Growth Welfare Innovation Productivity

Working Paper

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19/2021 May

This project has received funding from the European Union Horizon 2020 Research and Innovation action under grant agreement No 822781

From organizational capabilities to corporate performances: at the roots of productivity slowdown[*]

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Abstract

This paper is one of the first attempts at empirically identifying organisational capabilities – in this work concerning Italian firms. Together, it proposes new evidence on the link between capabilities and economic performances. In order to do so, we employ the *Indagine Multiscopo del Censimento Permanente delle Imprese* (IMCPI), a survey carried out by the Italian Statistical Office (ISTAT) in 2019, covering the three-year period 2016–2018, addressing a wide range of organizational characteristics including various organizational routines, human resource management, internationalisation strategies and many others. Our contribution is threefold: first, we aim at detecting what practices and combinations of them result in underlying different capabilities; second, we propose a taxonomy of the production system, both at firm- and sector-level based on the mapping of such capabilities, third we study the performance outcomes of different capability-taxa in terms of productivity and employment growth.

JEL classification: D21, D22, D83, J24, J53

Keywords: Organizational capabilities, productivity slowdown, employment growth, learning

[*]We gratefully acknowledge support by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 822781 GROWINPRO – Growth Welfare Innovation Productivity. M.E. V. also acknowledges support from the Italian Ministry of University and Research (MUR), PRIN 2017 project: "Lost highway: skills, technology and trade in Italian economic growth, 1815-2018" (prot. 2017YLBYZE).

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1 Introduction

How do firms do what they do? How do they change what they do and how they do it? And how effecting are they in both activities?

A growing literature has addressed these questions by pointing at the nature and dynamics of firm-specific capabilities (Amit and Schoemaker, 1993; Dosi et al., 2000; Helfat and Peteraf, 2003; Dosi et al., 2008; Helfat and Winter, 2011). Firms are more or less complex organizations which in order to reach their objectives set-up a series of procedures, call them *organizational routines* and *heuristics*. The procedures aimed at building an artefact entail the acquisition of inputs of production, transforming them along the production process, hiring new personnel, implementing forms of learning on-the-job and training schemes. But firms do not only perform ordinary procedures, they are also the locus of the generation of new knowledge. Search and discovery activities are performed sometimes inside R&D departments and other times outside them; whenever successful, innovations, entailing new products and new methods of production, are brought to the industrialization phase. All these activities require relational processes with external actors, from suppliers to financiers. Finally, firms have to face markets, therefore they require heuristics to set prices and to open new opportunities to commercialize their products. All these procedures are inbuilt in the *procedural knowledge* upon which organizations strive and if possible expand.

Organizational capabilities are indeed the collective manifestation of ensembles of these procedures. Spotting, within organizations, the exact segment or function where such capabilities exactly lie is a very tall and futile task. They are the result of *combinations* of specific routines and heuristics, and seldom decomposable in the contribution of single activities (Simon, 1991a; Marengo and Dosi, 2005). If anything, then the analytical task becomes the identification of the properties of *different combinations* of such organizational routines and heuristics.

Equally difficult is detecting how the internal organizational structures and capabilities map into the external performance of the firm. That is, to put it with a biological metaphor, how the *genotype* reflects into the *phenotype*. Addressing this issue means going beyond standard sources of firms performance, such as size, access to international markets and more recently age, and study the actual link between *how firms do things* and *how they do perform*.

It is important to notice that the distinction "genotype" vs "phenotype" in the social domain should not be taken literally as it is much more blurred than in biology. So far, in human organizations their quasi-genetic traits (Cohen et al., 1996) basically coincide with the *recurring action patterns*. Precisely due to such a reason, in order to identify capabilities in a non-tautological way, i.e. firm "x" embodies great capabilities because it displays outstanding performances, the researcher has to first identify such action patterns and only later try to map them into performances. This is what we shall do in the following, making use of a unique dataset, *Indagine Multiscopo del Censimento Permanente delle Imprese* (IMCPI), carried out by the Italian Statistical Office (ISTAT) in 2019, covering the period 2016–2018, addressing a wide range of organizational routines and heuristics, concerning e.g. hiring practices and human resource management, price setting rules, software-aided decision methods, position in the market vis-à-vis suppliers, and strategies e.g. internalization, new product developments, new investments in advanced technologies. This qualitative information is then matched with quantitative balance-sheet data revealing firm performances in terms of productivity and employment growth.

We undertake a factor analysis on the foregoing behavioural traits and strategic orientations of the firms. By means of a K-means algorithm, we identify four clusters of firms in terms of the co-occurrence of such characteristics which we label as *Essential, Managerial, Interdependent, Complex* firms. We map such clusters into performance variables, including labour productivities, wages, employment absorption and their dynamics thereof.

Our findings reveal that, first, organizational capabilities, our "state" variables, are more important in determining firm performances than managerial practices, the "control" variables.[1] In line with our hypotheses, we do not identify a unique and dominant set of *best practices*, while we do find strong complementarity between different organisational practices. Indeed, the best performers are those firms able to develop more complex behaviours – i.e., able to implement a variety of actions with respect to a given purpose, e.g. investing in digitalization. Higher complexity – captured by the range and variety of actions put in place by firms – is reflected in better performance. Together with organizational capabilities, also managerial skills and relational dependence, both external – i.e., with suppliers in terms of orders, contracts, R&D acquisition – and internal – with its workforce – are crucial explaining factor variance.

Second, econometric estimations, both in level and in growth rates, reveal that belonging to Interdependent and Complex clusters sizeable increases firm performance in terms of labour productivity. Notably, Complex firms are also strongly characterised by a neater labour absorbing attitude. The estimations, robust with respect to the introduction of size, age, exporting status and other fine-grained control variables, highlight diverging growth patterns in productivity between the "low-level" clusters – Essential and Managerial – and the "high-level" clusters – Interdependent and Complex firms. In order to control for potential size effects, that at a first glance might be confounded with complexity attributes, we also perform the analysis by sub-samples of small, medium and large enterprises. Additionally, we also focus on a special subset of firms, which we label as "good-gazelles", meaning those who simultaneously increase productivity and employment.

Differences in capabilities, as captured by the taxonomies introduced above, not only appear to be crucial as determinants of widely heterogeneous corporate performances, but are also likely to be instrumental in accounting for the contemporary dynamics and distributions in industrial productivity. Italy, in this respect, is an extreme case to the point.

The stagnation of Italy's productivity has deep roots and has been observed since the beginning of the 2000s (Daveri and Jona-Lasinio, 2008; Calligaris et al., 2016). However, it appears to be not only an Italian phenomenon, but an emerging trait of the current phase of contemporary capitalism, that has become more pronounced after the 2008 economic crisis (Foster et al., 2016; Syverson, 2017) and will certainly be affected by the COVID-19 downturn. This comes upon a secular microeconomic evidence pointing at a considerable heterogeneity in productivity levels among firms.

Few high-performance firms co-exist with a large population that exhibits modest and stagnant levels of value added per worker, regardless of the degree of sectoral disaggregation (Dosi et al., 2012). Therefore, we are witnessing the emergence of "neo-dual" or "winners take the most" configurations, featuring a productive structure increasingly quasi-dichotomous with respect to organisational skills, technological innovation and presence on international markets. This is mirrored by a progressive divergence in performance (Dosi et al., 2019). Dimensional aspects, rather than sectorial ones, appear to have a significant impact on such a dichotomy; however, size is not the only explanation: there are indeed small firms recording increasing

[1] Hereby, the notion of state vs control variables has to be intended in the words of (Winter, 1997), according to which state variables represent inner firm characteristics relatively invariant, while control variables are those ones on which managerial choices might influence the direction of the evolution of the organization.

productivity trends (Monducci and Costa, 2019; ISTAT, 2020), especially for those productive units that invest in technology and worker abilities (ISTAT, 2019), or that successfully operate on an international scale (Costa et al., 2017; ISTAT, 2017).

Our analysis in terms of heterogeneous capability taxa introduces a novel and crucial dimension to the interpretation of the evidence concerning both neo-dualistic tendencies in productivity levels and slowdown in growth. In brief, high-capability firms, those mainly responsible for industrial dynamism, might be a small, and possibly shrinking, minority of firms. Therefore, the Italian productive structure is populated by a large fraction of *Essential* firms, while *Complex* ones only represent 9% of the whole population with at least 10 employees.

The analysis also bears more macro-developmental implications in so far as capabilities impinge also upon the introduction of new products, practices and techniques of production. In general, our micro evidence may be seen as complementary to the broader macroeconomic literature that has identified product and sector *diversification* as determinants of economic development (Dosi et al., 2021; Tacchella et al., 2013).

The remainder of this paper is organised as follows. Section 2 discusses the notion of organizational capabilities. Section 3 describes the dataset and presents the structure of the questionnaire we analyse. Section 4 develops a capability-based taxonomy of Italian firms whose descriptive evidence is then corroborated by econometric estimations in Section 5. Section 6 concludes.

2 Organizational capabilities

In order to define what an organizational capability is we rely upon Helfat and Winter (2011), according to which:

- the possession of a specific capability requires that an organization or its constituent parts have the capacity to perform a particular activity in a reliable and at least minimally satisfactory manner;
- a capability has an intended and specific purpose, e.g. the capability of building a car;
- a capability, differently from an ad hoc activity which does not reflect predicted or patterned behaviours, enables repeated and reliable performance of the underlying procedure.

Firms, in their hierarchical structure and functional division, are the locus of continuous and evolving learning, and their performance is driven by highly idiosyncratic technological and organisational capabilities grafted into their procedural knowledge – who does this, who sends the signal to whom, what should be done in case of errors (Dosi and Nelson, 2010; Winter, 1997). Complementarity in the use of inputs and in the organisational forms are the norm rather than the exception. Alternative knowledge configurations are present at all levels of the organisation, from R&D divisions to assembly lines, and are associated with different innovation regimes – in terms of new products, processes and organisational practices. Organisational routines represent the *trait d'union* between technology and business organisations. In this perspective, therefore, there are no optimal configurations of organisational practices that lead to maximising performance metrics (Dosi and Marengo, 2015).

Firms – and more in general all types of organisations – are understood as *behavioural entities*, inertial over time and tolerant of errors (Simon, 1991b). Organisational forms, technological practices, business cultures and learning processes result in hybrid configurations, far from the e.g. lean/agile or Taylorist archetypes (Vidal, 2017). If the firm is a collective problem-solving entity, knowledge does not lie in individual know-how and therefore individual practices of command and control might completely miss the goal of monitoring deviations from expected outputs. Technological and organisational capabilities are ultimately build up gradually and show a high degree of persistence in their quality (*good* versus *bad* practices). The heterogeneous set of idiosyncratic organisational capabilities leads to ample degrees of heterogeneity in their characteristics and economic performance.

