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Abstract

We study how investments in emerging technologies reshape firm hierarchies. Extending Garicano's (2000) knowledge-based model, we distinguish between emerging information technologies (EIT) and robots (RT), and derive testable hypotheses on their effects on hierarchical depth and span of control, driven by changes in information costs, learning costs, and production predictability. Using longitudinal firm-level data from Italy (2014-2021), we find that EIT investments increase depth and reduce span of control relative to non-investing firms, while RT increase span of control when combined with EIT. Our layer-level analysis shows that EIT are associated with the addition of managerial and middle-management layers, whereas RT are associated with the addition of middle-management layers and the removal of top management layers; moreover, EIT reduce span of control at higher levels, while RT expand it among blue- and white-collar workers. Results are robust to alternative estimators, anticipatory-effect tests, investment switchers, common support restrictions, and alternative clustering.

JEL Classification: D22, D23, L22, L23, O33.

Keywords: firm hierarchy, organizational depth, span of control, emerging technologies.

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1. Introduction

The question of how to optimally organize knowledge has long intrigued scholars across economics and organizational studies. While Hayek (1945) framed markets as the most effective mechanism for collecting information and coordinating dispersed knowledge, subsequent contributions by Simon (1947), March and Simon (1958), and Arrow (1974) highlighted the central role of hierarchies in managing information and knowledge within cognitively constrained environments.

Inspired by the seminal work of Garicano (2000), which models firm hierarchy as a cognitive system that enhances knowledge use, we theoretically and empirically examine how investments in emerging technologies shape changes in two fundamental dimensions of hierarchies: depth, the vertical dimension measured by the number of layers, and span of control, the horizontal dimension measured by the number of subordinates per supervisor. At the core of our conceptual framework lies the idea that firm hierarchies economize on the scarce time of agents with broad and comprehensive knowledge sets by delegating routine problems to agents with more limited knowledge sets. This idea is well illustrated by Alfred Sloan's 1924 description of his role as a manager at General Motors: "We do not do much routine work with details. They never get up to us. I work fairly hard, but it is on *exceptions*, not on routine or petty details" (Sloan 1924:195; italics added).[1] Put differently, firm hierarchies operate as cognitive systems in which routine problems are resolved at lower layers, whereas exceptional issues require intervention from higher layers (supervisors or managers) endowed with broader knowledge sets. For example, production-floor machinists handle routine operations, while unexpected malfunctions require supervisory involvement.

Within this conceptual framework, investments in emerging technologies, comprising emerging information technologies (EIT) and robots (RT), play a role in shaping firm hierarchies. The diffusion of EIT across industries (OECD, 2024; Eurostat, 2024),[2] such as the Internet of Things (IoT), Augmented and Virtual Reality (AR/VR), Big Data Analytics and Cloud Computing (BDA), and Information Security and Upgrading (ISU), can, on the one hand, facilitate communication across hierarchical layers and streamline knowledge transmission in production processes. The associated reduction in the cost of communicating knowledge within firms may improve the returns to

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[1] An analogous conceptualization of hierarchy appears in the Hebrew Bible (Exodus 18:25-26; italics is added): "Moses chose able men out of all Israel and made them heads over the people, chiefs of thousands, of hundreds, of fifties, and of tens. They judged the people at all times; *any hard case they brought to Moses, but any small matter they decided themselves*." This passage parallels our conceptual framework by highlighting how lower layers handle routine tasks, while exceptional cases escalate upward (at the extreme to Moses himself).

[2] The legal industry has also markedly intensified its investments in emerging technologies. A 2022 survey of lawyers from large law firms in the US, UK and Canada revealed that a large majority (84%) expects increasing their technology expenditures within the next 12 months, with 23% expecting a significant rise. This surge in technology adoption has prompted law firms to employ allied professionals such as legal knowledge engineers, knowledge management experts, data analysts and project managers to manage technology more effectively (Litera 2022). This survey underscores the transformative role of technology investments within the legal sector.

specialized knowledge and support the creation of upper hierarchical layers. On the other hand, these technologies also introduce new organizational challenges, as both subordinates and managers must acquire the knowledge needed to integrate and use EIT tools in the production process. The increase in the cost of acquire new knowledge may limit supervisors in overseeing larger teams. As a result, the net effect of EIT on a firm's hierarchy is theoretically ambiguous, depending on whether improvements in information flow outweigh the additional learning costs. Similar ambiguities characterize the diffusion of RT (OECD, 2025). By automating tasks and reducing human error (and, in some cases, even replacing human labor[3]), RT can increase the predictability of production processes and lessen the need for upper managerial intervention to solve exceptional problems. At the same time, however, robots may generate greater complexity, particularly when malfunctions and unexpected stoppages arise.[4] Such events reduce the predictability of the production process and require specialized oversight, potentially reinforcing hierarchical layers rather than flattening them. Taken together, these considerations suggest that emerging technologies (EIT and RT) can reshape firm hierarchies in multiple, and potentially opposing, ways.

These considerations motivate our research question: how do emerging technologies influence changes in the hierarchical structure of firms, specifically their depth and span of control? To address this question, we combine a theoretical framework with an empirical analysis.

On the theoretical side, we extend the model proposed by Garicano (2000) to incorporate the effects of emerging technologies on firms' hierarchical structures. This framework yields four testable hypotheses, organized along two dimensions of hierarchy (depth and span of control) and two categories of emerging technologies, EIT and RT. Table 1 summarizes the theoretical predictions underlying these hypotheses.

[Insert Table 1 about here]

With respect to span of control, investments in EIT are expected to widen supervision when reductions in information costs outweigh any increases in learning costs, while investments in RT are predicted to expand span of control, as they increase the predictability of production processes. As for depth, our model predicts that investments in EIT lead to an increase the number of hierarchical

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[3] As Robert Shiller notes, it should come as no surprise that the word robot derives from the Czech term for "worker," and that, prior to its adoption, the expression commonly used was labor-saving invention (Shiller 2019, p. 181), underscoring the idea that robots are perceived as substitutes for human labor. However, while the potential of RT to reshape the landscape of work is undeniable, its empirical evidence and its implications remain the subject of intense and growing debate (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021; Chen et al., 2022).

[4] In a 2018 CBS News interview, Musk attributed Tesla's "production hell" to an overly complex system of robots, making the production process less predictable and harder to manage. In response, Tesla scaled back robotics and reintroduced human workers to improve productive predictability.

layers when they shift relative learning costs in favor of individuals in the additional layer compared with their supervisors, thereby generating net gains from adding organizational layers. By contrast, RT are expected to increase depth only in more limited cases, namely when higher predictability is accompanied with the condition that the knowledge base of the added layer exceeds the combined knowledge of its adjacent lower and upper layers. Overall, the framework highlights that the organizational effects of emerging technologies are inherently ambiguous and depend on how these technologies reshape information costs, learning costs, predictability, and the distribution of knowledge across hierarchical layers.

