables instructing about the possibility of "Solving complex problems", showing the degree of "Active learning" and "Distributed attention", and finally the presence of "Team-working", in line with Lorenz and Valeyre (2005). Overcoming the strict, and somewhat poor, dichotomy between "routine" and "non routine" work, we want to know the role played by learning by-doing and cumulated experience which allow to act under conditions of uncertainty and possibly to react to unpredictable events (Pfeiffer and Suphan, 2015), being the latter rather tempting abilities even in automatized manufactured processes usually considered to be routinesed. The learning processes and the organizational practices shaping them clearly map into the degree of "Autonomy" of the workers in performing their activity (Vidal, 2013; Cirillo et al., 2018), influencing the space of actions in terms of decision making, "Planning your own work" and "Setting and establish the time-path" (Harley, 1999). But, to genuinely account for the degree of autonomy one needs to explicitly consider the diffusion and concentration of power in the decision making process, which can be manifested both in terms of "Leadership" and "Influence" over the others.[12] Notably, although the two latter variables might be considered as peculiar of the managerial activity only, we deem interestingly to examine the diffusion of these abilities across the entire range of occupations for two reasons: first of all, forms of power are exerted at all levels of the hierarchical structure of organizations[13] and range from explicit disciplinary scopes toward more blurred and implicit ones (e.g. limitation of the space of actions, definition of the border of the admissible acts, Thompson, 1995), and second, after thirty years of managerial rhetoric of HPWPs (high-performance work practices), empowerment of the workforce, and agile systems, we theoretically expect some degree of power along the entire layers of the organizational architecture. Lastly, variables belonging to the domain of Digital skills are intended to describe the extent to which ICT technologies are adopted in the workplace and whether they complement specific attributes of work organisation and knowledge. Indeed, we inserted three different questions in order to distinguish intensities in the adoption of technologies, from the simple use of e-mail correspondence, to a more integrated adoption of the computer at work, to the necessity of acquiring and update professional knowledge in computer science and electronics.

Indeed, the capability of being a leader does not consist only in guiding others but also in persuading them, getting their support and obedience. For this reason, we selected "Leadership".

[10]For instance, "Programming skills" intensity exhibits very low values across all occupations. The only two groups showing a high intensity are intellectual and scientific workers and technical professionals, confirming its nature of occupation-specific characteristic.

[11]A useful example for this purpose are the two variables "Attention to detail" and "Being always busy": since they both show very high and similar values across all occupational groups, this might suggest a potential subjective bias when answering to questions evaluating individual effort and accuracy in performing its own job.

[12]Influence is the only variable in our dataset constructed as the average of two variables.

[13]Take the case of the team-leader or the head of unit which in many cases *do not present* different contractual frameworks, but have the ability to exert a ruling role.

Domain	Variable	Question
Knowledge and Learning		
	Update and Use	*Keep up to date with technical changes and apply new knowledge.*
	Creative Thinking	*Develop, design or create new applications, ideas, relationships and new systems and products (including artistic contributions).*
	Active Learning	*Understand the implications of new information for the solution of present and future problems and for decision-making processes.*
	Selective Attention	*Ability to focus on a task for a long time without distraction.*
	Distributive Attention	*Ability to follow two or more different activities or sources of information at the same time.*
Digital Skills		
	PC Use	*Use computers and computer systems (software and hardware) to program, write software, adjust functions, enter data, or process information.*
	Mail Use	*How often does your profession require the use of e-mail?*
	ICT Knowledge	*Computer science and electronic knowledge.*

(continue...)

Table 1: Domains, variables and related questions

Domain	Variable	Question
Work Organization		
Autonomy in decision	Goal Strategies	*Establish long-term objectives and specify strategies and actions to achieve them.*
	Evaluate and Decide	*Evaluate the costs and benefits of possible actions to choose the most appropriate.*
Autonomy in planning	Organizing Priorities	*Set specific objectives and plan the work defining priorities, organization and timing of implementation.*
Autonomy in doing the job	Tool Select	*Identify the tools needed to do a job.*
	Solving Problems	*Determine the causes of operating errors and decide what to do to solve them.*
	Solving Complex Problems	*Identify complex problems and collect information to evaluate possible options and find solutions.*
Routinariety and automation	Hands Dexterity	*Ability to quickly move hand, hand and arm together or both hands to grab, manipulate or assemble objects.*
	Automation Degree	*How automated is your work? (linked to automatic processes)*
	Repetitive Movements	*In your work how long do you perform repetitive movements?*
Control over people	Influence	*How often do your decisions affect other people or your employer's image or reputation or financial resources in your work and what impact do they usually have? (Average of two questions)*
	Leadership	*The work requires the willingness to guide people, to take charge and to give opinions and directives.*
Control over the process	Inspecting	*Inspect equipment, structures or materials for causes of error, or other problems or defects.*
	Standards Evaluation	*Use relevant information and individual opinions to determine whether events or processes comply with standards, laws or regulations.*
	Machine Control Importance	*How important is it in your work to keep sequences of machinery and equipment under control?*
Social organisation structure	Relations	*Create constructive and cooperative working relationships and maintain them over time.*
	Coordinating with others/Team Work	*Coordinate their actions with those of others.*
	Competition	*How competitive is your job? (requires constant comparison with the performance of colleagues/other workers)*

Variables	Task Based Approach	Other approaches (Eurofound, LPT, Pfeiffer)
Creative Thinking	"Thinking Creatively" in Non Routine Cognitive Analytical (Acemoglu and Autor, 2011)	
Active Learning		"Learning new things" (Lorenz and Valeyre, 2005)
Distributed Attention		"How often does it happen (...) that you have to keep an eye on different work processes or sequences at the same time?" in situation of specific unpredictability (Pfeiffer and Suphan, 2015)
Goal Strategies	"Direction, Control and Planning" in Non routine interactive (Autor et al., 2003)	"Autonomy in decision making" (Harley, 1999)
Evaluate and Decide	"Evaluating and planning" in Non routine analytical (Spitz-Oener, 2006)	"How often does it happen (...) that you have to take difficult decisions autonomously?" in situation specific handling of complexity (Pfeiffer and Suphan, 2015)
Organizing priorities	"Direction, control and planning" in Non routine interactive (Autor et al., 2003)	"Autonomy in the pace or rate at which work is carried out" (Lorenz and Valeyre, 2005); "Autonomy in how work is done, start and finish time" (Harley, 1999)
Solving Complex Problems	"Frequency of problem solving tasks requiring at least 30 minutes to find a good solution in Abstract (Autor and Handel, 2013)	"Solving problems" (Lorenz and Valeyre, 2005); "How often does it happen (...) that you have to react to and solve problems?" in situation specific handling of complexity (Pfeiffer and Suphan, 2015)
Hands Dexterity	"Finger Dexterity" in Routine Manual (Autor et al., 2003); "Manual Dexterity" in Non routine manual physical (Acemoglu and Autor, 2011)	
Automation Degree	"How automated is the job?" in Routine task intensity (Deming, 2017); "Pace determined by speed of equipment" in Routine manual (Acemoglu and Autor, 2011)	"Automatic constraints linked to the rate at which equipment is operated or a product is displaced in the production flow" (Lorenz and Valeyre, 2005)
Repetitive Movements	"Spend time making repetitive motions" in Routine Manual (Acemoglu and Autor, 2011)	"Monotony" and "Repetitiveness of tasks of less than one minute" (Lorenz and Valeyre, 2005)
Influence		"Hierarchical constraints linked to the direct control exercised by one's immediate superiors" (Lorenz and Valeyre, 2005)
Leadership	"Guiding, directing and motivating subordinates" in Non routine cognitive interpersonal (Acemoglu and Autor, 2011); "Managing Personnel" in Non routine interactive (Spitz-Oener, 2006); "Proportion of workday managing or supervising other workers" in Abstract (Autor and Handel, 2013)	Hierarchy intended as occupational groups (Harley, 1999)
Standard Evaluation	"Set limits, tolerance and standard" in Routine cognitive (Autor et al., 2003)	"Quality assessment" (Lorenz and Valeyre, 2005)
Machine Control Importance	"Controlling machines and processes" in Routine Manual (Acemoglu and Autor, 2011), "Operating and controlling machines" in Routine Cognitive (Spitz-Oener, 2006)	
Relations	"Establishing and maintaining personal relationships" in Non routine cognitive interpersonal (Acemoglu and Autor, 2011); "Social perceptiveness" in Social skills (Deming, 2017)	
Coordinating with others	"Coordination" in Social skills (Deming, 2017)	"Team work"/Horizontal constraints linked to way one is dependent on the work of colleagues" (Lorenz and Valeyre, 2005)

Table 2: Variables and theoretical validation

3.3 Factor analysis

Given the unique richness of information contained in this type of data, different empirical analyses can be potentially implemented. In fact, the O*NET has already been used to build the Routine task index (Autor, 2015), whose application originates an important stream of literature on job polarization. Furthermore, the American survey has been screened adopting different methodologies - as the factor analysis - in order to deepen the knowledge on occupational characteristics, providing a taxonomy of skills and industry capabilities (Consoli and Rentocchini, 2015) or detecting the emergence of "green skills" (Consoli et al., 2016). In our case the choice of the factor analysis, which allows to identify constructs accounting for the correlation between variables (Kline, 2014), is motivated by the aim of grasping the most relevant underlying factors characterizing the anatomy of the Italian occupational structure. In fact, taxonomies allow to identify characteristic traits of a given dataset and to search for differences and similarities with respect to its internal categories (Peneder, 2010). To the best of our knowledge, this is the first time a similar empirical study is presented using the ICP database.

In matrix form, the statistical model underlying the factor analysis reads as:[14]

$$Y = \Lambda X + \Psi E \tag{1}$$

where Y is a $(n\text{x}1)$ vector of random variables, X is a $(r\text{x}1)$ vector of common factors and E is a $(n\text{x}1)$ vector of unique factors, with $n > r$; Λ is a $(n\text{x}r)$ matrix of common factor coefficients and Ψ is a $(n\text{x}n)$ diagonal matrix of unique factor coefficients. According to Equation 1, the vector Y is therefore a weighted combination of common and unique factors. Λ and Ψ contain respectively the weights of the common and unique factors, where the former is populated by non-zero common weights attributed to each factor per variable, while the latter consists of a diagonal of unique non-zero weights per each

[14]In the following paragraph, we follow the theoretical explanation provided by Mulaik (2009).

variable. Common and unique factors are assumed to be uncorrelated. The goal of the factor analysis is to identify common factors able to account for linear combinations among the variables under study, distinguishing source of common variance from unique variance, which can depend both on random errors or specific variance of each variable.