The literature further distinguishes between *ordinary* capabilities, roughly measuring the ability to do "business as usual" and "dynamic capabilities" broadly meant as the ability to fruitfully *alter* precisely the usual way of proceeding (Teece et al., 1997; Winter, 2003). Four aspects are fundamental in the appreciation of organizational capabilities. *First*, in a changing and evolving world the distinction between the two types of capabilities is inevitably blurred, and, if pushed too far, might well be interpretatively misleading. *Second*, both types do belong to the "quasi-genetic traits" of the organization, are relatively sticky and path-dependent, and in a short-term, only limited subject to discretion of strategic management (see Pisano, 2017 for a discussion on the thorny issue of managerial discretion with respect to organizational capabilities). *Third*, as emphasised by Helfat and Winter (2011), capabilities are a matter of degree, ranging from minimally satisfactory to say exceptional. *Fourth*, capabilities have essentially a *procedural nature* in their collective organizational equivalent of "playing well a violin in an orchestra". In that, they are very different both from strategies and from endowments.

In order to appreciate such aspects, it is revealing to compare this theoretical view with other interpretations of the observed strikingly heterogeneous firm performances – in terms of productivity, profitability, sales or employment levels – as entirely driven by managerial actions and functions, combined with the use of inputs of production.

More in detail, a widespread set of approaches among economists, to which we refer to as the *best managerial practices* approach, are deeply rooted in the production function paradigm on the one hand, and upon contract theory on the other. In this perspective, management comes before organizational routines, and performance can be traced back to the levels and dynamics of production inputs. Managerial abilities, rather than organisational routines, are, in this view, the key drivers of performance heterogeneity and therefore those firms adopting the best managerial practices are expected to perform better. Managerial functions entail (i) monitoring behaviours, (ii) setting targets or objectives, and (iii) defining incentives. Best practices should thus include the ability to define continuous monitoring processes – i.e. taking action in case of errors – as well as the capacity to reward (punish) behaviours that are in line (or not) with defined targets.

This general view is shared across approaches ranging from those addressing workers empowerment all the way to those more interested at efficiency of management systems, from Piore and Sabel (1986) to Bloom and Van Reenen (2007) and Bloom et al. (2012), among many others. Bloom and Van Reenen (2007) look at the presence of particular managerial practices and their impact on productivity, through telephone questionnaires administered to firms in various countries and sectors. These practices are interpreted as direct expressions of managerial strategies and include the definition of individual incentive schemes and systems to control the performance of individuals and processes. In that, the emphasis on rewarding and punishing devices, and thus on monitoring the work process, reveals also a Taylorist vision of the organisation, in which the real organisational levers are command and control, albeit at times mitigated by forms of de-hierarchisation and autonomy (Adler, 1993). Management is considered crucial in determining performance. In this top-down approach, rather than being a unit coordinator, the manager becomes a motivator/controller that rewards or punishes subordinates through continuous control processes.

So, an example reported as a *best managerial practice* put in place at a US firm where the manager, able to promptly remove the organisation's dead spots, fired four people during last couple of months due to underperformance follows:

> We move poor performers out of the company or to less critical roles as soon as a weakness is identified [Bloom and Van Reenen (2007)]

The capability-based view is clearly very different, and, admittedly, with empirical predictions much more difficult to detect as one cannot look for single "best strategies" but rather for combinations of organizational procedures. This is precisely what we shall do in the following.

3 From theory to empirics: mapping firm *genetic* traits

Let us begin with an overview of the data in Subsection 3.1, describing in some detail the structure and organization of the questionnaire. Next, in Subsection 3.2, we proceed with a factor analysis in order to reduce the high dimensionality of information, as a first step toward the identification of taxa of capabilities/firms.

3.1 Dataset overview

Over the last couple of decades, the demand for high-quality firm-level micro-data has increased significantly, both for the purpose of measurement of economic phenomena and for policy reasons. In order to meet such demand, European statistical offices have accelerated the design and production of new data-sets able to accurately capture heterogeneities and changes within productive systems, as well as factors underlying e.g. the competitiveness and resilience of firms, competitive and backward segments, and profiles of growing or declining firms.

In this context, as mentioned above, the Italian Statistical Office (ISTAT) has undertaken a strategy of designing and implementing a new generation of micro-founded statistics, in which the microeconomic component plays a central role. This new approach has been based on the implementation of a twofold integrated strategy in statistical production:

a) massive use of administrative data for the construction of multidimensional statistical registers, with extensive possibilities to link individual data to additional administrative sources and direct surveys;

b) direct statistical surveys focused on economic units with multi-purpose modules able to measure their organisational structures, behaviours and strategies, not detectable when using administrative sources only.

This new system guarantees also a high level of accuracy of aggregate estimates that can be largely derived from the direct aggregation of individual data. Furthermore, the consistency between the micro and macroeconomic perspectives lends solidity to micro-founded analyses of heterogeneity within various universes (e.g., economic units) in different dimensions (e.g., performance, geographical positioning, workforce utilisation, international openness, remunerations). Moreover, the annual replication of the Register System collecting information on firm balance-sheets (called FRAME-SBS) makes multi-level dynamic analyses possible. This innovative approach has already proved to be particularly useful in studying the factors that have supported firm competitiveness during the last recession and recovery.

The first wave of *Indagine Multiscopo del Censimento Permanente delle Imprese* (IMCPI) was carried out by ISTAT in 2019. The survey involved a sample of about 280 thousand firms with 3 or more employees, representing a universe of over 1 million units, corresponding to the 24.0% of total Italian firms, which, however, accounts for 84.4% of national value added, employs 76.7% of workers (12.7 millions) and 91.3% of employees.

The questionnaire administrated to firms is structured along nine macro-sections: 1) Ownership, control, management; 2) Human resources; 3) Relations between companies and other organizations; 4) Market; 5) Technology, digitalisation and new professions; 6) Finance; 7) Production internationalisation; 8) New trajectories of development; 9) Environmental sustainability, social responsibility and workplace security. The integration of qualitative information derived from the survey when integrated with the register system (FRAME-SBS), enables in-depth analysis of the structure, behaviour and performance of Italian firms, and it is particularly useful in the study of productivity dynamics.

In the following, restricting the scope of the analysis to firms with at least 10 employees to ensure a minimum firm-organizational structure, we obtain a sample of more than 109 thousand units, representative of a universe of about 215 thousand firms, with 9 million workers (54.7% of the total), of which 8.8 millions are employees (74.7%), with 2,300 euro billion revenues (75.3%) and 557 billion (71.4%) value added. Within this segment, there are approximately 3,700 large firms (250 and more workers), with employment and value added shares of 38.5% and 44.8% respectively. SMEs (10-249 workers) thus constitute the majority of structured Italian firms in all the main macro-sectors (including both manufacturing and services), not only in terms of employment but also in terms of value added.

3.2 Factor analysis

The IMCPI, for its process-centred features, is particularly apt to investigate the characteristics of Italian firms with the spectacles of the capability theory outlined above.

The study of the impact of organizational forms upon performances is not new: the literature has investigated the impact on innovation or labour productivity of the application of internal labour market practices – such as high-performance work practices (HPWPs) or human resource management (HRMs), defined in terms of continuous improvement processes, team meetings and teamwork, workforce rotations, career advancements and decentralised decision-making processes. Prennushi et al. (1997) focuses on US steel finishing lines and studies the effects of such practices on labour productivities; Ichniowski and Shaw (1999) compare the effect of adoption of Japanese HRM practices between US and Japanese firms; Koski et al. (2012) study the impact on innovation outcomes in Finnish manufacturing firms; Osterman (2006) looks at effects on wages, and Cappelli and Neumark (2001) analyses the effects on both labour cost and labour productivity. Notwithstanding the differences in the foregoing studies, they share a strong emphasis on the relevance of *complementarity* and the absence of a unique best performing organizational models. Such complementarities are highlighted in our dataset.

We adopt a data-driven, multi-step approach. First, we select a subset of items covered by the questionnaire in tune with a capability theory that should cover the most distinctive operational attributes of firms. These range from questions on ownership structures, personnel management practices, relations with other firms within the supply chain and customers, market relations, technological set-ups, future investments and development prospects, to social relations, workforce safety and well-being. After our informed selection we retain forty questions. More in detail, we focus on subsections of the survey belonging to the seven macro-areas: *Ownership, control and management*; *Human resources*; *Relations between firms and other entities*; *Market*; *Technology, digitalisation and new professions*; *New trajectories of development*; *Environmental sustainability, social responsibility and safety*. Table 1 shows the selected questions for each of the thematic sections of the survey.

A descriptive analysis of the response rate suggests strong heterogeneity in the examined questions. The long tail of the distribution in Figure 1 shows that in general the response rate is higher in questions of a simple nature (yes/no) and gradually decreases as the complexity of the question increases. This hints at the corresponding dominance of simple behaviours. Figure 2 displays the average response rate to the questionnaire per section. Indeed, the nature of the information extracted in each section is different, as it is the degree of complexity of its underlying actions. The selection of the questions reflects the search of firm characteristics in terms of *state variables* – i.e. relatively invariant structural characteristics of the firm – and *control variables* – attributes of the decisional-managerial dimension, i.e. business strategies.

As a second step, given the high dimensionality of the information, we carry out an analysis of multiple correspondences in the set of questions we selected and, by operating a dimensionality reduction, we extract seven latent factors that summarise the informative content of each of the seven subsections taken into consideration. Then, we perform a further factor analysis on these initial seven factors, as a result of which we obtain three latent factors that account for 69% of total variance. The sampling adequacy, which yields a KMO (Kaiser-Meyer-Olkin) test of 86% (thus above the 80% required threshold) confirms the robustness of the factorization. These three factors are ascribable to different sets of capabilities. The first factor is linked to work organisation, employee training processes, the presence of HPWPs, recruitment mechanisms, technological-organisational skills linked to investments in digitalisation, the use of management software and platforms. The second factor concerns managerial strategies, in terms of both past and future targets, pricing and investment strategies. The third is connected to processes of external relations with other firms in terms of contracts or supplies, and processes of internal relations with workers.

Table 2 summarises the three factors sorted by explained variance. The weights (or factor loadings) of each of the seven sections of the questionnaire are positive, with the three main weights deriving from the variables contained in the sections *Technology, digitalisation and new professions* (0.80 factor loading), *Human resources* (0.75) and *Ownership, control and management* (0.73). This first factor, which we refer to as *behavioural complexity*, accounts for 46% of the variance in the answers to the survey and it is an indicator of the complexity of the firm's organisational capabilities. It combines traits attributable to firm organisational structure – i.e. the organisation of work and the degree of digitalisation – with elements that can be associated with pure managerial activity, such as investment strategies and business targets. We label this factor as *Technological-organisational capabilities*.