On the empirical side, we test these hypotheses using comprehensive longitudinal firm-level data from the *Rilevazione Imprese e Lavoro* (RIL), a mandatory survey conducted in Italy by the National Institute for Public Policy Analysis (INAPP), which allows us to track changes in firms' technological investments and organizational structures over time. The dataset covers a representative sample of Italian partnerships and limited liability companies across all size classes in the non-agricultural private sector over the period 2014-2021. Our empirical results highlight distinct roles for EIT and RT in shaping changes in firm hierarchies. Focusing on estimates from inverse probability weighted regression adjustment (IPWRA), which is our preferred specification, we find that investments in EIT are associated with an increase in depth and a reduction in the average span of control, relative to firms that do not invest. By contrast, investments in RT do not exhibit robust standalone effects on changes in the firm's average span of control. However, when investments in RT are combined with investments in EIT, span of control expands relative to non-investing firms, indicating a complementary relationship between the two technologies that enables supervisors to oversee larger teams. A layer-level analysis further clarifies the mechanisms underlying these patterns. Consistent with the firm-level results, EIT-driven increases in depth are primarily explained by the addition of managerial and middle-management layers, while the associated reduction in span of control is concentrated at upper hierarchical levels. In contrast, the firm-level effects of RT reflect offsetting dynamics across layers: RT increase the likelihood of adding middle-management layers but simultaneously raise the probability of eliminating top managerial layers. With respect to span of control, RT-related expansions are concentrated among blue- and white-collar workers at the base of the hierarchy. These findings are robust across alternative empirical approaches, including OLS and regression adjustment (RA) models. A battery of robustness checks, including anticipatory-effect tests, specifications based on investment switchers, checks addressing measurement issues and alternative sample definitions, trimming of the propensity score to the common support region, and alternative clustering structures for the error term, confirms the robustness and causal interpretation of our findings. Taken together, the results underscore that ET reshape firm hierarchies in differentiated ways, with EIT tending to deepen hierarchies and narrow spans of control, and RT reducing firms' depth, while supporting broader supervision of the lower layers, when complemented with EIT.

Our paper contributes to the literature on knowledge-based hierarchies, which studies the returns to hierarchical organization in the utilization of knowledge. Theoretical contributions include Garicano (2000), Garicano and Rossi-Hansberg (2004, 2006, 2012), Garicano and Hubbard (2007), Caliendo and Rossi-Hansberg (2012), Garicano and Wu (2012), Garicano and Prat (2013), Fuchs et al. (2015), Carmona and Laohakunakorn (2024), and Altomonte et al. (2026). Recently, Ide and Talamàs (2025) have further extended this framework to the domain of AI, highlighting that while human knowledge utilization is constrained by time, AI is instead bounded by computational resources (assumed to be abundant relative to human time). Therefore, AI fundamentally transforms problem-solving within firms by automating cognitive processes and mitigating bottlenecks related to individual knowledge and temporal limitation. This leads to a predicted reduction in hierarchical depth and ambiguous effects on span of control, depending on how AI capabilities compare to human knowledge. Complementing these theoretical works, a large empirical literature documents the emergence and evolution of knowledge hierarchies across industries and countries. Notable contributions include Rajan and Wulf (2006), Garicano and Hubbard (2007, 2016, 2018), Caliendo and Rossi-Hansberg (2012), Bloom et al. (2014), Caliendo et al. (2015, 2020), Cooke et al. (2021), Gumpert et al. (2022), Adhvaryu et al. (2023), Ewens and Giroud (2025), and Altomonte et al. (2026). Our article advances this literature in several respects. First, we extend the model of knowledge hierarchies to incorporate the effects of emerging technologies. While prior research has predominantly focused on Information and Communication Technologies (ICT), both theoretically (Garicano and Rossi-Hansberg, 2004, 2006, 2012) and empirically (e.g., Bloom et al., 2014). Our analysis moves beyond this traditional focus on ICT to examine newer technologies, including IoT, AR/VR, and robotics, and provides novel evidence on their heterogeneous effects on both hierarchical depth and span of control. Second, we distinguish between EIT and RT to formulate specific hypotheses and test their distinct roles in transforming the hierarchical structure of firms. Third, by complementing the firm-level analysis with a layer-level analysis, we empirically examine the automation of the management of exceptions.[5] Our layer-level findings indicate that RT increase the

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[5] Herbert Simon (1960) predicted that technological advancement might ultimately replace management, describing this phenomenon as the "automation of management" in his article "The Corporation: Will It Be Managed by Machines?". More than a century earlier, Charles Babbage likewise observed: "When each process has been reduced to the use of some simple tool, the union of all these tools, actuated by one moving power, constitutes a machine" (Babbage 1846, Ch. 19, § 225). This insight captures how technologies can substitute not only workers but also managerial roles by decomposing tasks into simpler elements.

likelihood of eliminating the top managerial layer, while simultaneously raising the probability of adding middle-management layers. This pattern suggests that new technologies can substitute not only lower hierarchical levels but also the highest tiers of management. The key implication is that even high-skill occupations, such as managerial roles, are no longer insulated from technological substitution. This evidence is consistent with recent empirical findings for Canadian firms (Dixon, 2020; Dixon et al. 2021), though our argument is different but complementary to theirs. While we argue that investments in robots reduces the incidence of human error (that is, the frequency of exceptions), thereby decreasing the demand for managers whose primary role is to handle such exceptions, Dixon et al. (2021) base their explanation on a reduction in agency costs. Because robots do not pursue self-interested behavior, agency problems arising from information asymmetries are mitigated, which in turn lowers managerial monitoring costs (i.e., the time managers devote to supervising employees and production activities) and, consequently, reduces the overall demand for managers.

More broadly, our paper builds on the long-standing tradition in the institutional and organizational economics of hierarchy,[6] which traces back to Ronald Coase's (1937) seminal insight that firms rely on hierarchical organization as a more efficient governance mechanism than market transactions.[7] Coase's pioneering contribution gave rise to a vast literature across economics, law, and management, documenting that hierarchy is a multifaceted organizational form serving a range of functions, including coordination (e.g., Chandler, 1977), the incentivization of specific investments (e.g., Williamson, 1985; Hart, 1995; Blair and Stout, 1999; Rajan and Zingales, 2001), the promotion of cooperation among firm participants (Blair and Stout, 1999; Rajan and Zingales, 2001), and the resolution of conflicts inherent in team production and incomplete contracts (Williamson, 1991; Blair and Stout, 1999). Our study advances this- rich tradition by examining the hierarchical nature of the firm (*à la* Coase, 1937) as itself shaped by cognitive constraints and technological progress.[8] Because individuals face inherent constraints on time and knowledge, firm hierarchies emerge and evolve in response to technological change as mechanisms for enhancing the utilization of knowledge.