Assuming $R_{XE} = R'_{EX} = 0$, from Equation 1 we derive:

$$E(YY') = R_{YY} = E(\Lambda X + \Psi E)(\Lambda X + \Psi E)' = \Lambda R_{XX}\Lambda' + \Psi^2 \tag{2}$$

Equation 2 is the fundamental theorem of factor analysis, from which the reduced correlation matrix R_c is derived. The latter is obtained by subtracting from the variance-covariance matrix of Y the matrix of unique factors:

$$R_c = R_{YY} - \Psi^2 = \Lambda R_{XX}\Lambda' \tag{3}$$

Since Ψ is a diagonal matrix, the off-diagonal coefficients of R_c will preserve the variables' communalities, that are correlations due to common factors only. Λ will be the focus of our empirical analysis as it represents the factor pattern matrix, whose coefficients correspond to the weights attributed to the common factors, once derived the variables of the sample as linear combinations of common and unique factors. Indeed, Λ can also be defined as follow:

$$\Lambda = R_{YX}R_{XX} \tag{4}$$

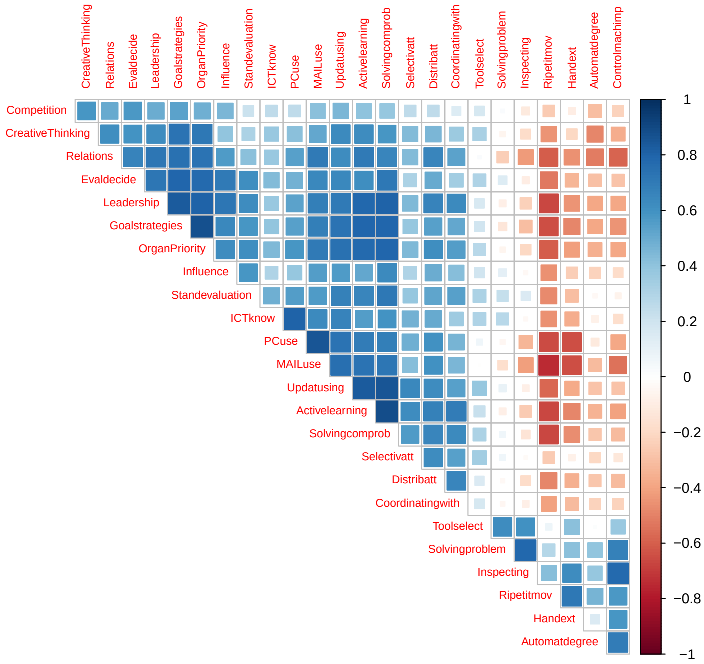
where R_{YX} is the factor structure matrix whose coefficients correspond to the covariances between variables Y and factors X, and R_{XX} is the correlation matrix between factors. Under the hypothesis of factors orthogonality Λ and R_{YX} are equivalent (being $R_{XX} = I$). However, as we shall see, the assumption of orthogonality among factors looks inappropriate for our study.

Different preliminary tests have been run in order to check the factorability of the database, whose sample size of 507 observations can be considered strongly reliable (Comrey and Lee, 1992). First of all, a preliminary analysis on the correlation matrix among the 25 selected variables has been performed to check the presence of an adequate correlation structure. The correlation matrix, shown in Figure 2, presents at a first-look the emergence of three clusters of variables: from the left-hand side to the right hand-side, the blue area shows the emergence of a positive correlation, the white one of a very low correlation, while the red one of a negative correlation among variables. Note however the general heterogeneity in the degree of correlation of each variable vis-a'-vis the rest.

In order to understand whether the selected dataset presents the characteristics to be factorised, we performed the Kaiser–Meyer–Olkin test that delivers a value of 0.92, confirming data adequacy. The latter indicator consists in the ratio of the sum of squared correlations to the sum of squared correlations plus the sum of squared partial correlations (Tabachnick et al., 2007, p.614): the closer to 1, the lower is the value of partial correlations, and therefore the higher the adequacy of the sample. Moreover, we run the Fligner non-parametric test that assesses variance homogeneity similarly to the Bartlett sphericity test, the former being more robust to departure from normality than the latter. The test rejects the null hypothesis on the equality of the distributions (and on the assumption of an identity correlation matrix). Additionally, the Alpha Conbrach test confirms the internal consistency of the set of chosen variables.

Once ascertained data factorability, the number of factors has been chosen taking into account different criteria: parallel analysis, factors' variance explained and Kaiser's criterion (eigenvalue>1) which are alternative and reliable selection methods to retain only the significant eigenvalues. The parallel analysis, presented in Figure 3, indicates the significant number of eigenvalues to select by comparing the actual matrix with a simulated and re-sampled random matrix with the same characteristics of the original matrix. The blue line indicates eigenvalues from actual data, whereas the two (overlapping)

Figure 2: Correlation matrix



red lines report simulated and re-sampled data. In this case, we identify the number of factors to retain whereby the distance between the blue and red lines is minimum: the selected number of factors equals five. This outcome is supported both by the compliance with the Kaiser criterion and the satisfactory amount of variance explained by the 5 factors.[15]

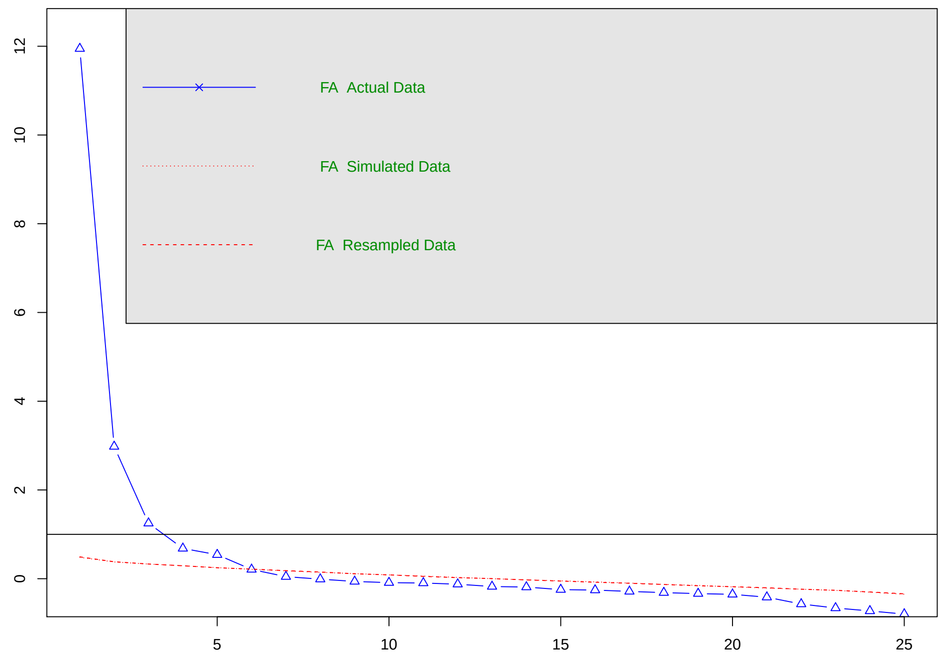
Different extraction methods have been adopted (principal axis, minimum residuals, weighted and unweighted least squares), all delivering very similar outcomes. In the following figures we display the outcomes of the principal axis analysis, that is based on an iterative algorithm computing eigenvalues and eigenvectors of the characteristic equation in order to obtain, at the end of the process, the most representative factors able to account for the maximum amount of variance.[16]

In order to improve results interpretability, Promax rotation has been applied. Indeed, we opted for oblique rotation that allows the possibility of correlation among factors since we assume that, as usual in social science (Tabachnick et al., 2007), also in our case factors explaining occupational characteristics might present correlation. In fact, we found out the presence of significant correlation among four out of five factors. Furthermore, factor scores have been calculated with different methods without delivering significant difference but, for the sake of simplicity, only regression's scores are reported.

[15]The last factor shows an eigenvalue only slightly higher than 1, however given the result of the parallel analysis, the amount of variance explained and the factor interpretability we are confident in keeping it in our model.

[16]For further details on the psych package on R, see `http://personality-project.org/r/psych/HowTo/factor.pdf`.

Figure 3: Parallel Analysis



3.4 Results

Figure 4 shows the results of the factor analysis. The circles represent the five factors in descending orders by the variance explained (neglecting the enumeration), while the arrows departing by each circle connect the loaded variables, black and red corresponding to positive and negative loadings. The numbers indicate the respective loads. Complementary, Table 3 displays the pattern matrix that in the case of oblique rotation can be opportunely interpreted as variable loadings (Tabachnick et al., 2007). The five factors explains more than 70% of the variance of the dataset, with the first three contributing the most. Finally the arrows linking each one circle represent the degree of between factors correlation, which ranging from 0.4 up to 0.7 is not negligible and calls for the Promax rotation method, removing the hypothesis of factor orthogonality.

The first factor predominantly collects those variables belonging to the domains of *autonomy (in decision, planning, and doing the job)* and *control over other people*, cf. Table 1. As can been seen from Table 3, the loads of the selected variables are approximately in the range of $[0.9 - 0.45]$.[17] Notably, those variables related to routinariety indicators as the frequency of repetitive movements and hand dexterity, negatively load. By loading all variables related to the domains of autonomy and control, we deem appropriate to label this factor *Power*. The choice is driven by the fact that this factor describes behaviours and attributes typical of the expression of forms of power, intended as:

> "the ability of some agent (the 'ruler', the authority) to determine the set of actions available to the other agents (the 'ruled') [or even] the ability of the authority to influence the choice within the 'allowed' choice set."
>
> (Dosi and Marengo, 2015, p. 4)

This factor explains one fourth of the total variance and the loaded variables represent the predominant traits in determining 4-digit inter-occupational variation. Clearly, activities as establishing long-term objectives and specifying strategies and actions to achieve them, or setting specific goals and plan the

[17] Three is the minimum number of variables to appropriately define a factor.

work, or defining priorities, organization and timing of implementation, are typically performed by the upper hierarchical layers inside organizations. In this respect, the sheer finding that the most important factor in determining cross-occupational variation is linked with hierarchies signals that understanding what actually people do at work dramatically depends on the internal distribution of power. Note however that the variables loading in the *Power* factor are not only those explicitly signalling hierarchical control, such-as "Leadership", but also variables referring to forms of more general "Autonomy" in judgement and decision-making, which affect, with different degrees, the entire range of occupational categories.

The second most important factor which explains an additional 15% of variability across 4-digit occupations collects six variables related to the execution of cognitive activities manifested as forms of control over the process, e.g., selecting machine tools or inspecting equipments, and by the execution of tasks which present a high degree of repetitive and automated motions and involve manual dexterity. We labelled this factor *Cognitive and manual dexterity*. Differently from our ex-ante classification (cf. Table 1), this factor loads positively both activities related to the use of machinery and equipment (controlling machines, automation degree, inspecting) and activities reflecting a certain manual ability and autonomy of judgement in the choice of work tools and in the resolution of unexpected problems that may arise in the performance of tasks. This factor presents comparability with the Routinised task index proposed by Autor (2015), but extends from the simple consideration of routinization and comprises elements related to the theory of the human capacity index proposed by Pfeiffer and Suphan (2015) and Pfeiffer (2018), which, to repeat, focus on the role played by experience and ability to face unpredictable events. These aspects are captured in our case by the positive loadings of variables such as "Tool select" and "Solving problems". Indeed, especially in the assembly line - considered as one of the production context most susceptible to automation - it might be necessary to perform a constellation of non routine tasks in order to prevent incidents, developing a high sensitivity to unpredicted changes, "keeping track of the whole environment with peripheral vision" (Pfeiffer, 2016, p.12).