The second factor, which adds a further 13% of explained variance, is predominantly determined by variables associated to managerial practices, in particular those contained in the *Market* section of the survey that concerns mainly market power and product quality (factor loading 0.80), *Ownership, control and management* (0.24), and *Environmental sustainability, social responsibility and safety* that provides information on internal company relations and shows a negative factor loading (-0.27). We label this factor as *Managerial strategies*. Finally, the third factor, which adds a further 10% of explained variance, thereby reaching a cumulative 69%, is determined by the relational variables or the information on the dependence/interdependence of the firm, in particular those contained in the sections *Environmental sustainability, social responsibility and safety* (factor loading 0.63) and *Relations between firms and other entities* (-0.56). We label this factor as *Relations*.

The factor analysis provides a number of relevant results. First, it is not possible to clearly distinguish between practices attributable to managerial strategies and those hinged on the organisation's established practices. In fact, all variables that concern e.g. training processes, learning mechanisms, problem-solving development and team working are at least as relevant as the management strategic orientations in accounting for firm taxa. This implies that interpretations of inter-firm heterogeneity exclusively based on managerial practices are at best incomplete. Moreover, managerial visions and strategies cannot be put in place without sustained investments in technology, that represent a sort of pre-condition for their effective implementation.

A second noteworthy remark is the apparent relevance of the structure of relations and interdependencies with clients, suppliers and contractors, and of the ensuing hierarchy and positioning inside such a network of interdependencies. In this respect, our analysis captures the importance of the value chain fragmentation that a firm can alternatively dominate as a leader or be subject to. Finally, this dimension is also associated with the relevance of internal relations, especially with regard to work-life balance and workforce safety.

1. OWNERSHIP, CONTROL AND MANAGEMENT	
X.1.3	Past strategic objectives and their outcome
X.1.4	Future strategic objectives
2. HUMAN RESOURCES	
2.1	Acquisition of new human resources
2.2	Type of human resources acquired
X.2.3	Methods of selection of human resources
X.2.4	Functional areas where human resources have been acquired
2.5	Most important transversal skills in the selection of human resources
X.2.7	Personnel management practices
2.8	Practices to attract and/or retain qualified personnel
2.9	Non-compulsory corporate training activities
X.2.10	Type of non-compulsory training
X.2.11	Compensation subject to non-compulsory training activities
3. RELATIONS BETWEEN FIRMS AND OTHER ENTITIES	
3.1.	Relations with other firms (orders, contracts, subcontracts, etcetera)
3.2	Parties with whom relations have been entered into (in Italy or abroad)
X.3.3	Functions of relations with other firms
3.4	Relation reasons
X.3.8	Sectors of economic activity of the firms with which relations have been maintained
4. MARKET	
X.4.5	Criterion for setting the prices of goods or services in the reference market
X.4.7	Strengths
5. TECHNOLOGY, DIGITALISATION AND NEW PROFESSIONS	
5.1	Innovation activities (internal or through external supplier)
5.3	Use of digital platforms
X.5.7	Use of business management softwares
X.5.8	Software for business management functions
X.5.9	Use of cloud services
X.5.10	Type of cloud services used
X.5.12	Past and future investments in digital technologies
X.5.14	Type of training for technology adoption
X.5.15	Relevant digital skills adequately possessed by personnel
X.5.16	Future change in the share of personnel dedicated to tasks relevant to digitilisation
5.17	Methods to deal with future management consequences

(continue...)

8. NEW TRAJECTORIES OF DEVELOPMENT	
8.1	Past and future areas of specialisation
8.4.1	Type of enabling technologies produced
8.4.2	Enabling technologies used to innovate processes, goods and services
8.5.1	Past investment intensity
8.5.2	Future intensity investments
8.7	Services purchased by the firm
8.9	Development processes undertaken
9. ENVIRONMENTAL SUSTAINABILITY, SOCIAL RESPONSIBILITY AND SAFETY	
9.10	Measures to improve work well-being and ensure equal opportunities
9.10bis	Measures to support parenting and work-family balance
9.18	Actions taken to ensure various aspects of work safety

Table 1: Selection of forty questions from *IMCPI* (2018). Questions flagged with X represent nested alternative practices.

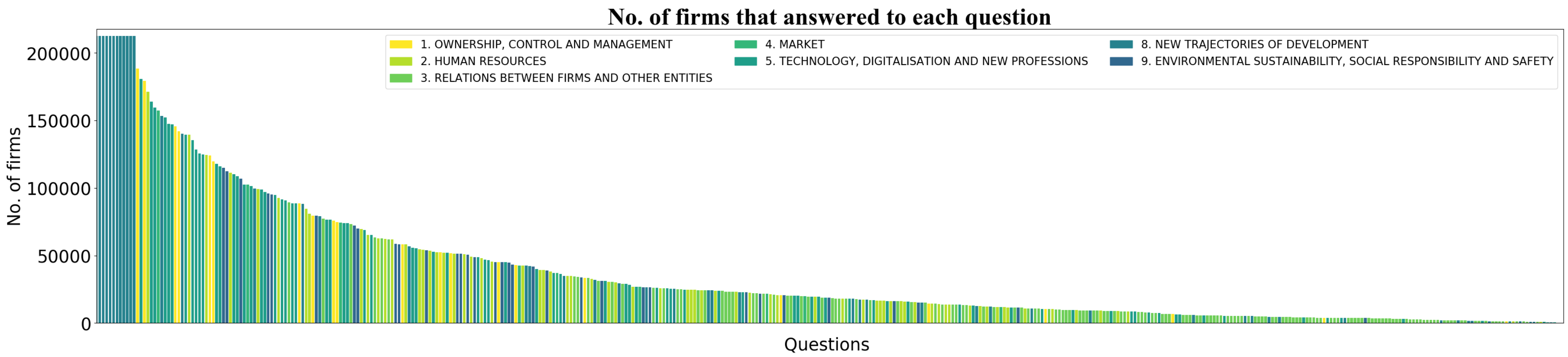

Figure 1: Response rate of the examined questions.

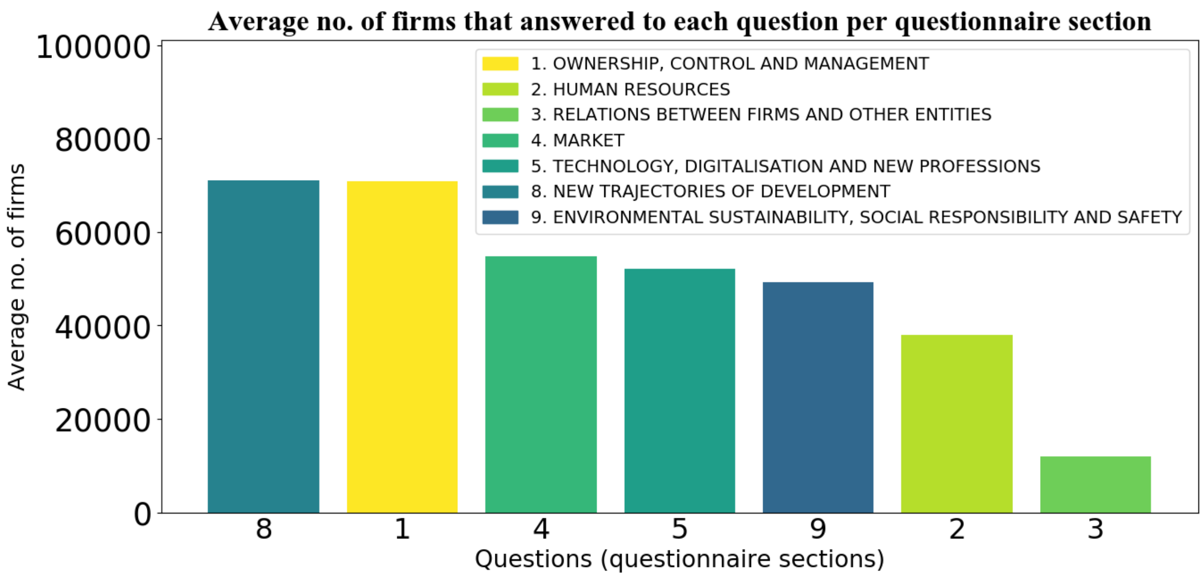

Figure 2: Average number of answers to the questions employed in the analysis.

Practices and Explained variance	Main key actions					
Technological-organisational capabilities (46%)	Staff training activities (for new recruits, or continuous training and retraining)	Investment in the workers' digital skills	Investments in advanced automation and interconnected machines	Investments in technology, digitalisation, R&D, and work organisation	Use of management softwares (ERP, CSM, SCM)	Use of remote management services (cloud)
Managerial strategies (13%)	Product quality as competitive strength	Market power (in setting the selling prices)	Expansion strategies (widening of the product range, extension of activities)			
Relations (10%)	Adoption of good practices for the staff professional development and equal opportunity protection	Adoption of measures for work-family balance (leave, furloughs leave, hourly flexibility)	Articulation of inter-company production relations (contracts, subcontracting, agreements)			

Table 2: Organisational-strategic profiles of firms. Results based on a factor analysis conducted on the questions presented in Table 1.

4 Mapping a behavioural taxonomy of the Italian firms into their performances

After studying the latent structure underlying the multi-purpose questionnaire, we map what we defined the "genetic" traits and the strategic orientations of firms into their performances. We use therefore a database that integrates the information from IMCPI with that from the FRAME-SBS business register and perform a K-means clusterization. The latter is a non-hierarchical algorithm for partitioning empirical data that allows us to identify four clusters of firms (see the *Appendix* for a more detailed description of the procedure). The number of clusters is selected using the Elbow criterion, with a total explained variance of 88%. Tables 3 presents, for each cluster, the intensity of the three factors.

Recall that the first factor captures the complexity of technological-organisational capabilities covering practices aimed at fostering the diffusion of knowledge inside workplaces, problem-solving and learning regimes, and is linked to the technological dimension embodied in digital technologies and management software. Such technological-organisational factor shows a very low weight in the first cluster and gradually increases its weight in the other clusters. According to factor weights, we define as *Essential* the firms belonging to the first cluster (with a 14.2 weight) and, at the opposite, as *Complex* those ones belonging to the fourth cluster (with a 49.4 weight). The two intermediate clusters have a very high weight in both managerial and relational strategies. We label those firms in the second cluster as *Managerial* since they show the highest value of the factor that incorporates managerial strategies (75.5). While, we label *Interdependent* the firms belonging to the third cluster, as they feature a very high relational factor (64.3) and present the second most relevant contribution in the technological-organisational factor (36.3), which hints at the possibility that those firms might be suppliers and having relationship with more complex firms.