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[6] We use the term "hierarchy" to mean a rank ordering among individuals. More generally, a hierarchical relationship involves one party (the hierarch or superior) framing decisions and directing the behavior of another (the subordinate), with the expectation that instructions will be followed (see, among others, Rantakari, 2025).

[7] Adopting a Coasian perspective on knowledge-based hierarchies, Pieri and Vatiero (2025) show that hierarchy is not the sole mechanism for managing exceptions within firms. Instead, firms may also "buy" solutions from external knowledge markets rather than relying on hierarchical escalation (see Garicano and Hubbard, 2016 for a similar mechanism in the legal industry).

[8] Notably, Coase (1937) had already identified both key elements as central in determining the boundaries of firm hierarchies: the cognitive limitations of individuals, captured by his notion of the "diminishing returns to management" (Coase 1937: 395, 396) or "diminishing returns the costs of organising certain transaction within the firm" (Coase 1937: 396), and the role of technological development (exemplified at the time by the telegraph and the telephone).

Finally, our paper relates to the literature examining the trade-offs inherent in hierarchical organizations. Choe and Ishiguro (2012) analyze the tension between coordination and motivation, showing that centralized hierarchies can enhance the coordination of complex, interdependent tasks but may weaken the incentives of skilled agents to invest in task-specific expertise. Aghion et al. (2014) study the trade-off between centralized control and decentralized delegation. While centralized control may reduce information loss and promote alignment with firm-wide objectives, it can also create managerial bottlenecks. By contrast, decentralized delegation can strengthen local decision-making autonomy but may weaken control and increase the risk of divergent or conflicting objectives. Our paper identifies and examines a further trade-off inherent in hierarchical organizations and investments in emerging technologies. While such investments can improve information flows across hierarchical layers and potentially increase the predictability of production processes, they may also generate new and more frequent exceptions, thereby raising learning costs and reducing overall predictability. This non-univocal dynamic ultimately shapes the architecture of firm hierarchies.

The remainder of the article is organized as follows. Section 2 presents the theoretical framework grounded in the knowledge-based theory of the firm and derives two hypotheses on the effects of EIT and RT on changes in organizational depth, as well as two hypotheses concerning their impact on changes in span of control. Section 3 tests these hypotheses empirically. Section 4 discusses the findings and draws out implications for managers and policymakers. Section 5 concludes.

2. Our theoretical framework

2.1. Information costs, learning costs, and predictability

Individuals allocate their limited time to pursue economic outputs that depend on their cognitive resource and differ in the complexity of the problems they entail. Output is produced when an individual solves the confronted problem, a condition met whenever the individual's knowledge exceeds the problem's difficulty. If the individual cannot solve a problem on her own, she may seek assistance from someone more skilled. Such assistance, however, is costly in terms of time.

According to Garicano (2000), to model this within a firm, assume that all agents engaged in production can spend one unit of time. Let $\Omega \subset R^+$ be the set of all production problems a firm may encounter and let $A_i \subset \Omega$ be the subset of problems solvable by agent i. When a productive problem $z \in \Omega$ can be solved, which occurs whenever $z \in A_i$, the firm produces output Q. Conversely, if agent i cannot solve the problem, it is passed to a superior or manager at the higher hierarchical layer for a solution.[9]

This mechanism incurs information costs h (in terms of units of time), with $h < 1$. These costs encompass the time necessary to communicate, clarify, and verify instructions flowing down the hierarchy from superior to subordinate layers, representing the opportunity cost of time that manager could otherwise devote to other activities. If the manager has the solution, a fraction h of her unit of time is spent conveying it downward. Otherwise, escalation proceeds further up the firm hierarchy until reaching the apex, occupied solely by the entrepreneur. In this mechanism, we assume information costs are uniform across layers.

Moreover, each agent i can acquire the knowledge at a cost c_i, with $c_i < 1$. These learning costs represent the units of time required to acquire knowledge. We assume that the cost of acquiring a knowledge set A is proportional to its size, i.e., the number of problems in it, so problems within the interval $[0, z]$ incur costs equal to $c_i \cdot z$. A core assumption is that learning costs decline at higher hierarchical layers; without this, hierarchy would not serve as a cognitive system. Formally, the learning cost at layer l is higher than at the layer above, l+1, i.e., $0 < c_{l+1} < c_l < 1$.

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[9] This mechanism reflects Henri Fayol's (1919) foundational principles of organizational theory: the scalar chain and the unity of command. The scalar chain principle conceives of a vertical hierarchy with each member reporting to a superior, while the unity of command principal requires that each subordinate has only one superior, in order to avoid confusion. However, Beane and Anthony (2024) document "inverted apprenticeships," wherein senior individuals occupying higher hierarchical layers acquire new technological skills from their juniors and subordinates. Moreover, while Reitzig and Maciejovsky (2015) show that subordinates may often withhold information due to fear of reprisal or negative feedback from higher levels in the hierarchy, potentially impairing hierarchical mechanism, our model abstracts from such potential distortions.

In this setting, firm hierarchy reduces learning burden of problem-solving but increases communication costs across hierarchical layers. Additional layers economize on learning (since $c_{l+1} < c_l$) but introduce higher information costs (h).

Finally, production problems are ordered from the most common to the most exceptional, following an exponential distribution.[10] A firm solves a fraction of problems, $F(z) = 1 - e^{-\lambda z}$. The parameter λ, with $\lambda > 0$, captures predictability of production: the greater λ, the more likely that problems are relatively simple and solvable with the available knowledge z. Conversely, when the production process is less predictable, novel and exceptional problems arise more frequently, increasing the demand for managerial attention and time.[11]

Learning costs (c), information costs (h), and predictability (λ) jointly determine whether and how production problems are resolved via a hierarchical mechanism, thereby shaping a firm's hierarchy in terms of depth L (number of layers) and the span of control B (subordinates per supervisor).