The third factor, responsible for an other 14% of variance, collects variables related to learning activities and ICT skills. In particular, the use of computer and the knowledge of ICT represent the two variables exhibiting the highest loadings. Additionally, learning variables such as the need of keeping up to date with technical changes and applying new knowledge load positively, whereas hand dexterity shows a negative load. We labelled this factor *Digital* in order to emphasize the relative importance of those variables revealing the presence of digital skills and active learning processes.

The fourth factor positively loads three variables characterized by processes requiring an intensive use of cognitive knowledge, therefore mainly belonging to the first dimension of Table 1. The variables are "Active learning", "Selective attention" and "Distributed attention". The coexistence of two seemingly contrasting variables, such as the ability to be focused on a single task on the one hand, and the ability to simultaneously perform several activities on the other, signals a required degree of versatility to quickly react to the surrounding environment. Additionally, the other variable presenting a high loading factor is related to processes of coordination with other workers. We labelled this factor, which contribute to explain an additional 12% of variance, *Team*, being team-work an activity generically involving high degree of collaboration, responsiveness to external stimuli, multi-functionality but at the same time, concentration on specific tasks. Therefore, in line with Lorenz and Valeyre (2005) we find that forms of cooperation among workers tend to exhibit notable learning dynamics.[18]

Finally, the last factor, accounting for the remaining 9% of variance, is mainly characterized by three variables: the absence of automated processes, the presence of a certain degree of competition and the need to think creatively and develop new ideas.[19] We labelled this factor *Creative* since it identifies tasks

[18]The authors make explicit reference to a "lean" model. In our case, we do not have sufficient elements (i.e. the presence of job rotation mechanisms) to define as "lean" the factor.

[19]The lower percentage of the variance explained by the last factor is unavoidable, considering the descending order according to which factors are displayed. However, the presence of two "marker variables" - Creative Thinking and Competition, largely

involving a degree of creativity, but also forms of competition among workers. These variables mainly belong to both learning and social dimensions, according to Table 1.

How does the ex-post factor analysis face vis-a'-vis the ex-ante theoretical categorization presented in Table 1? Overall, we do observe that the latent factors tend to capture our categorization: the variables related to autonomy and control load in the first factor, those related to routinarity and automation load in the second factor, while those one related to ICT skills load in the third factor. A notable exception is our predefined domain *Knowledge and Learning* which spans its variables into three factors, namely *Digital*, *Team* and *Creative*.

Is it possible to identify any hierarchical structure in the selected variables? Figure 5 shows the underlying hierarchical structure behind them. The dendogram is constructed defining the Euclidean distance among clusters measured by the height in the y-axis, and the Ward's method, as agglomerative clustering method, which minimizes the total within-cluster variance in each pairwise comparison. Numbers reported in the dendogram correspond respectively to approximately unbiased (AU) p-values in red, and bootstrap probability (BP) p-values in green. Normally, AU p-values higher than 95 do validate the existence of the clusters, being highly supported by the dataset.[20] The cluster analysis highlights the emergence of two main separated branches, namely, the one on the left-hand side collecting those variables clearly belonging to the *Cognitive and manual dexterity* factor, while the one on the right-hand side collecting all the other remaining variables, which percolates into other sub-branches. In some respects the cluster analysis confirms the ex-ante classification we put forward in Table 1, with e.g. variables as setting goal strategies, evaluate and decide, clustered together as a branch signalling autonomy in decision making. However, some other variables cluster in alternative branches vis-a'-vis our ex-ante classification. Overall, what we deem important is to signal the underlying hierarchical information covered by our variables and the fact that the chosen variables actually capture different, measured in terms of Euclidean distance, dimensions of the working activity.

loading in one factor only - can be considered as a "pure measure" of the factor (Tabachnick et al., 2007). This justifies, according to us, the inclusion of the fifth factor in our model, together with the result of the parallel analysis.

[20]For further information on the package used, see http://stat.sys.i.kyoto-u.ac.jp/prog/pvclust/.

Figure 4: Factor Analysis

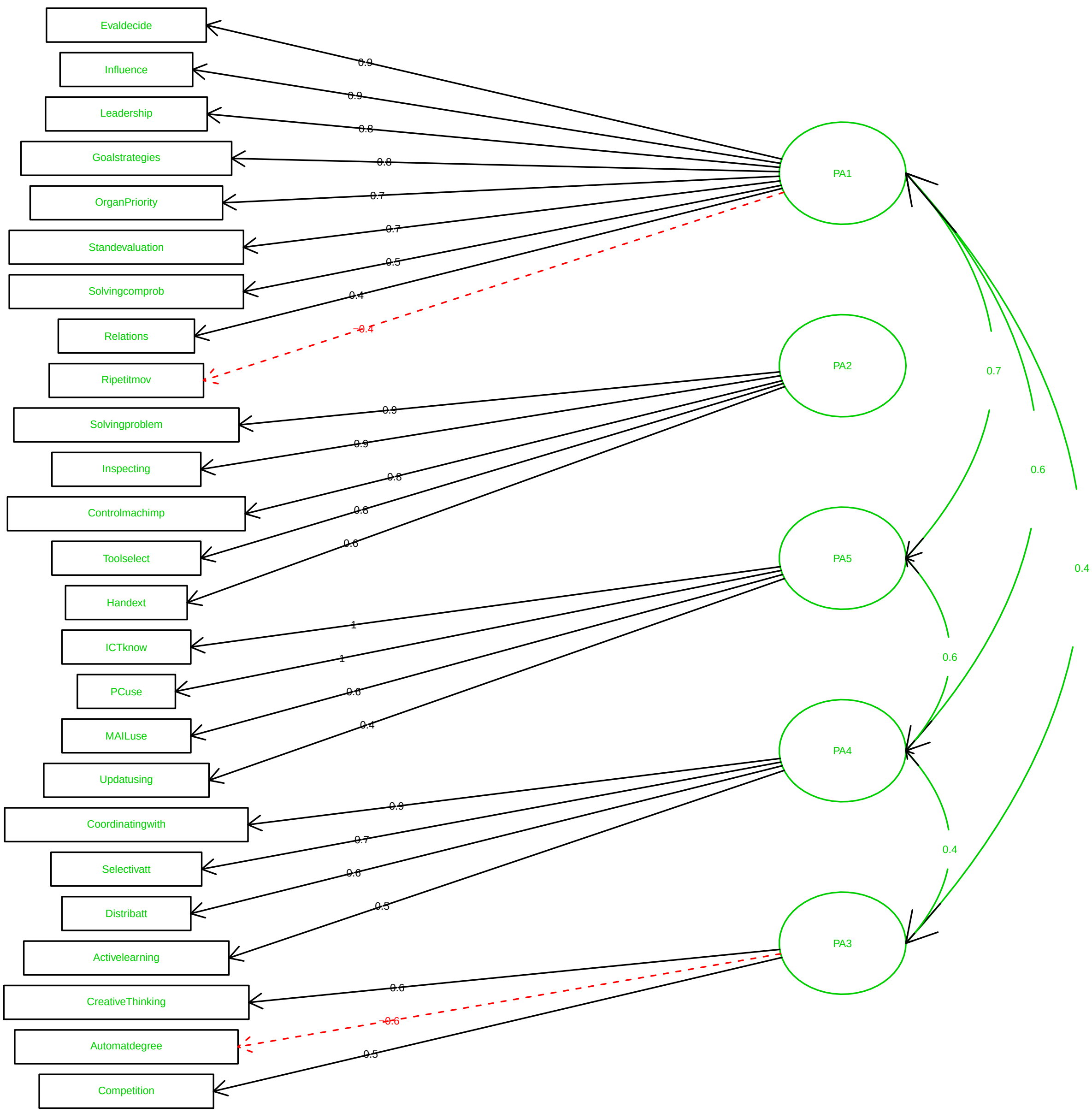
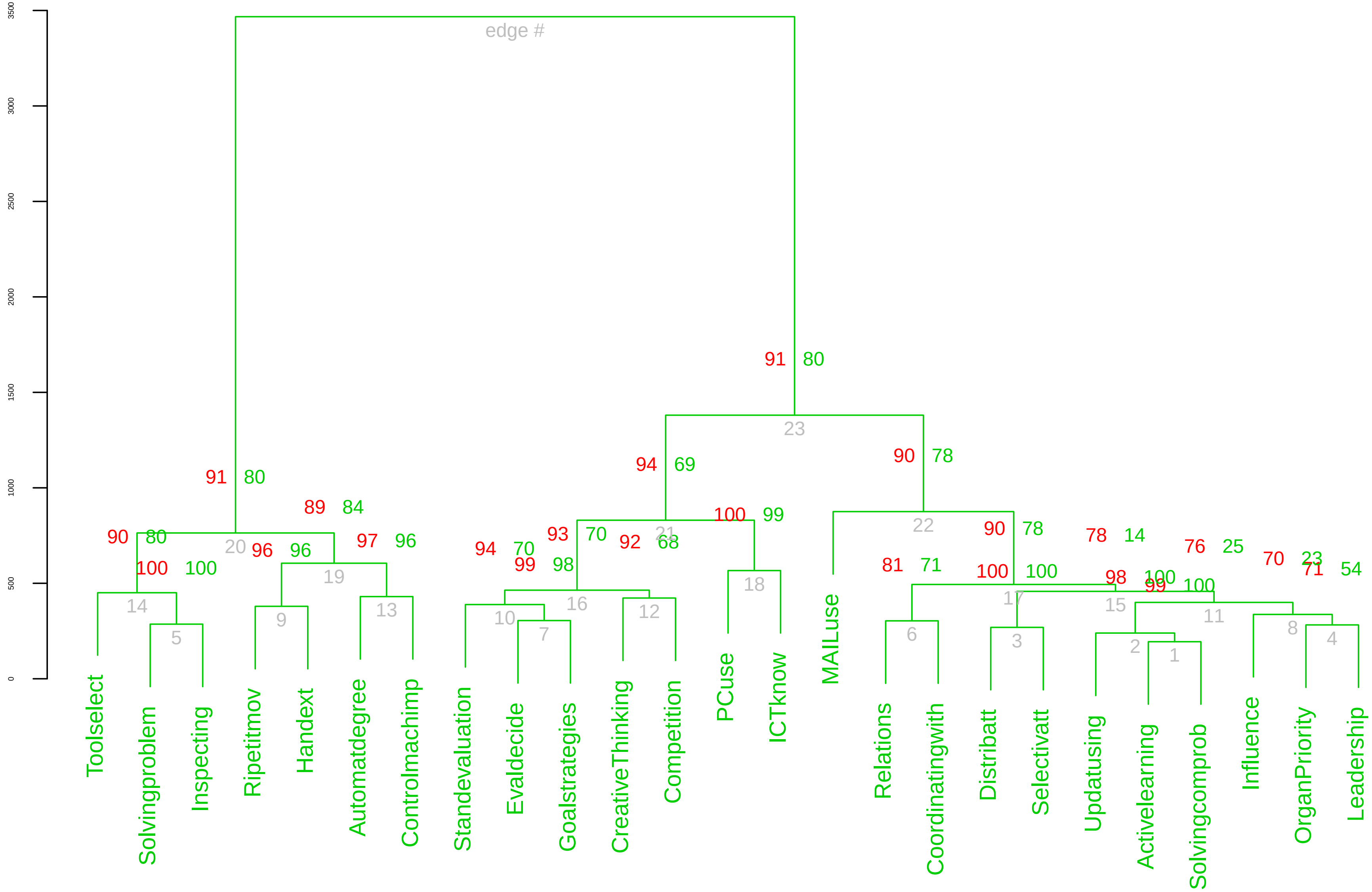


Table 3: Factor analysis results (pattern matrix). Principal axis extraction method applying Promax rotation method. Regression scores reported.