Table 4 presents some descriptive statistics about performance variables regarding the four clusters as measured in terms of labour productivities, profit margins and wages, and their relative frequencies. At a first glance we observe that about two thirds of Italian firms with at least 10 employees are Essential or Managerial – i.e., they belong to the first or second clusters – even though they contribute to less than one third of total value added. By contrast, the group of Complex firms in the fourth cluster, accounting for only 9% of the total universe, contributes for 42% of value added.

From a macro-sectoral perspective, in manufacturing Complex firms are 12.8% of the total and account for 46.7% of value added; in market services the ratio decreases to 7.8% of total firms and to the 39.4% of value added. Therefore, first we observe distinct differences among clusters in terms of size (21.2 average number of workers for Essential firms, 146.9 for Complex firms), and, second, remarkable macro-sectoral ones whereby advanced manufacturing firms, even if they are a small portion of the total, have a prominent role and contribute heavily to the overall value added.

Looking at the average productivity of each cluster, we observe that Complex firms are twice as productive as Essential firms (78 thousand and 36 thousand euros, respectively). Moreover, the intra-cluster variance is greater among the latter group, with a coefficient of variation of 2.1 compared to 1.4 in the former. In other words, the firms in the most productive Complex cluster not only do perform better, but are also more homogeneous among themselves than Essential ones. Additionally, we find a wide gap in average wages that increases by about 5 thousand euros, moving from the Essential to the Managerial cluster, and by 9 thousand euros from the Interdependent to the Complex ones. One may conjecture that higher average wages indicate more structured hierarchies and a higher number of layers in the firm, likely associated with larger sizes. However, as shown by the intra-cluster coefficient of variation, the difference in average wages may also be due to few firms with above-average remunerations, but with comparable size and number of layers. This might be ascribable to firms wage setting processes, that in Italy are also a result of the so called second-level bargaining which might take place at the firm-level on top of sector-wide national bargaining. Finally, conditional on larger average company sizes and higher productivity levels, the Complex cluster shows a stronger presence in international markets: more than half (54.2%) of the units of this group sells at least part of their products abroad, compared to 16% in the Essential group.

These structural characteristics may also be detected by examining clusters by firm size. We consider two main classes, small enterprises (with 10-49 workers, see Table 5) and medium and large enterprises (with over 50 workers, see Table 6). A first common element to both dimensional classes is that average firm size progressively increases in the transition from the Essential to the Complex cluster. Moreover, Complex firms show a limited, but non negligible, presence (7.3%) in the small enterprise segment, while they constitute 25.8% of the medium and large enterprise one. Indeed, among small enterprises, there are about 14 thousand units with more complex profiles than the three quarters of medium and large enterprises. Labour productivity levels consistently reflect this pattern: a high complexity profile appears to allow small firms to attain higher productivity compared to that of larger firms in the other three clusters. Despite having high wage levels, small Complex firms achieve also considerably high profit margins, lower only than those of medium and large-sized Complex ones.

From a dynamic perspective, the clusters exhibit significantly different performances (see Table 7). Between 2016 and 2018 – a phase of expansion of the Italian economy – we observe a general growth in revenues, value added and employment, differentiated however according to the complexity of their practices. On average, labour productivity changes range from -0.2% for Essential firms up to 0.8% for Interdependent firms. This holds particularly for *big complex* firms whose performance is unequivocally the best in terms of *median growth* of value added, labour demand and productivity, but much less impressive in average, especially concerning productivity growth which is nil – just better than the other clusters which display a *negative growth*.

The median of the distribution of each cluster has experienced a generalised positive shift, with Complex firms moving with a higher "jump" (3.8%) when compared to the overall shift (1.8%). Indeed, more marked movements of the medians compared to the movements of the means stand for increases in the left-skewness of the distribution: even within clusters and within size classes, one observes polarizing tendencies. Given the generalised shift, Figure 3 plots deviations of the average changes and median shifts of labour productivities *from* the respective total value by size class. While median shifts of Complex firms are always positive, average changes are positive only for big Complex firms. At the opposite Essential firms always record negative values both in average changes and median shifts. Small Interdependent firms signal positive dynamism both in average and median values when compared among their similar peers in terms of size.

Table 3: Firm clusters and organisational-strategic profiles (units with at least 10 workers).

Organisational-strategic profiles				
		Technological-organisational capabilities	**Managerial strategies**	**Relations**
Cl_1	Essential	14,2	69,8	62,5
Cl_1	Managerial	25,6	75,5	64,5
Cl_3	Interdependent	36,3	73,1	64,3
Cl_4	Complex	49,4	65,8	61,5
	Total	**27,4**	**72,4**	**63,6**

Table 4: Characteristics of firm clusters (units with at least 10 employees)

	Cluster	**Firm**		**Number of Workers**			**Value Added**		**Productivity**		**Profitability (Mol/Revenues)**		**Average salary (Cost per employee)**	
		Number	**%**	**Number**	**%**	**Average**	**Total (Euros Mln)**	**%**	**Average (Euros)**	**Cfc of Variation**	**Average (%)**	**Cfc of Variation**	**Average (Euros)**	**Cfc of Variation**
Cl_1	Essential	60.380	28,5	1.282.830	14,4	21,2	47.370,0	8,7	36.926	2,1	7,0	149,9	29.403,3	0,7
Cl_1	Managerial	77.040	36,4	2.106.065	23,6	27,3	103.816,5	19,2	49.294	1,1	7,4	60,9	34.714,9	0,5
Cl_3	Interdependent	54.267	25,6	2.595.343	29,1	47,8	159.340,2	29,4	61.395	1,3	7,9	3,5	40.543,2	0,4
Cl_4	Complex	20.070	9,5	2.947.326	33,0	146,9	231.373,3	42,7	78.503	1,4	10,1	35,8	49.655,7	0,5
	Total	**211.757**	**100,0**	**8.931.563**	**100,0**	**42,2**	**541.900,0**	**100,0**	**60.672**	**1,2**	**8,7**	**73,0**	**40.434,8**	**0,5**

Table 5: Characteristics of firm clusters (small enterprises, 10-49 workers)

Cluster		Firm		Number of Workers			Value Added		Productivity		Profitability (Mol/Revenues)		Average salary (Cost per employee)	
		Number	**%**	**Number**	**%**	**Average**	**Total (Euros Mln)**	**%**	**Average (Euros)**	**Cfc of Variation**	**Average (%)**	**Cfc of Variation**	**Average (Euros)**	**Cfc of Variation**
Cl_1	Essential	57.513	30,7	893.877	27,1	15,5	33.057,6	20,3	36.982	2,1	7,9	34,5	28.551,9	0,7
Cl_1	Managerial	70.509	37,7	1.229.414	37,2	17,4	59.054,9	36,2	48.035	1,1	8,4	56,1	33.125,7	0,4
Cl_3	Interdependent	45.376	24,3	881.117	26,7	19,4	51.414,3	31,6	58.351	1,3	8,8	2,7	37.437,6	0,4
Cl_4	Complex	13.697	7,3	296.762	9,0	21,7	19.395,3	11,9	65.357	1,7	9,6	45,7	41.077,9	0,6
	Total	**187.095**	**100**	**3.301.170**	**100,0**	**17,6**	**162.922,1**	**100,0**	**49.353**	**1,5**	**8,6**	**40,5**	**33.795,1**	**0,5**

Table 6: Characteristics of firm clusters (medium and large enterprises, over 50 workers).

Cluster		Firm		Number of Workers			Value Added		Productivity		Profitability (Mol/Revenues)		Average salary (Cost per employee)	
		Number	**%**	**Number**	**%**	**Average**	**Total (Euros Mln)**	**%**	**Average (Euros)**	**Cfc of Variation**	**Average (%)**	**Cfc of Variation**	**Average (Euros)**	**Cfc of Variation**
Cl_1	Essential	2.867	11,6	388.952	6,9	135,7	14.312,4	3,8	36.797	1,3	4,8	975,4	31.217,7	0,7
Cl_1	Managerial	6.531	26,5	876.651	15,6	134,2	44.761,6	11,8	51.060	1,7	6,3	19,1	36.802,3	0,6
Cl_3	Interdependent	8.891	36,1	1.714.225	30,4	192,8	107.925,9	28,5	62.959	1,3	7,5	5,8	42.073,2	0,5
Cl_4	Complex	6.373	25,8	2.650.565	47,1	415,9	211.978,0	55,9	79.975	1,3	10,2	0,0	50.672,1	0,4
	Total	**24.662**	**100**	**5.630.394**	**100,0**	**228,3**	**378.977,9**	**100,0**	**67.309**	**1,3**	**8,7**	**184,0**	**44.273,6**	**0,5**

		Value added		Turnover		Workers		Productivity	
		Average variation	**Median shift**	**Average variation**	**Median shift**	**Average variation**	**Median shift**	**Average variation**	**Median shift**
					All sample				
Cl_1	**Essentials**	5,1	8,6	4,8	6,9	5,4	7,0	-0,2	0,6
Cl_1	**Managerial**	10,5	9,0	13,1	8,8	9,8	6,4	0,6	1,7
Cl_3	**Interdependent**	12,9	11,6	13,4	11,2	12,0	7,2	0,8	2,5
Cl_4	**Complex**	9,9	15,9	11,8	16,8	9,6	9,7	0,2	3,8
	Total	**10,5**	**10,1**	**12,0**	**9,5**	**9,8**	**7,1**	**0,6**	**1,8**
					Small enterprises (10-49 workers)				
Cl_1	**Essential**	3,2	8,6	3,1	6,8	2,4	7,0	0,7	0,5
Cl_1	**Managerial**	9,5	8,9	9,9	8,6	6,6	6,3	2,7	1,7
Cl_3	**Interdependent**	14,2	11,6	16,6	11,2	7,8	7,2	5,9	2,6
Cl_4	**Complex**	11,9	17,2	12,7	18,3	8,7	11,0	3,0	4,3
	Total	**9,9**	**9,9**	**11,1**	**9,2**	**6,0**	**7,1**	**3,7**	**1,8**
					Medium and large enterprises (50+ workers)				
Cl_1	**Essential**	10,0	10,1	9,7	9,3	13,0	6,9	-2,7	1,2
Cl_1	**Managerial**	11,9	11,1	17,3	10,4	14,5	7,0	-2,3	1,6
Cl_3	**Interdependent**	12,3	11,6	12,0	11,5	14,1	7,1	-1,6	1,9
Cl_4	**Complex**	9,7	13,0	11,7	14,0	9,7	7,5	0,0	2,9
	Total	**10,7**	**11,7**	**12,4**	**11,7**	**12,0**	**7,2**	**-1,1**	**2,0**