2.2. Depth and span of control

Consider first the simplest case: an entrepreneur hires n workers and organizes a two-layer hierarchy, where the entrepreneur is at the top. Let subscript E denote the entrepreneur and w the workers. The firm addresses problems in the interval $[0, z_w + z_E]$. Specifically, workers solve a fraction $\left(1 - e^{-\lambda \cdot z_w}\right)$ of problems, while unsolved problems ($e^{-\lambda \cdot z_w}$) are escalated to the entrepreneur. The entrepreneur allocates h unit of time to communicate solutions to these problems. The firm's expected output (revenues) under this setup is: $Q \cdot \left[\frac{1-e^{-\lambda \cdot (z_w + z_E)}}{h \cdot e^{-\lambda \cdot z_w}}\right]$. Moreover, learning costs differ between the entrepreneur ($c_E \cdot z_E$) and the workers ($n \cdot c_w \cdot z_w$), with $c_E < c_W$. The net expected output is therefore expressed as:

$$y^2 = Q \cdot \left[\frac{1-e^{-\lambda \cdot (z_w + z_E)}}{h \cdot e^{-\lambda z_w}}\right] - c_E \cdot z_E - n \cdot c_w \cdot z_w \qquad (1)$$

Where the apex 2 indicates that the firm has two layers.

Since the entrepreneur spends h unit of time for communicating solutions and c_E unit of time for learning knowledge to solve problems that fall outside workers' knowledge set ($e^{-\lambda \cdot z_w}$), her time

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[10] The exponential distribution models independent event probabilities with decreasing likelihood, aligning with the idea that when agents have limited knowledge, their capacity to solve problems decreases as problem complexity or difficulty increases (Garicano, 2000).

[11] Early qualitative insights by Mintzberg (1973) and Kotter (1990) are complemented by the most comprehensive and systematic evidence to date provided by Bandiera et al. (2020), who examined 42,233 time-use observations from 1,114 manufacturing CEOs across six countries. Their findings reveal nuanced patterns in how managers allocate their time, including distinct modes of interaction with operational and strategic functions.

constraint is $n \cdot (h + c_E) \cdot e^{-\lambda \cdot z_w} \leq 1$. Thus, the span of control for the entrepreneur is: $n \leq \frac{e^{\lambda \cdot z_w}}{h+c_E}$. This means that the maximum number of workers an entrepreneur can supervise is inversely proportional to information costs (h) and the entrepreneur's learning costs (c_E), and directly proportional to the workers' problem-solving set (z_w) and the predictability parameter (λ). Thus, at maximum, the entrepreneur's span of control in a two-layer hierarchy is:

$$B_E^2 = \frac{e^{\lambda \cdot z_w}}{h+c_E} \qquad (2)$$

Substituting (2) into (1), the net expected output can be rewritten as:

$$y^2 = Q \cdot \left[\frac{1-e^{-\lambda \cdot (z_w + z_E)}}{h \cdot e^{-\lambda \cdot z_w}}\right] - c_E \cdot z_E - B_E^2 \cdot c_w \cdot z_w \qquad (3)$$

The firm hierarchy is thus characterized by depth $L = 2$ and span of control $B_E^2 = \frac{e^{\lambda \cdot z_w}}{h+c_E}$.

Generalizing (2) to a firm with L layers, there exist $(L - 1)$ spans of control. At layer l, the span of control is:

$$B_l^L = \frac{e^{\lambda \cdot z_{l-1}}}{h+c_l} \qquad (4)$$

Consider now the firm introduces an intermediate k-th layer between the workers and the entrepreneur. The firm will add this layer if net output with the k-th layer exceeds that without it. That is, if:

$$Q \cdot \frac{1 - e^{-\lambda \cdot (z_E + z_k + z_w)}}{h \cdot (e^{-\lambda \cdot z_k} + e^{-\lambda \cdot z_w})} - c_E \cdot z_E - B_E^3 \cdot c_k \cdot z_k - B_k^3 \cdot c_w \cdot z_w$$
$$> Q \cdot \frac{1 - e^{-\lambda \cdot (z_E + z_w)}}{h \cdot e^{-\lambda \cdot z_w}} - c_E \cdot z_E - B_E^2 \cdot c_w \cdot z_w$$

Simplifying further, the condition becomes:[12]

$$Q \cdot \frac{-e^{-\lambda \cdot (z_E + z_k + 2z_w)} - e^{-\lambda \cdot z_k} + e^{-\lambda \cdot (z_E + z_k + z_w)} + e^{-\lambda \cdot (z_E + 2z_w)}}{[e^{-\lambda \cdot (z_k + z_w)} + e^{-2\lambda \cdot z_w}]}$$
$$> h \cdot \frac{e^{\lambda \cdot z_k} \cdot c_k \cdot z_k \cdot (h + c_k) + e^{\lambda \cdot z_w} \cdot c_w \cdot z_w \cdot (c_E - c_k)}{(h + c_E) \cdot (h + c_k)}$$

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[12] See the Online Appendix A.1 for the detailed steps leading to this condition.

Generalizing to a firm with L layers, the firm adds the k-th layer if:

$$Q \cdot \frac{-e^{-\lambda \cdot (z_{k+1}+z_k+2z_{k-1})} - e^{-\lambda \cdot z_k} + e^{-\lambda \cdot (z_{k+1}+z_k+z_{k-1})} + e^{-\lambda \cdot (z_{k+1}+2z_{k-1})}}{\left[e^{-\lambda \cdot (z_k+z_{k-1})} + e^{-2\lambda \cdot z_{k-1}}\right]} > h \cdot \frac{e^{\lambda \cdot z_k} \cdot c_k \cdot z_k \cdot (h+c_k) + e^{\lambda \cdot z_{k-1}} \cdot c_{k-1} \cdot z_{k-1} \cdot (c_{k+1}-c_k)}{(h+c_{k+1}) \cdot (h+c_k)} \qquad (5)$$

In Equation (5), the left-hand side captures the *marginal benefit*, that is, the additional output stemming from the k-th layer's knowledge, which increases the probability of solving problems. The right-hand side reflects the *marginal cost*, which arises from the higher information and learning costs associated with adding the k-th layer.

2.3. Extension of the model and assumptions on emerging technologies

Building on the theoretical framework of knowledge-based hierarchies, we distinguish between two broad categories of emerging technologies and their differential effects on information costs, learning costs, and predictability. As outlined in the Introduction, the first category, EIT, comprises technologies related to the collection, storage, processing, and transmission of information, which we refer to as EIT. These include the IoT, AR/VR, BDA, and ISU. The second category, RT, consists of robots, which primarily substitute for physical and operational tasks.[13]

These two technology categories have distinct effects on information costs, learning costs, and predictability. EIT generally facilitate inter-layer communication and expedite knowledge acquisition in production processes. For instance, IoT sensors continuously monitor performance parameters such as vibration or temperature, triggering automatic alerts upon anomalies and thereby reducing information costs between lower operational layers and upper managerial layers (*The Economist*, April 2, 2022). AR glasses and VR-supported tablets provide real-time repair guidance, reducing learning costs by offering on-demand, stepwise assistance (Eversberg and Lambrecht, 2023). BDA synthesize complex sensor outputs into actionable operational insights, shortening interpretative time. Collectively, these tools enhance production by gathering IoT-derived data, processing it into