Variables	Power	C&M	Digital	Team	Creative
Distribatt	0,17	-0,06	0,11	0,61	0
Selectivatt	-0,27	0,11	0,24	0,71	0,19
CreativeThinking	0,29	0	0,07	0,02	0,65
Updatusing	0,26	0,15	0,43	0,27	0,2
Activelearning	0,32	-0,07	0,18	0,49	0,09
PCuse	-0,06	-0,12	0,95	0,09	-0,08
ICTknow	-0,2	0,19	0,99	0,03	0,07
MAILuse	0,34	-0,22	0,57	-0,03	0,08
Evaldecide	0,95	0,19	0,03	-0,26	0,26
Goalstrategies	0,81	-0,07	-0,07	0,02	0,26
OrganPriority	0,7	0,01	-0,01	0,14	0,23
Leadership	0,91	-0,05	-0,23	0,28	0,08
Influence	0,92	0,16	-0,19	0,02	0,03
Solvingcomprob	0,54	0,09	0,19	0,33	0,02
Solvingproblem	0,16	0,92	0,25	-0,15	-0,08
Toolselect	0,07	0,75	0,08	0,17	0,31
Ripetitmov	-0,42	0,35	-0,29	-0,02	-0,01
Automatdegree	-0,05	0,43	0,2	-0,12	-0,57
Handext	-0,29	0,56	-0,44	0,09	0,3
Controlmachimp	0,02	0,8	-0,11	-0,01	-0,34
Standevaluation	0,68	0,3	0,1	0,27	-0,27
Inspecting	0,11	0,9	-0,14	0,06	-0,14
Relations	0,45	-0,28	-0,02	0,2	0,31
Competition	0,48	0,08	0,01	-0,28	0,54
Coordinatingwith	0,22	-0,04	-0,17	0,85	-0,18
SS loadings	6.32	3.83	3.47	3.11	2.31
Proportion Var	0.25	0.15	0.14	0.12	0.09
Cumulative Var	0.25	0.41	0.54	0.67	0.76

Figure 5: Dendogram



3.5 From micro to macro: factors across occupational categories

In this section we perform a micro-to-macro analysis to understand how the identified five factors at 4-digit level *distribute* across occupational categories at 1-digit level of aggregation. In this respect we want to characterize which are the prevalent traits of the activities conducted by occupational categories and how they differ among themselves. The 1-digit level aggregation results into eight occupational categories namely: legislators, managers, entrepreneurs; intellectual and scientific workers; technical professionals; clerical support workers; service and sale workers; crafts, agriculture and specialised workers; plant and machine operators; elementary occupations.

Figure 6 presents five box-and-whisker plots for each of the identified factors, going from the left-hand- to the right hand-side, from the top to the bottom panel, according to the factor respective importance. The box-plots allow to identify the distribution of the median, interquartile ranges, maximum and minimum values, and outliers per each 1-digit occupational category.

Power, the first factor in Figure 6(a), presents a clear descending pattern across the eight categories, with legislators, managers and entrepreneurs presenting a higher than 1 median value and a low degree of variability. At the opposite end of the spectrum, elementary occupations have a negative, lower than -1, median level of power, with the maximum recorded value still less than zero. Together with the top-occupational category, only two other categories present a positive median value for power, namely intellectual and scientific workers, and technical professionals. However, the median value is lower than 1, and presents a low-end variability in both cases, reaching negative values. A complementary view comes from Figure 9(a) which presents the kernel density distribution per each factor grouped by occupational categories. From the figure clearly emerges how power is strongly concentrated in the top professional category and unevenly distributed across the rest of occupations.[21]

The second factor, *Cognitive and manual dexterity* presented in Figure 6(b), is clearly concentrated among crafts, agriculture and specialised workers, and plant and machine operators with median value around 1. The remaining occupations present negative values for this factor. However, the degree of variability is extremely high across categories. Notably, the kernel density distributions of intellectual and scientific workers, technicians and service and sales workers overlap, as shown in Figure 9(b). The latter finding highlights that there are some degree of commonality, probably in the cognitive activities performed across distinct occupations.

The third factor, *Digital* presented in Figure 6(c), mainly characterizes the first-four 1-digit occupations, with notably higher values for intellectual and scientific workers, presenting a median value around 1. Additionally, legislators, managers, entrepreneurs, which are characterised by the higher level of power, require similar use of digital tools and need to update their own knowledge to technical professionals and clerical support workers, as shown by the overlap of the kernel density distributions in Figure 9(c). The bottom-four occupations all present negative median values for the digital factor, although with a notable heterogeneity, particularly for service and sales workers, and for crafts, agriculture and specialised workers, with ample ranges of variation.

A similar pattern across occupations, although less evident, emerges also for the *Team* factor, again with a higher median value for intellectual and scientific workers, as presented in Figure 6(d). This factor presents multi-modality for the distribution of elementary occupations and bi-modality for technical professionals (Figure 9(d)) indicating that the variables behind the factor present a strong degree of inter-occupational heterogeneity.

Finally the last factor, *Creative*, mostly belongs to scientific workers. It is negative for many occupational categories, including clerical support workers and plant machines operators (cf. Figure 6(e)). It presents a strong degree of variability for sale and service workers, technical professionals and for crafts and artisans, whose distributions tend to overlap (cf. Figure 9(e)). In particular, the support of the dis-

[21] Fligner-Policello tests have been run to asses the equality of pairwise distributions per each factor. The test confirms our interpretation of the results, whenever we detect difference or alternatively equality in the distributions.

tribution of crafts, agriculture and specialised workers varies from negative to positive values probably because of the presence of highly specialised and creative craftsmen within this group.

In the following Table 4 we present the top-ten and bottom-ten occupations at 4-digit level of disaggregation for each factor in order to provide a further validation of our analysis. Notably, the *Power* factor shows cases in which top- and bottom-occupations in the same sector of activity present a specular opposite position: it is the case for non-qualified staff in catering services which rank second in the bottom-tier, while entrepreneurs and directors of large companies in accommodation and catering services rank fifth in the top-tier. This confirms that the factor is actually able to uncover the hierarchical structure of the sector of activity. By inspecting the other factors, the occupations that we extracted look to appropriately validate the factor-occupation nexus.

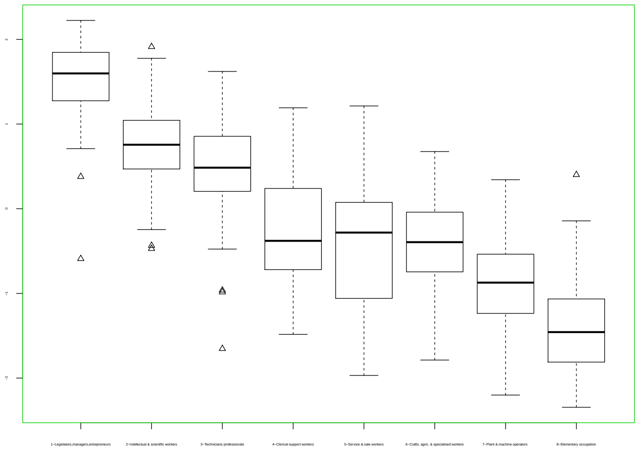
To sum up, we identify how the first factor in explaining 4-digit level occupational variation is also the most concentrated at 1-digit level of aggregation. Additionally, when comparing the distribution of the *Power* factor vis-a'-vis the *Digital* and *Creative* factors, our proxies of learning processes, we do find a discrepancy between managing power and being endowed by knowledge, with, on the one hand occupational categories, such as intellectual and scientific workers and technical professionals, exerting less power than managers and legislators, and on the other hand, the latter being characterised by a significant lower degree of knowledge but also of creativity, according to the distribution of our fifth factor. Therefore, contrary to learning models typical of Northern economies (Lorenz and Valeyre, 2005, p. 430), which are characterised by the coexistence of a high degree of autonomy, strong learning dynamics and horizontal constraints - even for managers, professionals and technicians -, we find that autonomy and control tend to diverge with respect to learning processes in the Italian economy.

Overall we dissect few activities, which map into occupational categories, requiring cognitive and manual dexterity as dominant traits, with generically negative median values, except for crafts and machine operators. Notably, the other occupational category which should be characterised by the predominance of this factor according to the RBTC classification, namely clerical support workers performing routinesed cognitive activities, does not present a positive median value.

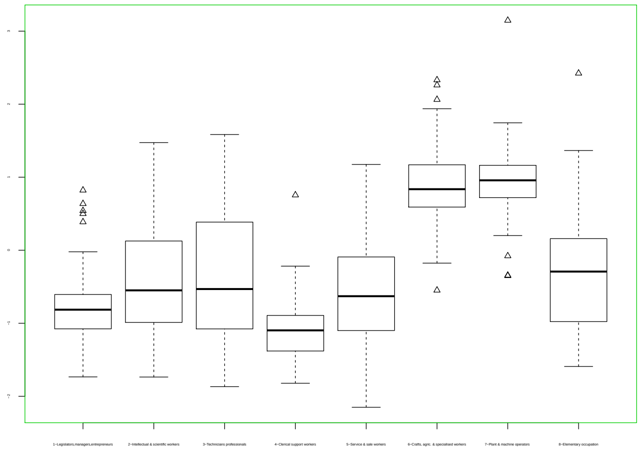
The level of team-working and practices of active learning are generically positive (but with low median level) only for the top-three categories of occupations, while remarkably the factor *Creative* presents top-end variability in occupations generically considered for low-skilled workers, such as sale and service operators and crafts and artisans. The latter might signal both the existence of creative practices or alternatively of high degree of competition among workers in the low-tier of occupations. Notably, all the three factors capturing attributes of learning processes and knowledge accumulation are more widespread distributed across 1-digit occupations with respect to the power factor.