Table 7: Dynamic performance of firm clusters (2016-2018)

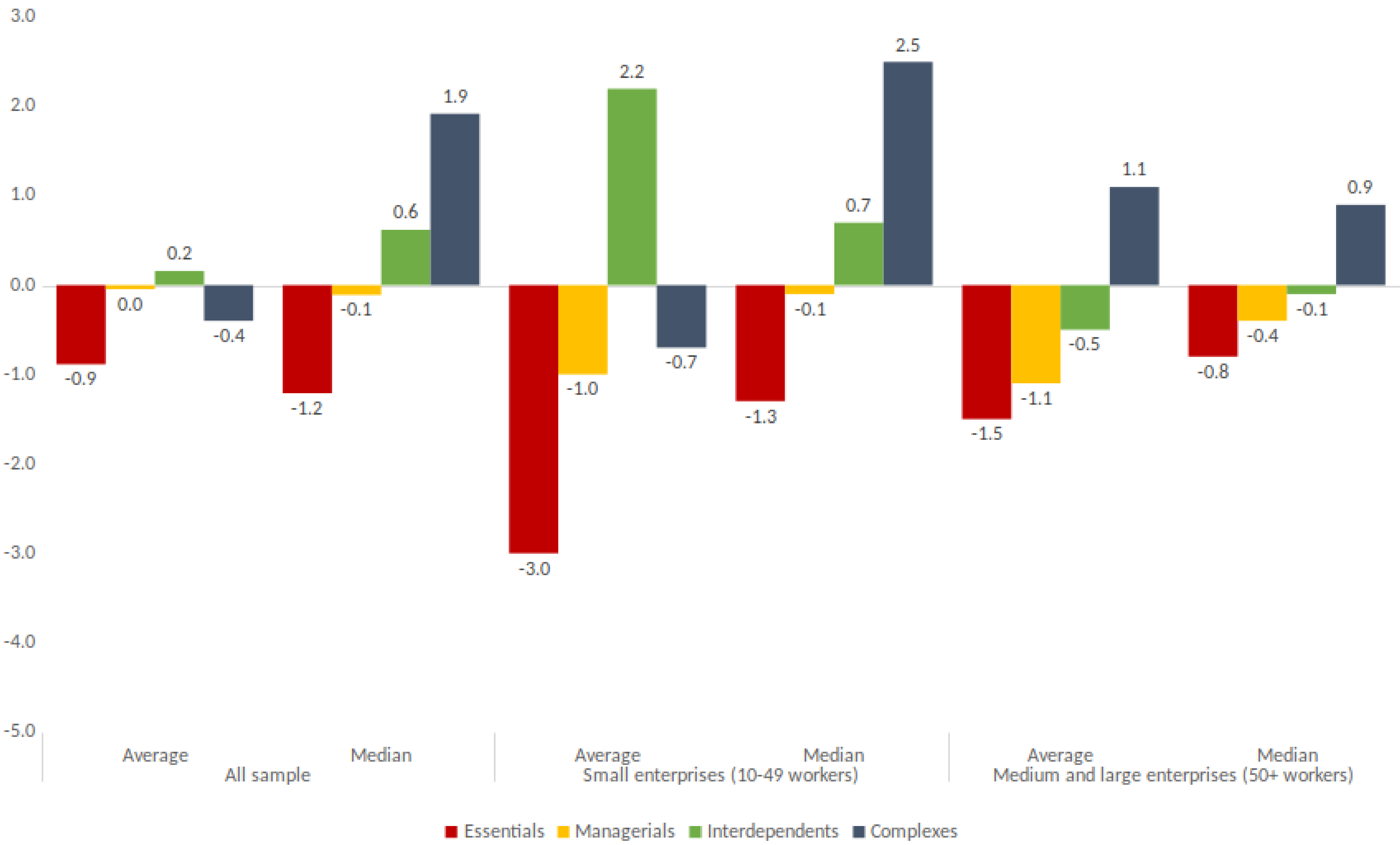

Figure 3: Deviations of average changes and median shifts of labour productivities from respective total values by size class.

To further characterise firm clusters, we look at the association between clusters and dominant co-occurring practices. In this respect, we analyse the co-occurrences in the answers within each cluster, as can be observed in Figure 4 where each circular chart refers to a cluster – Essential, Managerial, Interdependent and Complex in (a), (b), (c) and (d) respectively. By treating the answers as independent events, for each firm cluster and each question, we look at the positive or negative response frequency of the firms in the cluster and select the answers shown in Figure 4 using a χ^2 test. Our null hypothesis is that the answers are equally distributed, determined only by the number of firms in each cluster.

The simultaneous significance of two or more answers determines the co-occurrence of questions in the circular charts. For each cluster, answers with the higher positive χ^2 tests (those with a greater discrepancy between the observed and theoretical frequency predicted by the null hypothesis) are displayed, and text size is proportional to the answer's significance. The selection of significant questions, i.e. the χ^2 cutoff for each cluster, is carried out with a heuristic approach, close to Elbow's method.

In line with the descriptive analysis presented in Figure 1, we detect greater diversification in the number of significant questions as the complexity of the clusters increases. Whereby Essential firms display a fundamental lack of any systematic organisational structure and strategic plans, i.e. few significant characteristics in almost every macro-area of the survey, with particular emphasis on the absence of current and future strategic objectives (e.g., no investments in R&D and human resources, defensive strategies in local markets), Complex firms appear to be characterised by the co-occurrence of the majority of practices meant to achieve technological and skills upgrading (4th Industrial Revolution, upskilling).

More in detail, Essential firms (Figure 4.a) feature either low rates of current or future investment in innovative activities, R&D, digitalisation and cybersecurity or no investment at all, HR policies are mainly oriented toward cyber- and network security, while no process safety policy is undertaken. They are almost exclusively geared towards expanding the product/service range and domestic activities while pursuing defensive strategies. Whilst still featuring low capability diversification and no specific product or process safety strategy, Managerial firms (Figure 4.b) rely to some extent on promoting external collaborations, accessing to new markets and attention to localization.

By contrast, Interdependent and Complex firms (Figure 4.c and .d) present more nuanced and structured profiles, are diversified in their wide-ranging strategies and, especially Complex ones, answer positively to the majority of the questions. Both clusters emphasise R&D, innovation and different kinds of investments, with a large number of positive answers to the questions on a broad spectrum of workforce training activities and HR policies. Interdependent firms are often suppliers that operate mainly on order and are characterised by active market strategies as well as by active relations and partnerships with other local or international firms – primarily to provide services or management activities related to distribution, internationalisation, marketing and pre- and post-sales services. Whereas, for what concerns training and human resources, they mainly focus on IT and cybersecurity, as well as linguistic and technical-organisational skills, staff retraining, work organisation, and team working.

Conversely, what is most apparent for Complex firms are all characteristics linked to Industry 4.0, in terms of investments in digitalisation and big data, but also in terms of their main areas of specialisation, i.e., smart city and mobility, smart factory, aerospace and green chemistry. That is also reflected in training activities they carry out mainly concerned with advanced computer skills, 3d printing, big data, robotics, simulation between interconnected machines and augmented reality. Special attention is devoted to the acquisition of managerial and problem-solving skills, with HR policies especially focused on management and strategic planning. Moreover, Complex firms are also tightly connected with R&D and ICT related activities, as well as with the development of new products and professional services.

(a) Essential

(b) Managerial

(c) Interdependent

(d) Complex

Figure 4: Co-occurrences of capabilities and strategies in each cluster.

Finally, the sectoral distribution of the different taxa is far from homogeneous. Figure 5 illustrates it within manufacturing and service sectors (2-digit aggregation level of Nace Rev. 2 codes), in terms of number of firms and in Figure 6 in terms of share of value added. Those sectors that are defined as Supplier Dominated according to Pavitt (1984) taxonomy– such as apparel, leather goods and textiles – are largely populated by Essential and Managerial companies; by contrast those sectors (Science Based and a few Scale Intensive) with higher technological intensity and fast learning processes – such as pharmaceuticals and electronics – are largely populated by Complex firms. More in detail, in sectors 21-Pharmaceuticals, 26-Electronics, 20-Chemistry and 29-Automotive, we observe a prevalence of firms belonging to the Complex cluster. In services, the Complex cluster prevails in most knowledge-intensive sectors: 72-Research and Development, 62-Information Technology and 71-Engineering.

In terms of value added (Figure 6), the picture is more heterogeneous, with contributions ranging from 40% to 70% of Complex firms. In manufacturing, the weight in value added of the Complex cluster is particularly high in Scale Intensive and Specialised Supplier sectors, such as 30-Other means of transport (above 80%), 29-Automotive (74%), 27-Electrical appliances and 26-Electronics (60% in both), notwithstanding a relatively low share in terms of numbers (around 20% in both). Within services a greater polarization emerges: in some knowledge-intensive activities the Complex cluster accounts for almost all value added, e.g. 53-Postal services and 61-Telecommunications, and for a share not lower than two thirds for 60-Programming and broadcasting, 72-R&D, 62-ICT and 74-Other professional activities. In other market services such as 68-Real estate, 80-Security and 77-Housing, which are quite relevant in terms of number of firms and employment levels, the share of value added belonging to the Complex units is around 10%.

The sectoral analysis also highlights that Managerial firms tend to exhibit sectoral frequencies more similar to the Essential ones, while Interdependent firms tend to move alike those in the Complex cluster, in terms of both shares of value added and of number of firms.