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[13] This distinction is consistent with existing classifications in the literature. For example, Caselli et al. (2024) distinguish between Informational Digital Technologies (IDT), encompassing IoT, BDA, and AR/VR and primarily related to information collection and utilization, and Operational Digital Technologies (ODT), which are designed to perform manual and physical tasks. These categories map closely onto our EIT and RT classifications. Similarly, Martinelli et al. (2021) and Sestino et al. (2020) emphasize that IDT facilitate workflow redesign, operational efficiency, remote work integration, and the protection of firm knowledge, whereas ODT primarily automate routine manual labor. Pedota et al. (2023) propose a comparable taxonomy distinguishing "digital technologies" (AR, BDA, and cloud computing) from "physical technologies" (RT and 3D printing), which closely parallels our EIT-RT distinction. One notable difference concerns the IoT, which they classify as hybrid due to its digital-physical nature, whereas we classify IoT within EIT given its primary role in data capture and information flows.

intelligible information, and conveying solutions via immersive AR/VR devices. However, despite these advantages, EIT adoption also introduces organizational challenges. Subordinates and managers alike must acquire specialized knowledge to use these tools. This raises learning costs due to required skill upgrades. OECD reports corroborate this rising skill trend related to these emerging technologies (OECD, 2021; 2022). Caselli et al. (2024) further note that IDT (EIT, in our classification) adoption increases demand for skilled labor and spurs firm investments in IDT-specific training and human capital development. Thus, while EIT clearly reduces information costs, its effect on learning costs is ambiguous. The net impact of EIT on firms' hierarchy is not clear-cut, depending on the balance between gains in informational efficiency and burden of learning.

RT exhibit similarly ambiguous effects on information costs, learning costs, and production predictability. In automotive manufacturing, for example, robots perform precise welds that are essential for vehicle safety and durability, often outperforming human labor, which is subject to fatigue and distraction (International Federation of Robotics, 2025). In its retail e-commerce operations, Amazon has deployed more than one million robots globally and, in some warehouses, the number of robots exceeds that of human workers (Herrera, 2025). However, RT do not invariably enhance the predictability of production processes. In some cases, they may even reduce predictability. The well-known Tesla case illustrates how excessive automation can generate severe production disruptions. In 2018, Elon Musk acknowledged that the heavy reliance on robots in the production of the Model 3 contributed to what he described as "production hell," reflecting heightened system complexity and the eventual need to reintroduce human labor to address operational failures (CBS News, 2018). Similarly, in the same year, Volkswagen encountered difficulties integrating robots into its manufacturing processes, particularly in coordinating interactions between human workers and robots, leading to operational inefficiencies and delays in vehicle output (Reuters, April 25, 2018).

Synthesizing the literature and related anecdotal evidence, as summarized in Table 2, we derive the following assumptions. First, EIT reduce information costs ($\Delta h < 0$) but have an ambiguous effect on learning costs ($\Delta c < 0$ or $\Delta c > 0$), since advanced digital tools lower barriers to information flow while simultaneously increasing skill requirements. Second, RT have an ambiguous effect on predictability ($\Delta\lambda < 0$ or $\Delta\lambda > 0$), often enhancing it by reducing exceptions but sometimes diminishing it through emergent operational complexities.

[Insert Table 2 about here]

2.4. Hypotheses

Using Equations (4) and (5), and considering Table 2, we now derive our main four hypotheses. For simplicity, all hypotheses are formulated as conditions under which investments in each emerging technology (EIT or RT) has a positive impact on one dimension of the hierarchy (span of control or depth). Specifically, Hypotheses 1 and 2 concern the *positive* impact of investments in EIT and RT on changes in the span of control, while Hypotheses 3 and 4 regard the *positive* impact of EIT and RT on changes in depth.

Hypothesis 1. EIT and span of control.

Since investments in EIT reduce information costs but have ambiguous effects on learning costs, a positive impact on the span of control, B_l*, requires that* $\Delta h + \Delta c_l < 0$.

According to Table 2, investments in EIT reduce information costs, facilitating communication across layers, while its effects on learning costs are mixed. Two scenarios are possible: under *Scenario A*, EIT reduce information costs ($\Delta h < 0$) and learning costs ($\Delta c_l < 0$); under *Scenario B*, EIT reduce information costs ($\Delta h < 0$) but increase learning costs ($\Delta c_l > 0$). Table 3 summarizes these scenarios. In both cases, since EIT do not affect the numerator of Equation (4), the span of control increases if $\Delta h + \Delta c_l < 0$; that is, either EIT reduce both information and learning costs (*Scenario A*), or the reduction in information costs is, in absolute value, greater than the increase in learning costs (*Scenario B*).

[Insert Table 3 about here]

Conversely, when $\Delta h + \Delta c_l > 0$, we predict that investments in EIT have a negative effect on the span of control. In this case, EIT increase learning costs, as in *Scenario B*, but the increase in learning costs outweighs, in absolute value, the reduction in information costs.

Hypothesis 2. RT and span of control.

Since investments in RT affect predictability in an ambiguous way, a positive impact on the span of control, B_l*, requires* $\Delta\lambda > 0$.

From Table 2, investments in RT do not affect the denominator of Equation (4), so the span of control increases if the numerator of Equation (4) increases, i.e. if $\Delta\lambda > 0$, as shown in *Scenario C* in Table 4.

[Insert Table 4 about here]

Hypothesis 3. EIT and depth.

Since investments in EIT reduce information costs but have ambiguous effects on learning costs, a positive impact on depth (L), i.e. the addition of the k-th layer, requires a specific relationship between changes in learning costs between the additional layer and its supervisors: $\Delta c_k - \Delta c_{k+1} < \frac{\Delta c_k \cdot (\Delta h + \Delta c_k)}{\Delta c_{k-1}}$.

This condition implies that investments in EIT shift relative learning costs in favor of individuals in the additional k-th layer compared with their supervisors at the $(k+1)$-th layer, making net gains from adding organizational layers positive.