Figure 6: The box-and-whisker plots

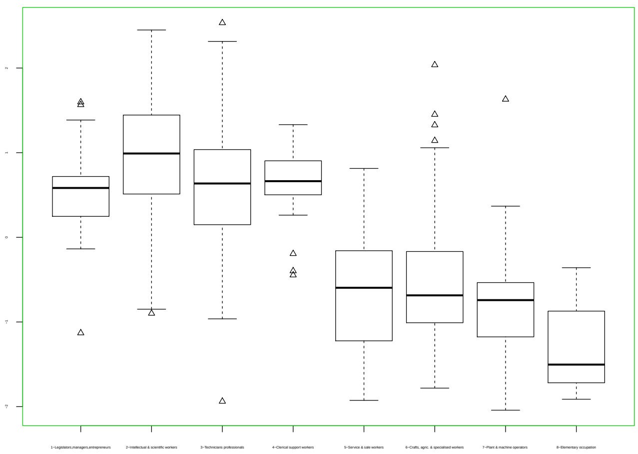
(a) Power



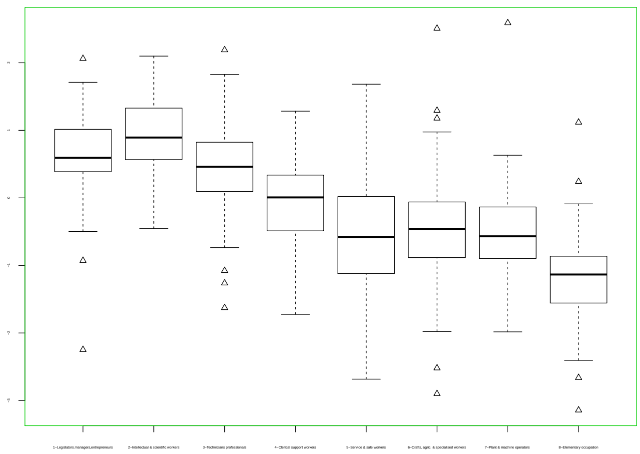
(b) Cognitive and manual dexterity



(c) Digital



(d) Team



(e) Creative

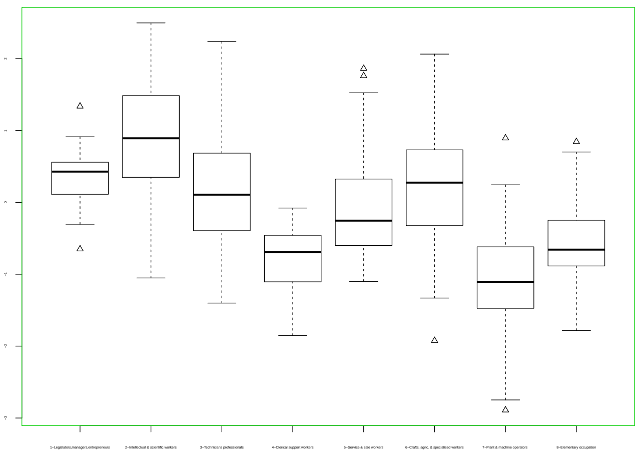
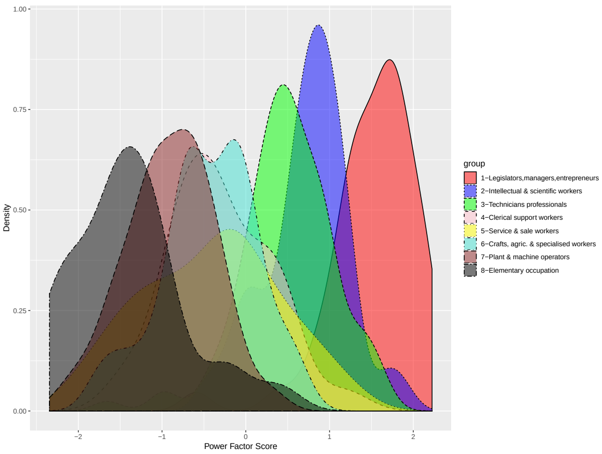
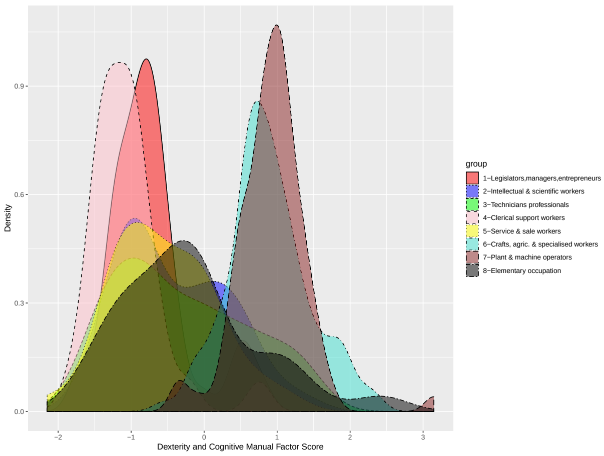


Figure 7: The kernel density distributions

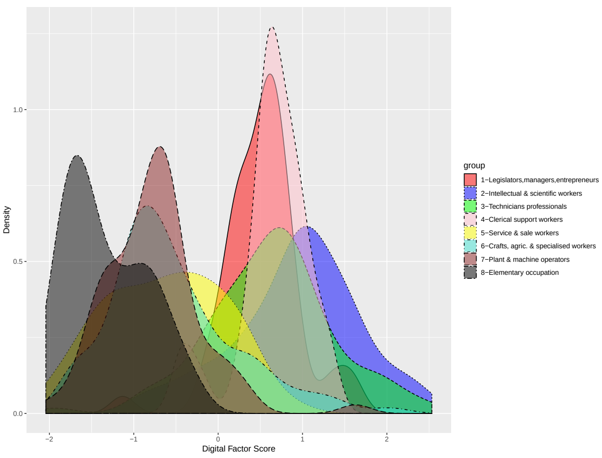
(a) Power



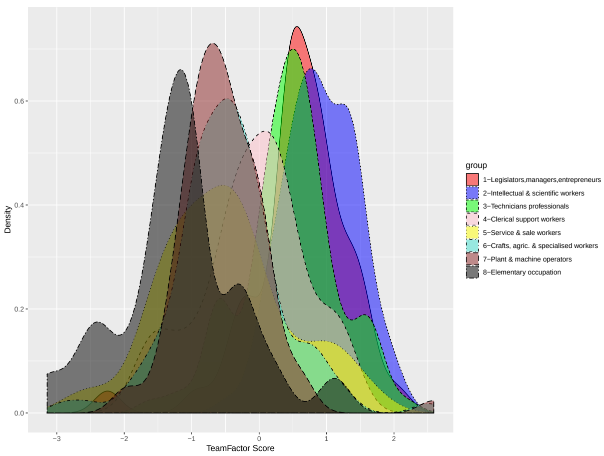
(b) Cognitive and manual dexterity



(c) Digital



(d) Team



(e) Creative

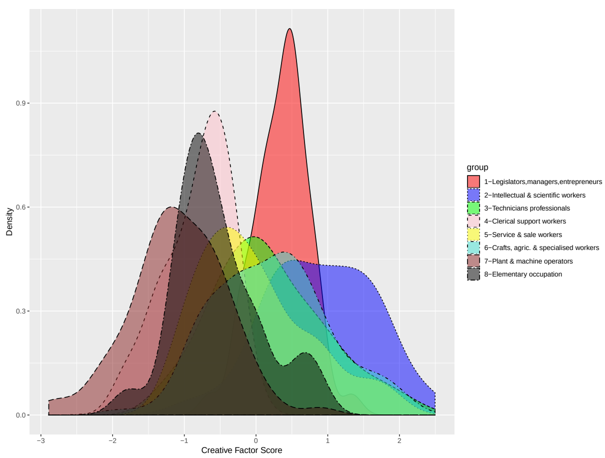


Table 4: Top and bottom 10 occupations (4-digit) by factor

	Bottom ten occupations - Power	
4-Digit code	**Loads**	**Description**
8421	-2,344334	Manual workers and unqualified personnel in civil construction and similar professions
8142	-2,332696	Non-qualified staff in catering services
8152	-2,27906	Porters and similar professions
7232	-2,200223	Conductors of machinery for the manufacture of other rubber products
8131	-2,11396	Freight forwarders and similar workers
8221	-2,100361	Domestic workers and related professions
7424	-2,032285	Animal-drawn vehicle drivers
7422	-1,973	Bus, tram and trolley drivers
5441	-1,9682	Company staff and qualified family service staff
8151	-1,959175	Bidding and related professions
	Top ten occupations - Power	
4-Digit code	**Loads**	**Description**
1124	2,223634	General managers, departmental managers and equivalent directors of state administrations, non-economic public bodies, local authorities, universities, research institutions and health
1121	2,220873	Ambassadors, plenipotentiary ministers and senior executives of the diplomatic career
1122	2,128179	Government commissioners, prefects and deputy prefects, heads and deputy heads of state police, quaestors, secretaries-general and related professions
1212	2,115432	Entrepreneurs and administrators of large companies involved in mineral extraction, manufacturing, production and distribution of electricity, gas, water and waste management activities
1215	2,113997	Entrepreneurs & directors of large companies in accommodation and catering services
1239	2,092362	Other departmental directors and managers not elsewhere classified
1228	2,085853	Directors & general managers of companies providing services to businesses and individuals
1227	2,041149	Directors and general managers of banks, insurance companies, real estate agencies and financial intermediaries
1123	1,932235	Directors of the local school offices, superintendents of the national cultural heritage and equivalent
2217	1,912723	Industrial and management engineers
	Bottom ten occupations - Dexterity and Cognitive Manual	
4-Digit code	**Loads**	**Description**
5131	-2,150587	Models and similar professions
3347	-1,868639	Agents and representatives of artists and athletes
4321	-1,821576	Accountants
5125	-1,740209	Home-based sellers, remote and similar professions
2523	-1,736517	Notaries
1112	-1,73457	Members of governing bodies and assemblies with legislative and regulatory power at the regional level and of autonomous provinces
1131	-1,667351	Executives of the ordinary judiciary (Courts, Tribunals, Courts of Appeal, Court of Cassation)
4223	-1,622512	Operators
8121	-1,591862	Bailiffs and related professions
3322	-1,56591	Banking Technicians
	Top ten occupations - Dexterity and Cognitive Manual	
4-Digit code	**Loads**	**Description**
7161	3,147084	Conductors of steam boilers and heat engines in industrial plants
8323	2,42289	Unqualified personnel involved in fishing and hunting
6232	2,331625	Engineers and repairers of aircraft engines
6216	2,261201	Divers
6238	2,062825	Naval mechanics and toolmakers
6451	1,937519	Aquaculture and related professions
6453	1,927718	Deep-sea fishermen
6215	1,871787	Equipment and assemblers of metal cables for industrial and transport use
6217	1,850692	Specialists in electrical welding and ASME standards
6551	1,819085	Stage machinists and toolmakers
	Bottom ten occupations - Digital	
4-Digit code	**Loads**	**Description**
7424	-2,041974	Animal-drawn vehicle drivers
3427	-1,938417	Athletes
5441	-1,926065	Company staff and qualified family service staff
8142	-1,912391	Non-qualified staff in catering services
5487	-1,910911	Lifeguards and similar professions
8421	-1,860218	Manpower and unskilled personnel in civil construction and related occupations
8221	-1,841311	Domestic workers and related professions
8141	-1,82795	Unqualified cleaning personnel in accommodation services and ships
8152	-1,794246	Carriers and related professions
7443	-1,791422	Conductors of cranes and lifting equipment
	Top ten occupations - Digital	
4-Digit code	**Loads**	**Description**
3123	2,532762	Web technicians
2114	2,449302	Analysts and software designers
2214	2,320413	Electronic and telecommunications engineers
3125	2,314395	Technicians managers of networks and telematic systems
2213	2,300651	Electrical engineers
2115	2,240808	System designers and administrators
3122	2,138143	Technical experts in applications
3124	2,056084	Technical database managers
2623	2,03621	Researchers and technicians with degrees in engineering and architecture sciences
6246	2,035943	Installers, maintainers and repairers of computer equipment

(continue...)