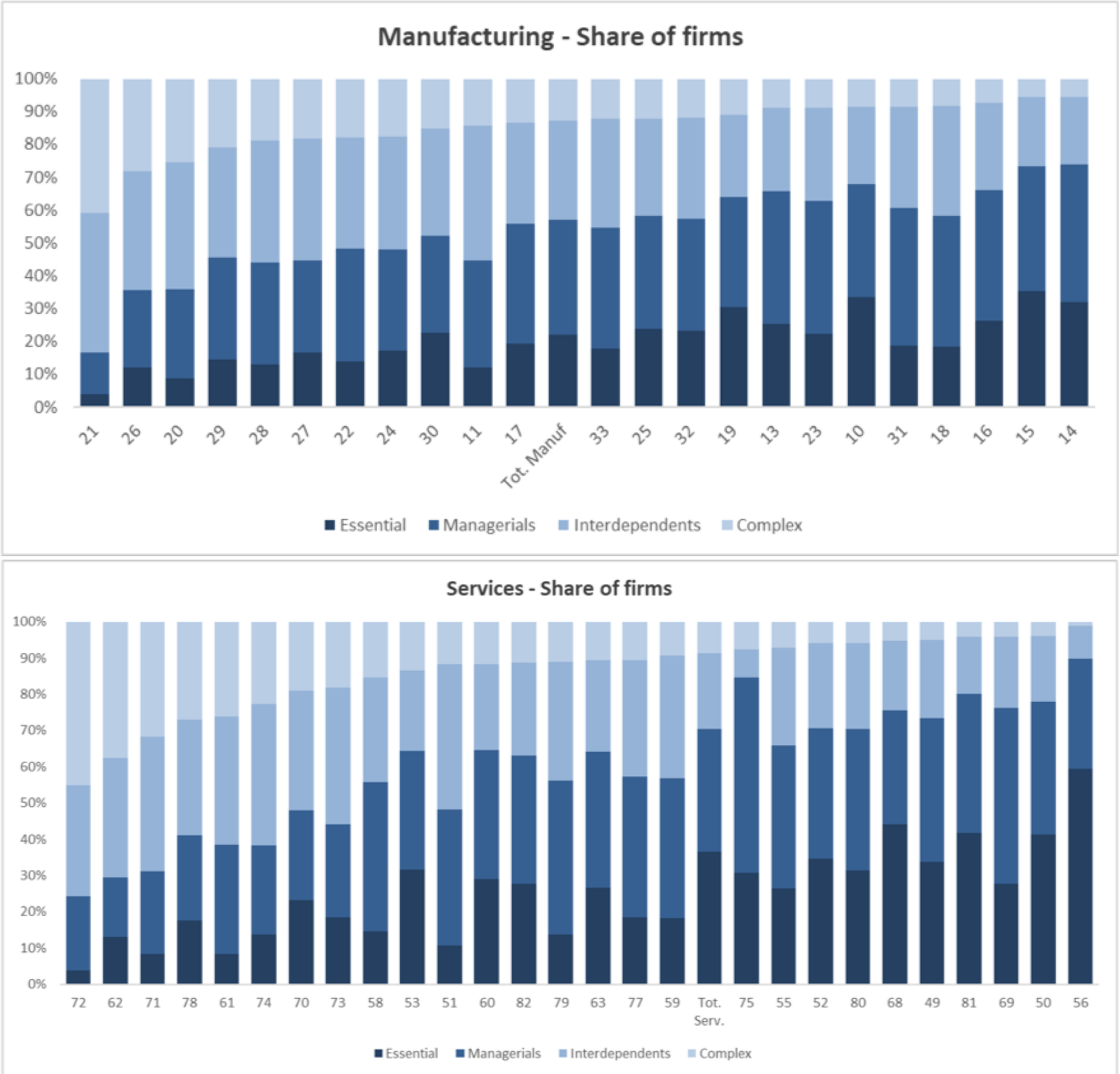

Figure 5: Incidence of firm clusters by economic activity sector (firms with at least 10 employees, manufacturing and market services, percentage values).
10 = Food; 11 = Beverages; 13 = Textiles; 14 = Apparel; 15 = Leather; 16 = Wood; 17 = Paper; 18 = Printing; 20 = Chemistry; 21 = Pharmaceuticals; 22 = Rubber and plastics; 23 = Non-metallic minerals; 24 = Metallurgy; 25 = Metal products; 26 = Electronics; 27 = Electrical appliances; 28 = Machinery; 29 = Automotive; 30 = Other means of transport; 31 = Furniture; 32 = Other manufacturing; 33 = Repair and maintenance of machinery and equipment; 49 = Land transport; 50 = Sea transport; 51 = Air transport; 52 = Warehousing; 53 = Postal services; 55 = Lodging; 56 = Catering; 58 = Publishing; 59 = Motion picture, TV, video and music production; 60 = Programming and broadcasting; 61 = Telecommunications; 62 = Computer software and consultancy; 63 = Other information and computer services; 64 = Financial services (excluding insurance and pension funding); 65 = Insurance and pension funding; 66 = Activities auxiliary to financial services and insurance; 68 = Real estate activities; 69 = Legal and accounting activities; 70 = Management consulting and advisory activities; 71 = Architectural and engineering firms; 72 = Research and development; 73 = Advertising and market research; 74 = Other professional activities; 75 = Veterinary activities; 77 = Rental and leasing; 78 = Labour recruitment and provision of personnel; 79 = Travel agencies and tour operators; 80 = Security services; 81 = Services for buildings and landscape; 82 = Other business services.

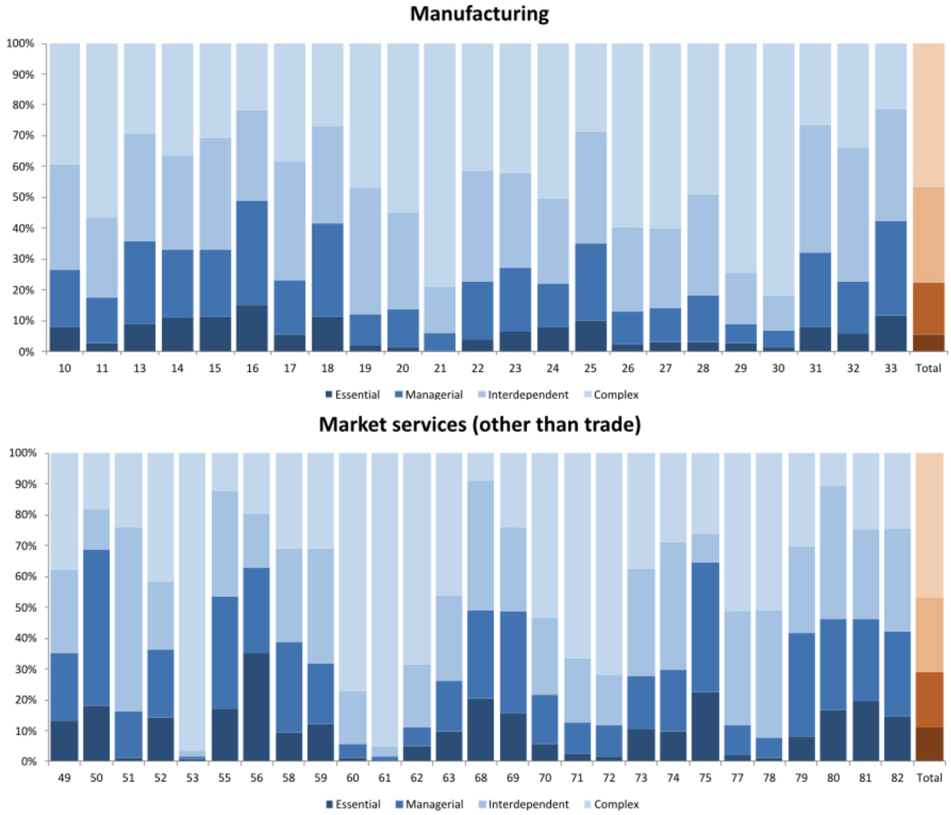

Figure 6: Weight of the firm clusters in terms of value added, by sector of economic activity (units with at least 10 employees, manufacturing and market services, percentage values).
10 = Food; 11 = Beverages; 13 = Textiles; 14 = Apparel; 15 = Leather; 16 = Wood; 17 = Paper; 18 = Printing; 20 = Chemistry; 21 = Pharmaceuticals; 22 = Rubber and plastics; 23 = Non-metallic minerals; 24 = Metallurgy; 25 = Metal products; 26 = Electronics; 27 = Electrical appliances; 28 = Machinery; 29 = Automotive; 30 = Other means of transport; 31 = Furniture; 32 = Other manufacturing; 33 = Repair and maintenance of machinery and equipment; 49 = Land transport; 50 = Sea transport; 51 = Air transport; 52 = Warehousing; 53 = Postal services; 55 = Lodging; 56 = Catering; 58 = Publishing; 59 = Motion picture, TV, video and music production; 60 = Programming and broadcasting; 61 = Telecommunications; 62 = Computer software and consultancy; 63 = Other information and computer services; 64 = Financial services (excluding insurance and pension funding); 65 = Insurance and pension funding; 66 = Activities auxiliary to financial services and insurance; 68 = Real estate activities; 69 = Legal and accounting activities; 70 = Management consulting and advisory activities; 71 = Architectural and engineering firms; 72 = Research and development; 73 = Advertising and market research; 74 = Other professional activities; 75 = Veterinary activities; 77 = Rental and leasing; 78 = Labour recruitment and provision of personnel; 79 = Travel agencies and tour operators; 80 = Security services; 81 = Services for buildings and landscape; 82 = Other business services.

5 Estimation strategy

Let us proceed to estimate a series of linear regression models in order to detect more precisely the extent to which belonging to the four clusters is linked to firm performances. We start by estimating a cross sectional linear regression model:

$$\pi_{i,t} = \alpha + Cl_k + X_{i,t} + \gamma + \eta + \epsilon_{i,t} \quad i = 1, ..., 98574, \quad k = 1, ..., 4 \quad t = 2018 \tag{1}$$

where $\pi_{i,t}$ represents log labour productivity, α the constant term, Cl_k the four clusters, $X_{i,t}$ a vector of firm-level control variables including size, years of schooling of employees, tenure of employees, age of the firm, profitability (calculated as the ratio between gross profit margins and sales), a dummy variable for exporting status, dummy variables for belonging to a domestic group, a multinational group with domestic control, and a multinational group with foreign control. Additionally, we add 2-digit sectoral and geographical dummy variables, γ and η respectively. The estimation, conducted over a 98574 firms in the year 2018, is firstly carried out for the whole sample and then repeated for small, medium and large enterprises.

Results are reported in Table 8. Starting with our variables of interest, that is the elasticity of performance to each cluster, we detect a positive and significant effect of belonging to each of the three "higher" clusters vis-à-vis the Essential baseline concerning labour productivity. The magnitude is considerable, in the range $[9 - 15\%]$, notably increasing along clusters, with Complex firms having an advantage in labour productivity of approximately 15% with respect to Essential firms.

As we have defined clusters in terms of underlying techno-organizational complexity, our results might be inflated by mixing firms of heterogeneous size. Therefore, we perform the estimation for small (10-49 employees), medium (50-249 employees), and large (more than 250 employees) firms in order to distinguish sheer size from complexity. Indeed, results are confirmed and techno-organizational complexity does not lose significance either for small, or for medium firms. Also the magnitude of the elasticity remains almost unchanged. With respect to large firms however, belonging to a cluster gets significance once a given complexity is reached: so large Managerial firms do not record productivity advantage vis-à-vis large Essential firms. However, starting with Interdependent firms, and particularly for Complex ones, the effects are positive and significant. Put in other words, for SMEs even a medium-low complexity may make the difference in order to attain higher productivity levels, while for large firms this occurs just in correspondence of highly complex organizational forms and strategies.