By rearranging Equation (5) and noting that EIT do not affect predictability (cf. Table 2), the impact of EIT investments on depth will be positive (i.e., the addition of the kth-layer will occur) if:

$$Q \cdot \frac{e^{-\lambda \cdot (z_{k+1} + z_k + z_{k-1})} + e^{-\lambda \cdot (z_{k+1} + 2z_{k-1})} - e^{-\lambda \cdot (z_{k+1} + z_k + 2z_{k-1})} - e^{-\lambda \cdot z_k}}{\left[e^{-\lambda \cdot (z_k + z_{k-1})} + e^{-2\lambda \cdot z_{k-1}}\right]} > \Delta h \cdot \frac{e^{\lambda \cdot z_k} \cdot \Delta c_k \cdot z_k \cdot (\Delta h + \Delta c_k) + \Delta c_{k-1} \cdot z_{k-1} \cdot e^{\lambda \cdot z_{k-1}} \cdot (\Delta c_{k+1} - \Delta c_k)}{(\Delta h + \Delta c_{k+1}) \cdot (\Delta h + \Delta c_k)} \quad (6)$$

Since the left-hand side of Equation (6) does not change relative to Equation (5) (according to Table 2, investments in EIT do not affect the components of the left-hand side of inequality (6)), the probability that the firm introduces a k-th layer increases if

$$\Delta h \cdot \frac{\Delta c_k \cdot (\Delta h + \Delta c_k) + \Delta c_{k-1} \cdot (\Delta c_{k+1} - \Delta c_k)}{(\Delta h + \Delta c_{k+1}) \cdot (\Delta h + \Delta c_k)} < 0 \quad (7)$$

This leads two scenarios (Table 5): that is, either EIT reduce both information and learning costs (*Scenario D*), or the EIT reduce information costs but increase learning costs (*Scenario E*).

[Insert Table 5 about here]

In summary, EIT can increase L in two ways: (i) by reducing learning costs more strongly at layer k than at layer $k+1$ (*Scenario D*), or (ii) by increasing learning costs less at layer k than at layer $k+1$ (*Scenario E*). More specifically, in *Scenario D*, because $\Delta h < 0$, $\Delta c_{k+1} < 0$, $\Delta c_k < 0$ and $\Delta c_{k-1} < 0$, then $\Delta h \cdot \frac{1}{(\Delta h + \Delta c_{k+1}) \cdot (\Delta h + \Delta c_k)}$ in Equation (7) is negative. Inequality (7) holds if $\Delta c_k \cdot (\Delta h + \Delta c_k) + \Delta c_{k-1} \cdot (\Delta c_{k+1} - \Delta c_k) > 0$ or, simplified, if:

$$\Delta c_k - \Delta c_{k+1} < \frac{\Delta c_k \cdot (\Delta h + \Delta c_k)}{\Delta c_{k-1}} \quad (8)$$

Inequality (8) is the condition indicated in Hypothesis 3. Since its right-hand side is negative, the *necessary* condition for an increase in depth is that $|\Delta c_k| > |\Delta c_{k+1}|$. In the *Scenario D*, investments in EIT must reduce learning costs more for the k-th layer than for their supervisors at the $(k+1)$-th layer.[14]

In *Scenario E*, EIT reduce information costs but increase learning costs. Here, because $\Delta h < 0$, $\Delta c_{k+1} > 0$, $\Delta c_k > 0$ and $\Delta c_{k-1} > 0$, then we can distinguish sub-scenarios E1 and E2, which are summarized in Table 5. In *sub-scenario E1*, the negative effects on information costs and the positive effects on learning costs sum up to a positive value, meaning $\Delta h + \Delta c_k > 0$ and $\Delta h + \Delta c_{k+1} > 0$. In this case, $\Delta h \cdot \frac{1}{(\Delta h+\Delta c_{k+1})\cdot(\Delta h+\Delta c_k)}$ is negative, and inequality (8) still holds. However, the right-hand side of it is now positive. Therefore, a *sufficient* condition for an increase in depth is that $\Delta c_{k+1} > \Delta c_k$. *Sub-scenario E2* occurs when the negative effects on information costs and the positive effects on learning costs sum to a negative value, meaning $\Delta h + \Delta c_k < 0$ and $\Delta h + \Delta c_{k+1} < 0$. Here the expression $\Delta h \cdot \frac{1}{(\Delta h+\Delta c_{k+1})\cdot(\Delta h+\Delta c_k)}$ is negative and inequality (8) still holds. Since the right-hand of it is negative, a *necessary* condition for an increase in depth is that $\Delta c_{k+1} > \Delta c_k$. This means, as in *sub-scenario E1*, investments in EIT increase learning costs for supervisors at the $(k+1)$-th layer more than for the k-th layer.

Hypothesis 4. RT and depth.

Since investments in RT affect predictability in an ambiguous way, a positive impact on depth (L), that is, the addition of the k-th layer, requires $\Delta\lambda > 0$ and that the knowledge base of the additional layer exceeds at least the combined knowledge bases of both its upper and lower layers, i.e., $z_k > z_{k-1} + z_{k+1}$.

When investments in robot positively affect predictability (Table 2), both sides of inequality (6) are influenced. An increase in predictability ($\Delta\lambda > 0$) raises its right-hand side of the inequality (through the terms $e^{\Delta\lambda\cdot z_k}$ and $e^{\Delta\lambda\cdot z_{k-1}}$). This, in turn, reduces the likelihood that inequality (6) will hold, thereby making it less likely that the firm will add the k-th layer. For inequality (6) to remain valid (i.e., the firm will increase its hierarchical depth), the left-hand side must also rise. Using a first-order Taylor expansion, the left-hand side can be expressed as $Q \cdot \frac{\Delta\lambda\cdot(z_k - z_{k-1} - z_{k+1})}{2}$.[15] Consequently, for organizational depth to increase as $\Delta\lambda$ rises, the term $\Delta\lambda \cdot (z_k - z_{k-1} - z_{k+1})$ must be positive. This requires that $z_k - z_{k-1} - z_{k+1} > 0$, that is, $z_k > z_{k-1} + z_{k+1}$. This necessary condition

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[14] This is a *necessary* but not *sufficient* condition: it does not capture every possible case where inequality (8) holds, but it provides a stringent requirement.

[15] The reader is cross-referred to Online Appendix A.2 for detailed steps.

represents a special case in which the knowledge base of the added layer k (z_k) is large enough to exceed the combined knowledge of its adjacent lower and upper layers ($z_{k-1} + z_{k+1}$). Under this condition, investments in robot may lead to an increase of hierarchical depth, as summarized in Scenario *F* of Table 6.

[Insert Table 6 about here]

However, under a more reasonable distribution of knowledge, i.e., $z_k \leq z_{k-1} + z_{k+1}$, the k-th layer does not possesses more knowledge than the sum of its adjacent layers. In this case, improvements in predictability brought about by investments in robots tend to flatten rather than deepen organization hierarchies, reducing the probability for additional layers.