Bottom ten occupations - Team		
4-Digit code	**Loads**	**Description**
8112	-3,142859	Walking service providers
6516	-2,899738	Tobacco leaf preparation and processing workers
5122	-2,683407	Retail sales clerks
8111	-2,661763	Street vendors of goods
6422	-2,519728	Sheep and goat breeders and specialised workers
8322	-2,405073	Unqualified staff for the care of animals
5488	-2,329368	Garage operators
8144	-2,317364	Vehicle washers
1314	-2,247225	Entrepreneurs and managers of small businesses in commerce
7265	-1,983322	Workers in textile printing machinery

Top ten occupations - Team		
4-Digit code	**Loads**	**Description**
7161	2,589912	Conductors of steam boilers and heat engines in industrial plants
6232	2,507941	Engineers and repairers of aircraft engines
3162	2,189592	Pilots of aircraft
2418	2,098573	Anaesthetists
1121	2,060832	Ambassadors, plenipotentiary ministers and senior executives of the diplomatic career
2612	1,975669	University lecturers in life and health sciences
2652	1,876487	School inspectors and related professions
3133	1,827193	Electrotechnics
2622	1,79445	Researchers and technicians with a degree in life and health sciences
2413	1,787756	Specialists in surgical therapies

Bottom ten occupations - Creative		
4-Digit code	**Loads**	**Description**
7264	-2,890833	Workers involved in machinery for the processing of industrial yarns and fabrics
7265	-2,748487	Workers involved in machinery for printing fabrics
7134	-2,357574	Conductors of ovens and other plants for the production of bricks, tiles and similar
7325	-2,210545	Machine operators for the production and refining of sugar
7213	-2,148034	Machine operators for the production of abrasives and mineral abrasive products
7143	-2,068876	Papermaking plant operators
7182	-2,061722	Conductors of furnaces and similar installations for the heat treatment of minerals
7313	-1,997809	Workers in the refrigeration, hygienic treatment and first-stage processing of milk
6516	-1,924072	Tobacco leaf preparation and processing workers
7233	-1,865177	Machinery operators for the manufacture of plastic and related products

Top ten occupations - Creative		
4-Digit code	**Loads**	**Description**
2555	2,497025	Artists of the popular culture and acrobats
2631	2,351236	Professors from academies, conservatories and similar educational institutions
2554	2,311913	Composers, musicians and singers
3423	2,238639	Instructors of techniques in the artistic field
3171	2,096844	Photographers and related professions
6324	2,062891	Painters and decorators on glass and ceramics
2551	2,016156	Painters, sculptors, designers and restorers of cultural heritage
6332	1,952672	Craftsmen of the artistic work of textiles, leather and the like by hand
2552	1,933819	Directors, art directors, actors, screenwriters and set designers
2614	1,89539	University lecturers in ancient, philological-literary and historical-artistic sciences

3.6 Employees and autonomous workers

In this section we intend to detect the extent to which our results might be affected by the forms of employment status behind occupations. Given that the primary factor in explaining cross-occupational variance derives from variables linked to autonomy in decision making, in planning and in doing the job, one may suspect that the strong importance of the *Power* factor stems from self-employed workers. For this reason, we split the overall sample in two sub-samples, namely autonomous and dependent workers. This information derives from the ICP dataset where it is specified whether each 5-digit worker presents an autonomous or an employee status. Given that our unit of analysis is at 4-digit level, we need to resort to an attribution criterion for each 4-digit level occupational category. We opted for a routine according to which if more than 60% of the 5-digit level occupations are autonomous, the corresponding 4-digit level will be autonomous as well. The same procedure applies to employee workers. Using this cut-off we are not able to attribute a status to only 74 occupations out of 507, therefore retaining the majority of them.[22]

Figure 8 presents the results of the factor analysis for the two sub-groups. The top panel 8(a) shows that only three out of the previous five factors are selected to be significant for employees. However, the order remains unaltered, with the *Power* factor explaining most of the variation (41%), followed by *Cognitive and manual dexterity* and *Digital*, that respectively explain 15% and 17% of the variance. Clearly, by clustering into three components some variables before attributed to the *Creative* and *Team* factors now conflate into the first factor, which also loads learning variables. The bottom panel 8(b) presents the same graph for autonomous workers. In this case, four out of five factors are retained, with *Power* explaining the highest percentage of variance (28%), *Cognitive and manual dexterity* explaining 17% of variance and *Digital* and *Team*, explaining almost the same proportion of data variability (14% and 12%). We therefore conclude that the clustering and relative importance of the *Power* factor is not driven by the employment status but it is instead an inherent trait characterizing the variability across occupations in the Italian economy. The same consideration applies to the remaining factors whose importance is relatively unaltered.

In the following we compare the kernel density distributions of employees versus autonomous workers for the common explaining factors, given the same occupational categories. Figure 9(a) and Figure 9(b) present the distributions for the factor *Power* recovered by performing two independent factor analyses, according to the results shown in Figure 8. By performing this exercise we are comparing two different populations of workers in terms of inherent characteristics of the working activities and in terms of size. However, we intend to understand how the factors behave according to the employment status, by macro occupational categories. Take the case of managers, legislators and entrepreneurs. Autonomous workers (purple distribution) present a much wider support in terms of the factor *Power*, more concentrated on the right hand side. When looking at technical professionals, the two populations present a largely overlapping support of the distributions, with a notably right long-tail, signalling stronger power attributes, for autonomous workers (cf. Figure9(b)). In this respect, we do observe inter-occupational variability of the factor, according to the employment status.

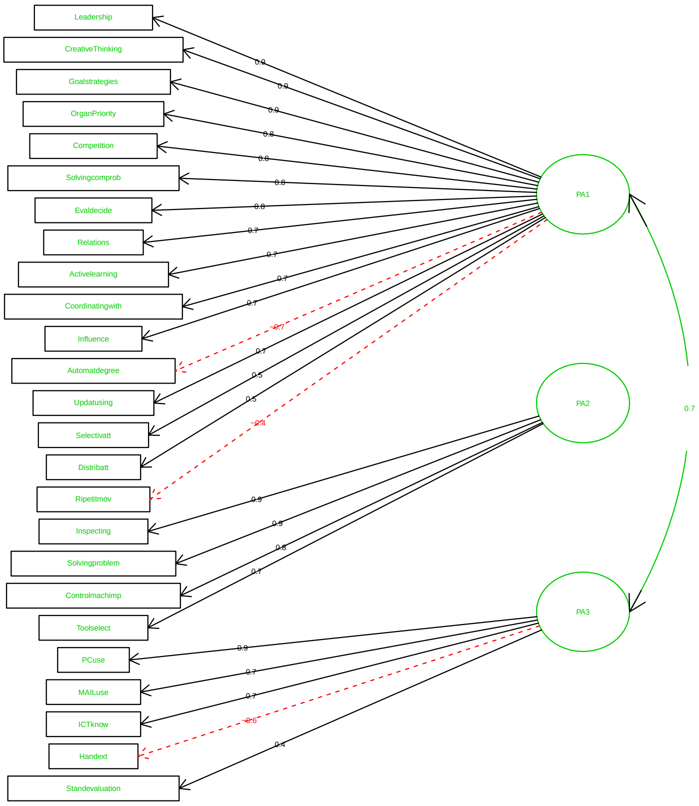
Looking at the *Cognitive and manual dexterity* factor, comparing Figure 9(c) and Figure 9(d) we detect a more invariant behaviour of the factor vis-a'-vis the employment status: machine and plant operators do not show strong differences in the support of the distributions when comparing employees and autonomous workers. Crafts, agriculture and specialised workers present a modal behaviour which is significantly different.

Finally, the *Digital* factor does not exhibit strong variability when comparing e.g. intellectual and scientific autonomous versus employee workers, but it does the opposite when looking at clerical support

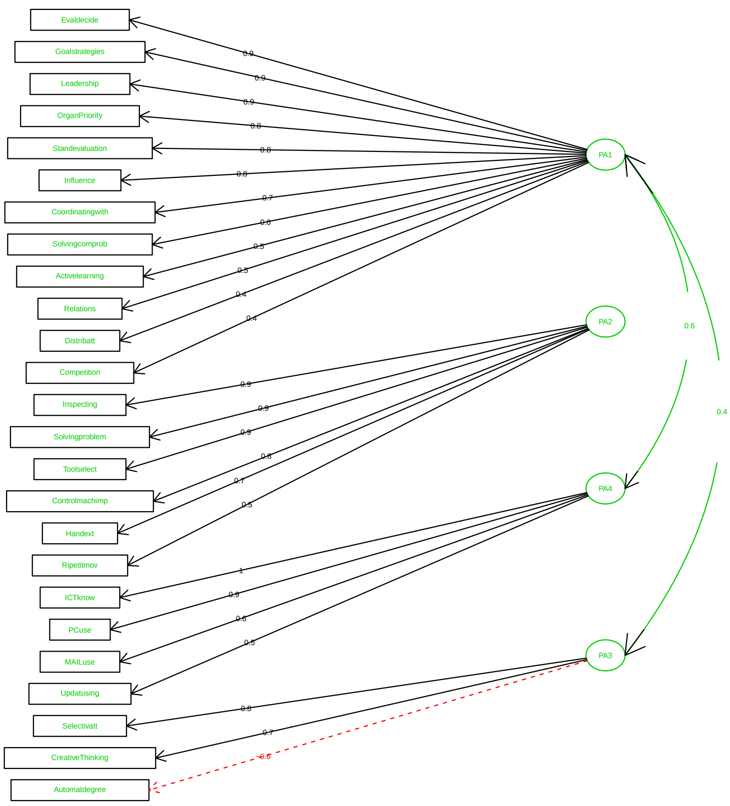
[22] Alternative thresholds have been employed (80:20; 75:25; 70:30). However too many observations are lost when using the alternative thresholds (229; 190; 161 respectively).