The introduction of a large set of firm-level controls, usually considered in the literature as potential determinants of labour productivity, reassures us about omitted variable problems. Notably, those variables related to accumulation of worker level capabilities, such as years of schooling and tenure, both exert positive and significant effects on labour productivity. Size, age and profitability are positively associated with labour productivity as expected, so is the export status. Finally, belonging to a group with respect to a baseline of being an individual firm, is positively associated with labour productivity, and particularly when the group is a multinational one, either under domestic or foreign control. All this notwithstanding, the capability taxa continue to matter.

Cross-sectional estimates clearly suffer from simultaneity of variables determination, thus potentially revealing sheer associations. In order to better grasp the effects of clusters we estimate a second model of productivity *changes*, with covariates expressed at initial (2016) levels which reads as:

$$\Delta\pi_{i,t} = \alpha + Cl_k + X_{i,t-1} + \gamma + \eta + \epsilon_{i,t} \quad i = 1, ..., 55992, \quad k = 1, ..., 4, \quad t = 2016, 2018 \tag{2}$$

The estimates in terms of growth rates, as expected, are able to account for a lower amount of variance, and the sample size also shrinks as reported in Table 9. Nonetheless positive and significant elasticities are recorded for the whole sample starting with the cluster of Interdependent firms, with elasticities in the range of $[3 - 4\%]$. The positive effect of complexity in techno-organizational capabilities limited to the two upper clusters militates in favour of the neodualistic hypothesis: at least in the Italian case, slowdown of productivity growth appears to be due to the coexistence of a small portion of growing and dynamic firms with a majority of slacking ones.

Indeed these results confirm our preliminary descriptive evidence on productivity dynamics. With reference to other control variables, introduced in levels a time $t - 1$, we notice the negative impact upon productivity growth of belonging to business groups and the positive one of years of schooling. A full model in growth rates including all set of covariates has been also estimated. Results, available upon request, corroborate the foregoing findings with respect to the effects of clusters.

When splitting the sample, the same basic picture appears with positive and significant elasticities along clusters for small enterprises, ranging from 3% to 6%. The same elasticities remain positive but non significant in the case of medium and large enterprises, possibly affected by the drop in sample size.

Finally, we focus on a particular sub-sample of firms, those recording positive growth in both labour productivity and in employment. We called them "good-gazelles", covering around one third of the whole sample. We look therefore at another proxy of firm performance, namely employment growth, and we estimate the following model:

$$\Delta l_{i,t} = \alpha + Cl_k + X_{i,t-1} + \gamma + \eta + \epsilon_{i,t} \quad i = 1, ..., 56818, \quad k = 1, ..., 4 \quad t = 2016, 2018 \tag{3}$$

where on the left-hand side appear variations in employment. Interestingly, belonging to a cluster looses significance in terms of productivity growth (Table 9) but maintains, indeed increases, importance with respect to employment (Table 10). Indeed, the effects upon employment of belonging to each of the four clusters are positive and statistically significant in all samples of analysis and with magnitudes comparable to cross-sectional estimates. Even when restricting the analysis to good-gazelles, more Complex firms in general grow in employment size 5% more than Essential ones. The stronger effects of techno-organizational capabilities on employment rather than on labour productivity growth might signal that among the "virtuous firms" – growing in both productivity and employment – Complex firms are those more able to expand in size and, thus, most likely in market shares, despite their improving production efficiency.

Covariates	All sample	Small $(10-49)$	Medium $(50-249)$	Large (>250)
Cl_2	0.087***	0.083***	0.094***	0.026
	(0.011)	(0.012)	(0.015)	(0.046)
Cl_3	0.131***	0.124***	0.145***	0.11**
	(0.012)	(0.013)	(0.015)	(0.046)
Cl_4	0.147***	0.133***	0.192***	0.187***
	(0.016)	(0.019)	(0.016)	(0.047)
$size$	0.037***	0.106***	0.059***	-0.002
	(0.004)	(0.008)	(0.010)	(0.016)
$schooling$	0.627***	0.567***	1.196***	1.498***
	(0.041)	(0.044)	(0.044)	(0.121)
$tenure$	0.155***	0.156***	0.145***	0.166***
	(0.008)	(0.009)	(0.009)	(0.020)
age	0.062***	0.061***	0.064***	0.029*
	(0.008)	(0.009)	(0.007)	(0.016)
$profitability$	0.786***	0.786***	0.741***	1.070***
	(0.046)	(0.054)	(0.068)	(0.195)
$exporting$	0.034***	0.035***	0.021***	0.031**
	(0.003)	(0.003)	(0.004)	(0.013)
$domesticBG$	0.192***	0.193***	0.109***	0.118***
	(0.009)	(0.010)	(0.009)	(0.031)
$multinationalBG1$	0.452***	0.519***	0.297***	0.226***
	(0.030)	(0.046)	(0.015)	(0.035)
$multinationalBG2$	0.298***	0.32***	0.185***	0.246***
	(0.014)	(0.021)	(0.011)	(0.034)
Constant	8.160***	8.117***	6.717***	6.239***
	(0.103)	(0.112)	(0.120)	(0.320)
N	98574	76538	18882	3154
R^2	0.492	0.479	0.533	0.641

Table 8: Linear regression estimation of Eq. 1. Dependent variable: labour productivity. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, robust standard errors in parenthesis. Essential firms are the benchmark group.

Covariates	All sample	Good Gazelles $\Delta\pi_{i,t} > 0$ $\Delta l_{i,t} > 0$	Small $(10-49)$	Medium $(50-249)$	Large (> 250)
Cl_2	0.019	0.014	0.036**	0.028	0.081
	(0.013)	(0.01)	(0.015)	(0.025)	(0.11)
Cl_3	0.033***	0.014	0.051***	0.03	0.11
	(0.012)	-0.009	(0.014)	(0.024)	(0.11)
Cl_4	0.042 ***	0.007	0.059***	0.034	0.137
	(0.012)	(0.01)	(0.014)	(0.025)	(0.112)
$Small_{2016}$	0.066***	-0.032***			
	(0.015)	(0.012)			
$Medium_{2016}$	0.055***	-0.071***			
	(0.016)	(0.013)			
$Large_{2016}$	0.044**	-0.109***			
	(0.018)	(0.016)			
$size_{2016}$			-0.017***	0.005	-0.009
			(0.007)	(0.008)	(0.011)
$schooling_{2016}$	0.027	0.123***	0.091***	0.06	-0.113
	(0.028)	(0.027)	(0.031)	(0.045)	(0.106)
$tenure_{2016}$	-0.009	-0.028***	-0.011	-0.003	0.026
	(0.007)	(0.008)	(0.007)	(0.009)	(0.018)
age_{2016}	0.002	0	0	0.002	0.009
	(0.005)	(0.006)	(0.005)	(0.007)	(0.013)
$profitability_{2016}$	-1.028***	-0.707***	-0.911***	-0.927***	-0.499**
	(0.051)	(0.063)	(0.061)	(0.129)	(0.225)
$exporting_{2016}$	-0.004*	0.01***	-0.002	0	-0.005
	(0.002)	(0.003)	(0.002)	(0.003)	(0.009)
$domesticBG_{2016}$	-0.024***	0.015*	-0.017	0.004	-0.03
	(0.009)	(0.008)	(0.011)	(0.009)	(0.031)
$multinationalBG1_{2016}$	-0.049***	0.054***	-0.058***	0.014	-0.025
	(0.011)	(0.012)	(0.016)	-(0.015)	(0.029)
$multinationalBG2_{2016}$	-0.035***	0.035***	-0.015	-0.003	-0.06**
	(0.008)	(0.009)	(0.011)	(0.01)	(0.030)
Constant	0	0.065	0	-0.055	0.397
	(0.073)	(0.070)	(0.080)	(0.127)	(0.306)
N	55992	19997	39103	12433	2300
R^2	0.081	0.12	0.080	0.095	0.067

Table 9: Linear regression estimation of Eq. 2. Dependent variable: labour productivity growth. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, robust standard errors. Essential firms are the benchmark group.

Covariates	All sample	Good Gazelles $\Delta\pi_{i,t} > 0$ $\Delta l_{i,t} > 0$	Small $(10 - 49)$	Medium $(50 - 249)$	Large (> 250)
Cl_2	0.093***	0.027**	0.07***	0.53***	0.804***
	(0.010)	(0.013)	(0.009)	(0.072)	(0.224)
Cl_3	0.119***	0.032***	0.087***	0.589***	0.849***
	(0.010)	(0.010)	(0.009)	(0.072)	(0.227)
Cl_4	0.162***	0.057***	0.121***	0.621***	0.88***
	(0.012)	(0.013)	(0.010)	(0.072)	(0.224)
$Small_{2016}$	-0.304***	-0.177***			
	(0.012)	(0.015)			
$Medium_{2016}$	-0.368***	-0.179***			
	(0.014)	(0.016)			
$Large_{2016}$	-0.375***	-0.195***			
	(0.018)	(0.018)			
$productivity_{2016}$	0.07***	-0.002	0.062***	0.103***	0.005
	(0.007)	(0.008)	(0.006)	(0.018)	(0.041)
$schooling_{2016}$	0.065**	0.031	0.045*	0.102	0.186
	(0.026)	(0.035)	(0.024)	(0.066)	(0.118)
$tenure_{2016}$	-0.062***	-0.085***	-0.032***	-0.08***	-0.045
	(0.006)	(0.007)	(0.005)	(0.016)	(0.035)
age_{2016}	-0.01***	-0.018***	-0.019***	0.031***	0.025
	(0.004)	(0.005)	(0.003)	(0.009)	(0.019)
$profitability_{2016}$	0.195***	-0.05	0.162***	0.344***	0.519*
	(0.044)	(0.058)	(0.042)	(0.109)	(0.289)
$exporting_{2016}$	-0.002	0.002	-0.001	-0.006	-0.009
	(0.002)	(0.002)	(0.001)	(0.005)	(0.008)
$domesticBG_{2016}$	-0.007	0.02***	-0.014**	-0.021	-0.065
	(0.006)	(0.007)	(0.006)	(0.014)	(0.073)
$multinationalBG1_{2016}$	-0.039***	0.018**	-0.031***	-0.074***	-0.044
	(0.012)	(0.009)	(0.012)	(0.026)	(0.052)
$multinationalBG2_{2016}$	-0.029***	0.011*	-0.044***	-0.043**	-0.033
	(0.009)	(0.007)	(0.011)	(0.018)	(0.054)
Constant	-0.538***	0.388***	-0.737***	-1.779***	-1.405***
	(0.104)	(0.130)	(0.095)	(0.230)	(0.433)
N	56818	20166	39647	12662	2333
R^2	0.137	0.352	0.056	0.126	0.142

Table 10: Linear regression estimation of Eq. 3. Dependent variable: employment growth. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, robust standard errors. Essential firms are the benchmark group.