3. Empirical analysis

3.1 Identification strategy

Building on the theoretical framework derived in Section 2, we define the average treatment effect (ATE) of investing in emerging technologies on changes in the organizational hierarchy of firm f, denoted O_f, conditional on a vector of changes in observables $\Delta \boldsymbol{V}_f$, as:

$$ATE = E\left[\Delta O_{1f} - \Delta O_{0f} \,|\, \Delta \boldsymbol{V}_f\right] \quad (9)$$

where ΔO_{1f} and ΔO_{0f} denote the potential changes in firm hierarchy if the firm does and does not invest in emerging technologies, respectively. The Δ prefix denotes the change in a variable from the previous period $(t-1)$ to the current one (t). We focus on two distinct dimensions of the hierarchy: the number of layers (L_{ft}) and the average span of control (B_{ft}). L_{ft} captures the vertical dimension (or depth) of the hierarchy, measured as the number of organizational layers within firm f in year t. B_{ft} reflects the horizontal dimension (or breadth) of the hierarchy, defined as the average number of subordinates per supervisor across adjacent non-empty layers within the firm. The fundamental challenge with observational data, such as the data used in this paper, is that for each firm *f*, we observe either ΔO_{1f} or ΔO_{0f}, but not both. For firms that do not invest in emerging technologies (the "controls"), the observed outcome (ΔO_f) equals ΔO_{0f}; for firms that do invest (the "treated") the observed outcome equals ΔO_{1f}.

3.2 Empirical specifications

To estimate the ATE in (9) in a panel setting, we specify an empirical model in first differences[16] as:

$$\Delta O_{ft} = \Delta \boldsymbol{ET}_{ft}^{\prime s}\boldsymbol{\beta} + \Delta \boldsymbol{X}_{ft}^{\prime}\boldsymbol{\gamma} + \Delta\tau_t + \alpha_j + \alpha_r + \Delta\varepsilon_{ft}\ . \quad (10)$$

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[16] This first-difference model is derived from a level specification in which the organizational hierarchy is expressed as a function of the stock of investments in emerging technologies (*ET*), a vector of firm-level characteristics, firm fixed effects, and year fixed effects. The levels equation is: $O_{ft} = \boldsymbol{ET}_{ft}^{\prime s}\boldsymbol{\beta} + \boldsymbol{X}_{ft}^{\prime}\boldsymbol{\gamma} + \alpha_f + \tau_t + \varepsilon_{ft}$. Taking first differences eliminates the firm fixed effects, α_f (yielding the specification shown in Equation 10), which is a central step in our identification strategy. By removing time-invariant unobserved heterogeneity, we get closer to the ideal experiment of comparing two otherwise identical firms, i.e. one that invests in emerging technologies and one that does not. A second reason for adopting a first-difference specification is that, in the dataset we employ (see Section 3.3), we do not directly observe the stock of emerging technologies, nor do we have information on the monetary value of firm-level investments. Rather, we observe whether a firm has made any investment in *RT*, in *EIT*, or in both, between periods $t-1$ and t; that is, what we observe is a multi-valued categorical treatment. We therefore assume that any reported investment corresponds to a positive change in the stock of the respective *ET* between the two observation periods, even if we cannot distinguish whether the reported investment represents the firm's first-ever investment (adoption) in that technology or an additional investment.

The dependent variable ΔO_{ft} denotes the change in either the number of layers or the average span of control of firm f. The treatment vector $\Delta \boldsymbol{ET}^{s}_{ft}$ refers to the change in the stock (superscript "S") of emerging technologies (*ET*) and includes four possible treatment states: no change in the stock, change in the stock of robots only (*RT*), change in emerging information technologies only (*EIT*), and change in the stock of both technologies (*RT* × *EIT*). The vector $\Delta \boldsymbol{V}_f$ in (9) as the set of conditioning variables for ATE identification, is operationalized through two components in first differences: the vector of time-varying firm-level characteristics $\Delta \boldsymbol{X}_{ft}$, and year effects $\Delta \tau_t$. The term $\Delta \varepsilon_{ft}$ denotes the idiosyncratic error in differences. We augment the model with industry (α_j) and region (α_r) fixed effects, which control for industry- and region-specific trends in both changes in the stock of emerging technologies and changes in a firm's organizational structure.

Leveraging data on firms' investment activities (see Section 3.3), and assuming that observed investments proxy for changes in the stock of *ET*, we estimate the effect of investments in *ET* on changes in firms' hierarchical depth and average span of control. Accordingly, Equation (10) can be rewritten as:

$$\Delta O_{ft} = \boldsymbol{ET}'^{\boldsymbol{I}}_{ft} \boldsymbol{\beta} + \Delta \boldsymbol{X}'_{ft} \boldsymbol{\gamma} + \Delta \tau_t + \alpha_j + \alpha_r + \Delta \varepsilon_{ft} \quad (11)$$

where $\boldsymbol{ET}'^{\boldsymbol{I}}_{ft}$ refers to investments (superscript "I") in emerging technologies. It is defined as a vector stacked as $\left[RT^{I}_{ft}, EIT^{I}_{ft}, RT^{I}_{ft} \times EIT^{I}_{ft}\right]$, where each element is a binary indicator equal to 1 if the firm reports an investment in that category between periods $t-1$ and t, and 0 otherwise.
The empirical model becomes:

$$\Delta O_{ft} = \beta_1 RT^{I}_{ft} + \beta_2 EIT^{I}_{ft} + \beta_3 RT^{I}_{ft} \times EIT^{I}_{ft} + \Delta X'_{ft} \gamma + \Delta \tau_t + \alpha_j + \alpha_r + \Delta \varepsilon_{ft} \quad (12)$$

where β_1, β_2, and β_3 capture the effects of investment in *RT*, in *EIT*, and in both technologies (*RT* × *EIT*) on changes in organizational hierarchy, relative to the baseline group of firms that made no such investments.

This specification, estimated via OLS, allows us to identify separate ATEs for each type of investment, provided that four assumptions hold. The first assumption is the Conditional Independence Assumption (CIA). The CIA requires that, conditional on the vector of covariates ΔV_f, the treatment assignment (i.e., whether a firm invests in *ET*), is independent of the potential outcomes. Formally, this means that:[17]

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[17] For simplicity, we use the treatment vector $\boldsymbol{ET}^{\boldsymbol{I}}_{ft}$, and collapse the covariates into a single vector ΔV_f, which includes both firm-level controls and fixed effects. Moreover, we omit the time subscript.

$$\left(\Delta O_{0f}, \Delta O_{1f}\right) \perp \boldsymbol{ET}_f^{\boldsymbol{I}} \mid \Delta V_f .$$

The second assumption refers to the correct model specification, including a homogeneous treatment effect across firms. The third assumption is that the data are independently and identically distributed (i.i.d.) draws from the population. This implies that each firm's potential changes in hierarchy and investment decisions are independent of those of other firms in the population. Finally, the overlap assumption requires that for all values of ΔV_f, the probability of each treatment category lies strictly between zero and one:

$$0 < P(\boldsymbol{ET}_f^{\boldsymbol{I}} = e_k \mid \Delta V_f) < 1, \text{ for } k = 0, 1, 2, 3 \,,$$

where $e_0 = [0{,}0{,}0]'$ (no investment), $e_1 = [1{,}0{,}0]'$ (*RT* only), $e_2 = [0{,}1{,}0]'$ (*EIT* only), and $e_3 = [0{,}0{,}1]'$ (investment in both technologies).