Figure 8: Factor analysis for employees and self-employed workers

(a) Employees



(b) Self-employed workers

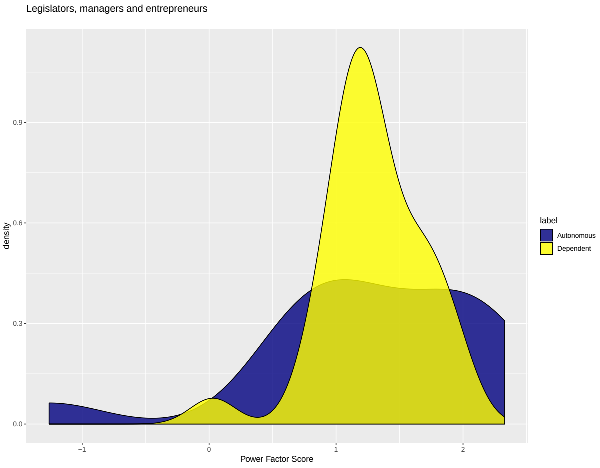


operators, whereby those one employed as autonomous workers present a distribution concentrated on the upper support, while dependent workers exhibit a far wider heterogeneity.

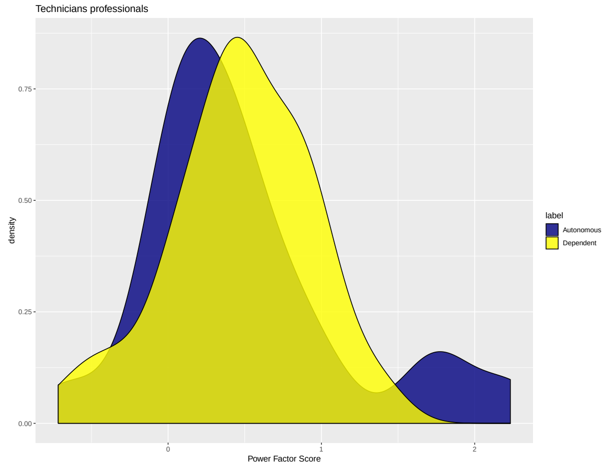
In general a word of caution is needed: in many respect the population of self-employed workers is composed by fictitious self-employed, who actually might durably contract even with a single buyer for repeated periods and are required to have their own VAT identification number, in order not to "weigh on" the firms for which they work. In this respect, the autonomous status "masks" the effective status as dependent worker. Unfortunately we do not have any reliable source to identify those forms of false positives, but there are clearly some 1-digit level occupations, such as clerical support workers, which are by the inherent characteristics of the jobs more "naturally" composed of employee workers although recorded as being self-employed. Related, we are not able to distinguish among incorporated self-employed workers, or formal business, and unincorporated self-employed ones, or informal firms (Levine and Rubinstein, 2017). However, the bimodal distribution emerging e.g. in technical professionals and machine operators hints at the underlying dichotomy characterising self-employed workers, with this unique status embracing both high-paid professional workers (lawyers, engineers, architectures, physicians) and also low-paid ones (street vendors, door-to-door salesman...).

Figure 9: The kernel density distributions for employees and self-employed workers

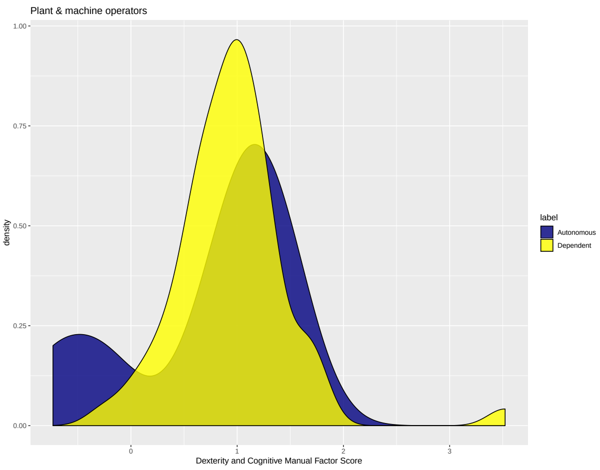
(a) Power - Legislators, managers, entrepreneurs



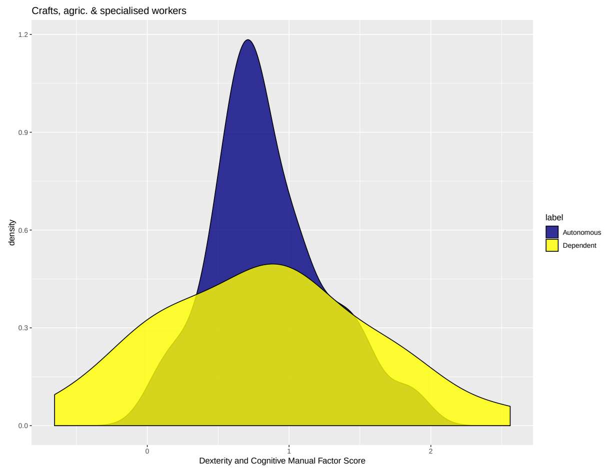
(b) Power - Technical professionals



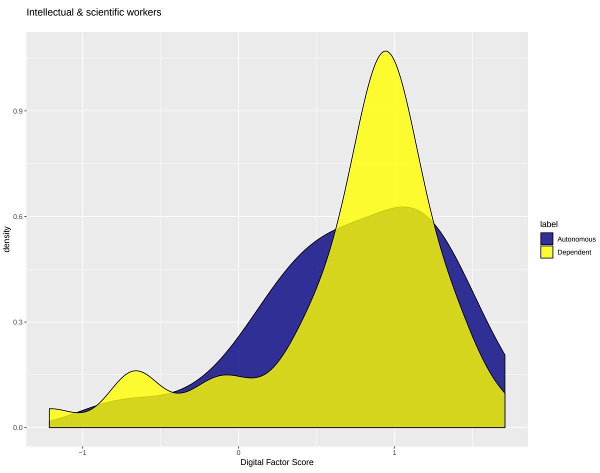
(c) Cognitive and manual dexterity -
Plant and machine operators



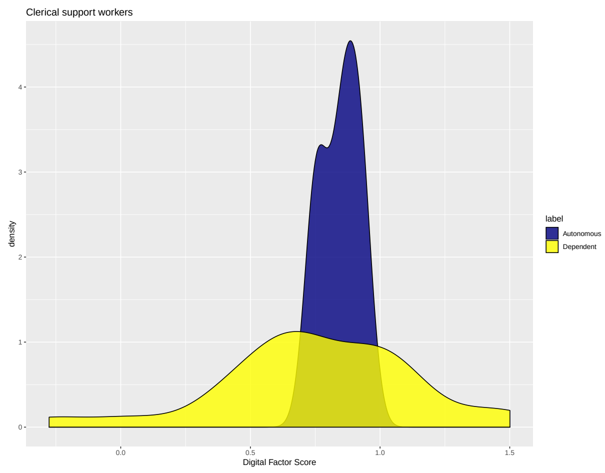
(d) Cognitive and manual dexterity -
Crafts, agriculture and specialised workers



(e) Digital - Intellectual and scientific workers



(f) Digital - Clerical support workers



4 Interpretations and conclusions

The goal of this paper is to detect and describe the dominant traits of the Italian occupational structure, exploiting the vast and unique amount of information contained in the ICP database. In a context of vibrant economic and political debates on the effects of technological change on employment, a tall task consists in understanding what actually people do at work, avoiding to fall in simplifying classifications.

We accomplish that by means of a multistep empirical strategy. First, we build an ex-ante theoretical categorization of the data-set focusing on technological, organizational and skill dimensions of the ICP questionnaire covering three key areas of analysis namely, *knowledge and learning*; *work organization*, including *degrees of autonomy, routinariety, automation, control and social interactions*; and finally *digital skills*. We then move from this theoretical classification to the factor analysis performed on the selected variables to detect the presence of some hidden factors able to describe the almost five hundred occupations at 4-digit level of aggregation. Five latent factors allow to explain the variance among our variables, with the factor collecting attributes of *power* explaining most of the variability. Other relevant factors that do emerge allow to bundle attributes such as *cognitive and manual dexterity, digital, creativity and team work*.

We find some rather striking results. First of all, occupational groups manifest strong heterogeneity in terms of the identified factors. This allows to conclude that the factor analysis pinpoints hidden components fuelling this heterogeneity. Second, with reference to the factor-occupation link, we do find that:

- *Power* is strongly uneven distributed across 1-digit occupational categories, concentrated among managers and legislators. Surprisingly, also categories expected to have a higher degree of power, such as producers of scientific knowledge, on average manifest a lack of it.

- Are those one making decisions more skilled in terms of digital knowledge and more exposed to active learning processes? Hardly so, in fact our *Digital* factor, collecting both learning activities and digital skills, is similarly concentrated among clerical support workers and managers and legislators.

- *Knowledge* appears to be the most multifaceted trait to define occupations. In fact, its attributes are widespread distributed both among factors, taking the forms of digital skills updating, cognitive manual capability and active learning, and across occupations, with clerical support workers and technical professionals presenting overlapping patterns, and with manual workers exercising authority of intervention to control machines, inspect equipments or identify errors. This signals the weakness of the "routine vs non routine" dichotomy to define activities and occupations.

- The degree of collaboration and team-work appears to be rather weak, both in service and manufacturing oriented occupational categories. The low degree of team-work activity clearly reflects the prevalence of self-employed occupations, and small enterprises, which undermine the possibility of collaborations.

- Being creative is a privilege for scientists and intellectual workers and, to a lesser extent, for specialized crafts and artisans. Note however that power, autonomy and creativity do not go hand in hand.

More specifically, the empirical result according to which the first 1-digit occupational group - legislators, managers, entrepreneurs - displays the highest *Power* factor score does reflect two complementary issues. On the one hand, this correctly points at occupations that hold decision-making roles, consistently with the structure of the ISCO classification. On the other hand, it does reflect the existence of usually neglected dimensions of control enhancement and hierarchical structure within organisations, which do not derive from the division of tasks among workers accordingly to their skills, but rather from the evolution of productive organisations shaped by social dynamics. If through the technical and bureaucratic organisation of work "power was made invisible" (Edwards, 1980, p.110), one of the contribution of this paper consists in disclosing the importance of this component to study the occupational structure.

Moreover, our analysis offers a different perspective on occupations usually labelled as routinesed by their degree of repetitiveness and related risk of substitution. Indeed, the second factor *Cognitive and manual dexterity* shows that a hidden level of complexity emerges in terms of continuous resolution of problems and dynamic selection of work tools, even in standardised work contexts. This finding is in line with Pfeiffer (2018) which cautiously warns against the adoption of a strict definition of routine - non routine activities.