6 Conclusions

Identifying organizational capabilities is a very daunting task, as it necessarily requires the search for relatively invariant behavioural traits, structures, routinised procedures which distinguish one firm from another even within the same domain of activities and lines of production.

To this end, in this work we have proposed a novel empirical strategy, relying upon a rich informative source, the multi-purpose questionnaire designed by the Italian Statistical Office in 2019 as part of a firm permanent census helping to identify what we have called the *quasi-genetic traits of organisations*. By using this newly integrated database, we have developed a taxonomy of the Italian firms, also capable of mapping organisational structures, routines and heuristics into different indicators of economic performance, in this work primarily labour productivity and employment.

Such exercise fundamentally entails the identification of the *complementarities* across different practices. Hence, a first novel advancement of this work follows: by means of a factor analysis, we are able to distinguish discrete taxa based on the structural and behavioural identities of the firms. These profiles are primarily characterised by learning processes implemented on the grounds of a sort of "technological substratum" – e.g., investments in digitalisation, business management software and platforms adoption – and by a complementary set of organisational practices – ranging from staff training processes and career advancement systems, to competences required to newly hired personnel.

The role of managerial strategies *strictu sensu* – i.e., as detailed above, everything that pertains exclusively to managerial functions, such as defining outlet markets, product quality and pricing mechanisms – emerges only as a second order set of determinants. Finally, company's positioning with respect to a system of relations – both externally in terms of value chains, as well as internally in terms of workforce safety and welfare – represents a further element that contributes to explaining the high degree of heterogeneity observed among different firms.

We identified four clusters of firms called Essential, Managerial, Interdependent, and Complex. Firms in the first two clusters, that account for almost half of the overall value added of the firms under consideration, tend to show similar characteristics, while Interdependent firms in the third cluster are closer to that in the Complex one. In general, the identified taxa, we suggest, are a promising way to operationalize the notion of organizational capabilities as *distinctive* and *persistent* ensembles of organizational behaviours able to account also for persistently different performances.

The frequency distribution of each taxa, at least in the Italian case, is in line with the empirical literature that emphasises the emergence of a neodualism (Dosi et al., 2012, 2019) even within manufacturing due to the presence of a relatively small core endowed with complex organizational practices, labour productivity, wages and profit margins, and a large fringe with opposite characteristics. Regression results corroborate the descriptive classification and also highlight the importance of such inner "genotypes" in affecting both productivity and employment growth conditional to the belonging to different clusters.

The perspective bears far reaching implications for both business analysis and public policy. Concerning the former, it might well be futile to search for *the one best practice*, or, in analogy with economists' production theory, for the contribution of each individual practice (often equated to a resource) to some overall production function. Rather, it might be much more useful to detect the properties of different *combinatorics of practices*.

In this respect, the contribution of (Fujimoto, 1999) concerning the origins and ingredients of "Toyotism", has been a path-breaking archetype. Nowadays, with the availability of census-type information on corporate structures, behaviours and strategies, it is possible to replicate the spirit of that classic study on a massive scale, even if of course at much lower depth.

The implications in terms of policy are equally far-reaching. If our analysis is correct, the policy emphasis should be on the process of learning and accumulation of technological capabilities. Thus, in the case we have analysed – Italy – tackling the productivity stagnation crucially implies fostering to transition those firms placed in the lower capability clusters – indeed the majority of Italian firms – up on the ladder. In order to achieve such objective, horizontal policies centred on incentives are hardly enough since they tend to perpetuate divergences.

Finally, concerning future venues of research, the robustness of our results reveals also their limitations. Indeed, our capability taxa appear to be so robust that they hold across sectors of manufacturing and services. However, the analysis must get deeper and identify finer properties of organizational capabilities which are sector- and technology-specific. After all, designing and building auto-mobiles is very different from making semi-conductors, or pharmaceutical products, or coding software. This, we believe, is the further frontier for the empirical analysis of capabilities.

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Appendix

Methods

The use of a multi-step data analysis process has enabled us to keep together summaries and analyses of ISTAT multi-purpose firm census, an extremely complex data-set, very rich in information both in terms of observations and available variables. We choose to rely on an exploratory analysis of the data since the methods of *analyse de données* is the most effective and relevant when adopting an exploratory perspective, and it also provides a first description of the data useful to develop new research hypotheses. This approach, given the thematic and computational complexity of the data-set, has involved the combination of several multidimensional and classification techniques.

The first step of our empirical strategy consisted in a multiple correspondence analysis (MCA), whose main field of application are questionnaires in which information of different nature coexists, i.e. numerical, ordered (intensity scales, agreement, preference), disconnected/nominal (alternative/multiple choices), or dichotomous (yes/no). When simultaneously dealing with sets of heterogeneous data, poor in information because they are largely ordinal/qualitative structures but rich in relationships as they are multidimensional, MCA allows to compare the characteristics of the different layers of data, a very useful tool for studying the global information contained in the multi-purpose questionnaire. However, a global analysis of extremely heterogeneous sets of variables may not always yield synthetically meaningful or interesting dimensions (in our case, the selected portion of the questionnaire questions comprises more than 450 answers on different topics). In such a very rich and structured survey, when there are large and nested sets of items that can generate dozens of variables, it is advisable to carry out an exploratory and preliminary examination of the data able to provide synthetic indicators that can then be included in the final analysis. If this procedure is applied to each macro-area of the questionnaire it is possible to obtain meaningful but partial summary statistics.

The thematic division of each macro-area of the survey questions into sub-sections, i.e. coherent subsets of variables, allowed us to study the complex phenomenon from different angles. The fundamental characteristics of Italian firms were captured through seven synthetic indicators that, for each thematic macro-area, reflect some latent and otherwise unobservable dimensions and capture the structural relations between variables. In particular, in our case, the seven factors that we have identified synthetically express the different strategic profiles of the Italian firms. Each of these profiles defines a cluster and characterises the firms that comprise it.

On the basis of these indicators of latent characteristics we operate a further partial analysis, able to provide synthetic quantitative descriptors of the qualitative characteristics of each productive units in the clusters, i.e. measurements of a higher level than the starting information. The interpretation of the axes is based on the patterns of the modality points and on their relative absolute contributions.[2]

It should be noted that the orientation of the factorial axes is not affected by the shape of the point cloud. Therefore, it is possible to indifferently rely on a representation in which an axis is **u** or -**u**. In replicating different data processing it is thus possible to obtain similar axes with opposite orientation that yield meaningful indicators with opposite signs. In these cases, for ease of comparison, the starting vectors are multiplied in an appropriate way allowing a semantic interpretation for all the factorial axes, i.e. common factors. These factors represent multidimensional rankings that can be interpreted as metrics through which it is possible to differentiate the sample units on the basis of dimensions otherwise unobservable.

In a second step of the analysis, the synthetic strategic profile of firms was obtained by carrying out a further factorial analysis on the seven partial indicators obtained in the first step. Similarly to the above, a first common factor summarising the starting information in a single indicator was extracted.

In the third stage of the analysis on the basis of this single factor we employed a factorial typological model for automatic classification purposes. Indeed, factorial techniques permit to visualize point clouds generating rankings, but they do not allow to build partitions on the observed universe. These can instead be obtained by employing cluster analysis techniques.

[2]The absolute contributions express the contribution of each element to the construction of the factorial dimension, i.e. the variability of the phenomenon explained by that axis (the eigen-value).

The aim of these techniques is to develop a taxonomic model that identifies clusters of the interviewed firms so as to outline their most salient behaviours and characteristics. The steps of such a clustering strategy are:

1. data matrix identification and standardisation of the variables of interest;

2. choice of the metric (diversity measure) to apply to the data to be classified;

3. selection of data classification criteria (agglomerative/divisive approach to clustering);

4. assessment of the results, consolidation of the partitions and interpretation of the taxonomy.

Before reaching point 4), an iteration of points 2) and 3) is required to improve the final result. The implementation of this last step has been facilitated by the two previous stages of information synthesis. Generally these techniques converge towards a local optimum. That is, the aim of clustering algorithms is to identify a partition of the total variance of the chosen variables able to maximise the between (inter-group) variance and thus to minimise the within (intra-group) variance. Since the cluster analysis was applied to a large number of units, we opted for a classification technique based on a standard non-hierarchical algorithm (K-means – Euclidean distance), by virtue of its well-known properties of convergence and execution speed.

As mentioned, our choice was made using the firm synthetic behavioural profile as classification variables. The rationale of the clustering algorithm we adopted is the following:

1. we experimented with different taxonomies (all clusters between 2 - 8 groups) applying the optimal jump criterion to obtain the minimum number of groups with maximum internal homogeneity;

2. we evaluated the centroids of the entire final taxonomy (4 clusters), i.e. the profiles of each group;

3. in order to construct the taxonomy interpretation matrix, we put into light the relevant characteristics of each cluster by studying the structural variables of interest.

Further results

Table 11: Firm clusters and organisational-strategic profiles (small enterprises, 10-49 workers).

		Organisational-strategic profiles		
		Technological-organisational capabilities	**Managerial strategies**	**Relations**
Cl_1	Essential	14,2	70,1	62,6
Cl_1	Managerial	25,6	75,8	64,6
Cl_3	Interdependent	36,2	73,6	64,2
Cl_4	Complex	48,8	66,5	61,3
	Total	**26,3**	**72,8**	**63,6**

Table 12: Firm clusters and organisational-strategic profiles (medium and large enterprises, over 50 workers).

		Organisational-strategic profiles		
		Technological-organisational capabilities	**Managerial strategies**	**Relations**
Cl_1	Essential	14,4	64,5	61,2
Cl_1	Managerial	26,1	71,8	63,5
Cl_3	Interdependent	37,0	70,9	64,4
Cl_4	Complex	50,9	64,4	62,0
	Total	**35,1**	**68,7**	**63,2**

Table 13: Good gazelles descriptive characteristics

		Firms		**Value added**	**Turnover**	**Workers**	
		Number	**%**	**%**	**%**	**%**	**Average**
Cl_1	**Essentials**	20.835	36,2	38,7	35,6	35,8	20,8
Cl_2	**Managerials**	27.201	36,1	37,2	32,9	36,6	28,1
Cl_3	**Interdependents**	20.701	38,8	41,5	37,3	41,4	52,9
Cl_4	**Complexes**	8.676	43,8	37,8	33,9	40,1	138,5
	Total	**77.413**	**37,6**	**38,9**	**34,9**	**39,1**	**45,2**