In addition, the Italian occupational structure reveals to be fragile in terms of digital skills. These skills are concentrated in a restricted set of occupations and under-diffused among occupations characterized by a high degree of responsibility and power. This outcome confirms recent analyses pointing at the scarce level of digital literacy of the Italian population, which ranks 26th out of 28 EU countries in the human capital dimension defined by the Digital Economy and Society Index (EU, 2019). Moreover, the generalised low degree of the factor across occupations might be attributable to the size dwarfism of firms (more than 90% of companies have less than 9 employees) whose investment and adoption in ICT is usually lower than in big firms (Fabiani et al., 2005).

Italian occupations are also weak in terms of collaborative and worker involvement practices. At this stage we do not have sufficient elements to completely characterize the entire set of HPWPs (job-rotation schemes, rewarding systems, internal labour markets...). Nonetheless, this result is informative about the absence of managerial strategies intended at promoting workers participation in the production process. Indeed, the adoption of lean practices also depends on managers' cultural and political visions of the production system (Vidal, 2013). In this respect, the Italian economy looks to be characterized by a relatively higher diffusion of individual-based and Tayloristic forms of work organization with respect to Northern European countries (Lorenz and Valeyre, 2005).

To conclude, our analysis allows to pinpoint the role exerted by hierarchical structures, decision making autonomy, and knowledge as the most relevant attributes characterizing the division of labour. In so doing we expand beyond the atomistic discourse of being skilled-unskilled, or doing routine vs non routine activities, appropriately considering the role of organizations and hierarchical layers. Prospective lines of research include the dynamic analysis of the ICP database, the study of the occupational determinants of income inequalities, the impact of technical change and trade upon work organization.

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Appendix

Table 5: The list of the selected variables. Yes and No indicate the steps in which the variables have been used or discarded.

VARIABLE	QUESTION	1^{st} STEP	2^{nd} STEP	3^{rd} STEP
ProOthers	Those who carry out this work perform tasks that commit them to work also for the benefit of others	Yes	Yes	No
SupervisorSupport	Those who do this work can count on the support of their supervisors	Yes	Yes	No
SupervisorTrain	Those who do this work can count on supervisors who provide good training for staff	Yes	Yes	No
ExperIdeas	Those who do this work can experiment with their own ideas	Yes	No	No
AutoPlanning	Those who do this work plan their activities with little supervision	Yes	Yes	No
AutoDecisions	Those who do this work can make their own decisions	Yes	Yes	No
Leadership	The work requires the willingness to guide people, to take charge and to give opinions and directives	Yes	Yes	Yes
Adaptability	The job needs to be open to both positive and negative changes, as well as to strong variability in the workplace	Yes	Yes	No
DetailsAttention	The work requires attention to detail and to be thorough in completing the tasks	Yes	Yes	No
Independence	The work requires that you head without or with minimal supervision and depend solely on yourself to complete the work	Yes	Yes	No
Innovation	Work requires creativity and alternative ways of thinking to produce new ideas and answers to work problems	Yes	Yes	No
AnalyticThought	The work requires analyzing information and using logic to address issues and problems	Yes	Yes	No
ProcessControl	Check and review information from materials, events or the environment to identify or evaluate problems	Yes	Yes	No
Inspecting	Inspect equipment, structures or materials for causes of error, or other problems or defects	Yes	Yes	Yes
QualityEvaluation	Estimate the value, the importance or the quality of things or people	Yes	Yes	No
StandardsEvaluation	Use relevant information and individual opinions to determine whether events or processes comply with standards, laws or regulations	Yes	Yes	Yes
DecisionTaking	Analyze information and evaluate results to choose the best solution and to solve problems	Yes	Yes	No
CreativeThinking	Develop, design or create new applications, ideas, relationships and new systems and products (including artistic contributions)	Yes	Yes	Yes
GoalStrategies	Establish long-term objectives and specify strategies and actions to achieve them	Yes	Yes	Yes
PlanningWork	Schedule events, plans and activities or the work of other people	Yes	Yes	No
ManagMachine	Use both control mechanisms and direct physical activity to operate machines or processes (excluding computers and vehicles)	Yes	Yes	No
PcUse	Use computers and computer systems (software and hardware) to program, write software, adjust functions, enter data, or process information	Yes	Yes	Yes
Communicate	Provide information to superiors, colleagues and subordinates, by phone, in writing, by e-mail or personally	Yes	Yes	No
Relations	Create constructive and cooperative working relationships and maintain them over time	Yes	Yes	Yes
CoordinatOther	Ensure that the members of a group work together to accomplish the assigned tasks	Yes	Yes	No
ActivateTW	Encouraging and increasing mutual trust, respect and cooperation between members of a group	Yes	Yes	No
GuidingOthers	Guiding and directing subordinates by setting standards in performance and control of performance	Yes	Yes	No
TrainingOthers	Identify the growth needs of other people and train, mentor or help other people improve their knowledge and skills	Yes	Yes	No
MailUse	How often does your profession require the use of e-mail?	Yes	Yes	Yes
FaceToface	How many contacts with other people (by phone, face-to-face or otherwise) are you required to have in the course of your work?	Yes	No	No
TeamWorkImportance	How important is it in the performance of your work to interact personally with colleagues at work or to be part of teams or working groups?	Yes	Yes	No
GuidingOthersImp	How important is it in carrying out your work to coordinate or guide others in carrying out work related activities?	Yes	Yes	No
ProductResp	How much responsibility do you have for the production and performance of other workers in the course of your work?	Yes	Yes	No
RipetitiveMovements	How long does it perform repetitive movements in your work?	Yes	Yes	Yes
FreeDecision	How free are you in your job to make unsupervised decisions?	Yes	No	No
AutomationDegree	How automated is your work? (linked to automatic processes)	Yes	Yes	Yes
Precision	How important is it in your work to be very precise or accurate?	Yes	Yes	No
RipetitivActivities	How important are repetitive physical or mental activities in your work over a relatively short period of time (less than one hour)?	Yes	Yes	No
FreeGoalTasks	How free are you to define the tasks, priorities and objectives of your work?	Yes	Yes	No
Competition	How competitive is your work? (requires constant comparison with the performance of colleagues/other workers)	Yes	Yes	Yes
RigiDeadlines	How often does your work require deadlines that cannot be postponed?	Yes	Yes	No
MachineControlImport	How important is it in your work to keep sequences of machinery and equipment under control?	Yes	Yes	Yes
RegularOrganization	How regular is the organisation of your work?	Yes	Yes	No
WeeksHours	How many hours do you work in a typical week?	Yes	No	No
HandsDexterity	Ability to quickly move hand, hand and arm together or both hands to grab, manipulate or assemble objects	Yes	Yes	Yes

(continue...)

Variable	Question	1^{st} step	2^{nd} step	3^{rd} step
Tenure	How many years have you been in this profession?	Yes	No	No
Coordinate	Do you have the task of coordinating the work done by other people?	Yes	No	No
Update	How do you generally carry out the updating required by your profession?			
	It is promoted by the company for specific work needs	Yes	No	No
	It is promoted by the company through systematic updating programmes	Yes	No	No
	It's entrusted to the personal initiative	Yes	No	No
UpdateFrequency	How often does the update take place?			
	Occasionally	Yes	No	No
	Once a year	Yes	No	No
	Several times a year	Yes	No	No
	It is a continuous activity	Yes	No	No
Updatuse	Keep up to date with technical changes and apply new knowledge	Yes	Yes	Yes
EntryTraining	If someone were hired (..), would they be required to follow a professional training course organised by the company?	Yes	No	No
CollegueTraining	If someone were hired (..), would they be required to work alongside colleague?	Yes	No	No
Innovation	In the last three years, have external factors intervened and changed the way in which your profession is carried out?			
	New/other technologies or machines introduced	Yes	No	No
	New/other products or services produced	Yes	No	No
	New/other materials used	Yes	No	No
	New/other work organisation or organisation of the undertaking or body	Yes	No	No
	New/other regulatory references	Yes	No	No
ItalKnowledge	Knowledge of the italian language	Yes	No	No
ForeignKnowledge	Knowledge of a foreign language	Yes	No	No
CriticalThinking	Use logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems	Yes	Yes	No
ActiveLearning	Understand the implications of new information for the solution of present and future problems and for decision-making processes	Yes	Yes	Yes
Monitor	Monitor and evaluate the work performance of individuals, other people or organizations to improve or correct it	Yes	Yes	No
CoordinatWith	Coordinate their actions with those of others	Yes	Yes	Yes
SolvingComplProblems	Identify complex problems and collect information to evaluate possible options and find solutions	Yes	Yes	Yes
OperativeAnalysis	Analyze the characteristics and requirements of tools, services or products needed to implement a project	Yes	Yes	No
ToolSelect	Identify the tools needed to do a job	Yes	Yes	Yes
Programming	Writing computer programs for various purposes	Yes	Yes	No
QualityControl	Conduct tests and inspections of products, services or processes to assess their quality or performance	Yes	Yes	No
MachineSurveillance	Check level measurements, dials or other indicators to ensure that a machine is working properly	Yes	Yes	No
OperationsControl	Control the operation and activity of equipment and systems	Yes	Yes	No
SolvingProblems	Determine the causes of operating errors and decide what to do to solve them	Yes	Yes	Yes
SystemAnalysis	Determine how a "system" should work and how environmental, operational or situational changes can affect its results	Yes	Yes	No
EvaluateSystem	Identify measures or indicators of the performance of a system and the actions needed to improve or correct them (..)	Yes	Yes	No
EvaluateDecide	Evaluate the costs and benefits of possible actions to choose the most appropriate	Yes	Yes	Yes
ManageTime	Manage your own time and that of others	Yes	Yes	No
IdeasProduction	Ability to present a large number of ideas on a subject (the number of ideas is important, not quality, fairness or creativity)	Yes	Yes	No
Originality	Ability to produce unusual and witty ideas on given issues or situations or to find creative solutions to solve a problem	Yes	Yes	No
SelectiveAttention	Ability to focus on a task for a long time without distraction	Yes	Yes	Yes
DistributedAttention	Ability to follow two or more different activities or sources of information at the same time	Yes	Yes	Yes
Busy	Those who do this work are constantly engaged in	Yes	Yes	No
TasksAlone	Those who do this work perform their tasks alone	Yes	Yes	No
DifferentActivities	Those who do this work are busy every day in different activities	Yes	Yes	No
Upgrading	Those who do this work have the opportunity to make career advances	Yes	Yes	No
DirIstrucOthers	Those who do this work give guidance and instructions to others	Yes	Yes	No
Influence	How often do your decisions affect other people or your employer's image or reputation or financial resources in your work	Yes	Yes	Yes
ICTKnow	Computer science and electronic knowledge	Yes	Yes	Yes
OrgPriorities	Set specific objectives and plan the work defining priorities, organization and timing of implementation	Yes	Yes	Yes