We acknowledge that time-varying unobservables may still pose a threat to identification and, for this reason, maintain the CIA throughout the paper. At the same time, we relax other identifying assumptions by estimating alternative models and comparing their results to those obtained from the OLS estimation of Equation (12). We first adopt a regression adjustment model (RA), which allows for treatment effect heterogeneity. This is equivalent to a fully interacted model, where the relationship between covariates ΔV_f and changes in firm hierarchy is allowed to differ between firms that invest in emerging technologies and those that do not. The model can be written as:

$$\Delta O_{ft} = \boldsymbol{ET}'^{\boldsymbol{I}}_{ft}\boldsymbol{\beta} + \Delta\boldsymbol{V}'_f\boldsymbol{\gamma} + (\boldsymbol{ET}^{\boldsymbol{I}}_{ft} \times \Delta\boldsymbol{V}'_f)\boldsymbol{\delta} + \Delta\varepsilon_{ft} \qquad (13).$$

Second, to address the overlap assumption, we estimate an inverse probability weighted regression adjustment (IPWRA) model. In this model, we give greater weight to observations where the overlap condition is satisfied by using the estimated propensity scores (PS) as inverse weights in the outcome model (Equation 13).[18] We estimate the PS model using a multinomial logit specification, reflecting the multivalued nature of the treatment, and include all relevant observable confounders. Let $k = 0{,}1{,}2{,}3$ indicate the four mutually exclusive investment decisions, i.e. no investment ($k = 0$; baseline), RT only ($k = 1$), EIT only ($k = 2$), and RT × EIT ($k = 3$). Then

$$p_k\left(\boldsymbol{ET}^{\boldsymbol{I}}_{ft} = k \mid \boldsymbol{W}_{ft-1}\right) = \frac{\exp\left(g_k(\boldsymbol{W}_{\boldsymbol{ft-1}})\right)}{1+\sum_{j=1}^{3} \exp\left(g_j(\boldsymbol{W}_{\boldsymbol{ft-1}})\right)}, \qquad (14)$$

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[18] These scores represent the predicted probability that the firm (i) does not invest in emerging technologies, (ii) invests only in robots, (iii) only in EIT, or (iv) in both.

where $g_k\left(\boldsymbol{W}_{ft-1}\right) = \boldsymbol{W}_{ft-1}'\boldsymbol{\mu}_k$. The vector $\boldsymbol{W}_{ft-1}$ includes both all variables in the outcome model ($\boldsymbol{V}_{ft-1}$) in levels, and additional pre-treatment variables that may influence a firm's likelihood of investing in emerging technologies. We measure these covariates at $t-1$ (namely, before the investment decision) to minimize the risk that they are influenced by the treatment itself, which would violate the CIA. The inverse probability weight (IPW) associated with investment decision k is:

$$IPW_{ft} = \frac{1}{p_k(\boldsymbol{W}_{ft-1})}, \quad (15)$$

where k is the treatment category actually received.[19] These weights are applied in the outcome model (Equation 13). The IPW technique reduces the association between covariates and treatment, thereby improving covariate balance across the four treatment groups (Stürmer et al. 2010; 2021). Firms whose observed treatment category has a high predicted probability (for example a firm that invests in RT when its covariates strongly predict investments in robots) receive a weight close to one. Firms whose observed treatment is relatively unlikely, given their covariates, receive a larger weight so that their characteristics are proportionally up-weighted in the reweighted sample.[20]

In the linear, RA, and IPWRA models, we cluster standard errors at the firm level. However, changes in a firm's organizational hierarchy and its investment decisions may also be correlated across firms, particularly within the same region or industry. To address this concern, we conduct robustness checks by re-estimating the empirical model using two additional clustering structures that account for potential correlation across firms operating in the same sector and region.

To summarize, in the RA model, the ATE for each investment category ($k = 1, 2, 3$) is calculated as the unweighted mean of the difference between the predicted change in organizational hierarchy and the predicted change under the baseline of no investment ($k = 0$). In the IPWRA model, the ATE is weighted using the weights computed in Equation (15). The IPWRA model yields a doubly robust estimate of the effect of investing in emerging technologies on changes in a firm's hierarchical structure and, thus, it is our preferred empirical strategy.

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[19] Note that for each firm-year pair, the sum of the four PS is constrained to one, i.e. $\sum_{k=0}^{3} p_k(\boldsymbol{W_{ft-1}}) = 1$. Each observation (firm-year pair) is weighted by the inverse probability associated with its realized treatment.

[20] To further strengthen the IPWRA estimates, we conduct a robustness check that trims observations falling outside the region of common support.

3.3 Data and descriptive analysis

3.3.1 The RIL database

This study relies on firm-level data drawn from RIL, a longitudinal survey conducted by INAPP. The RIL survey is mandatory and covers a representative sample of Italian partnerships and limited liability companies across all size classes operating in the private, non-agricultural sectors. Italy represents a compelling case study for examining the impact of emerging technologies on firm hierarchy for three main reasons. First, Italy ranks as the second European country, after Germany, in terms of robot adoption (IFR, 2018; Dottori, 2021), making investments in robots relatively more widespread than in most other European economies. Second, the disappointing performance of the Italian economy over the past three decades, especially regarding productivity growth, has been widely discussed in both academic research and the popular press (see Krugman, 2012; Hassan and Ottaviano, 2013; Bugamelli et al., 2018, among others). In this context, emerging technologies may provide firms in both manufacturing and services with a key lever to improve internal organization and competitiveness. Third, given that Italian firms exhibit organizational structures comparable to those of firms in other European countries (Pieri and Vatiero, 2025), the analysis of the Italian case can yield insights that are broadly relevant for other advanced economies. A key advantage of the RIL database is its rich detail on firm-level labor organization. It provides information on the number of employees by occupational category, which allows us to construct firm-level measures of the number of hierarchical layers and the average span of control. Moreover, RIL collects extensive information on firms' investments in various types of emerging technologies.

The RIL survey has been conducted in six waves between 2005 and 2022, with varying time intervals between waves. The information collected in each wave refers to firm conditions at the end of the previous year.[21] The 2018 and 2022 waves include questions on firms' investments in emerging technologies undertaken during the previous three years. Based on this information, we construct two key binary treatment indicators. The first captures investments in EIT and equals one if the firm reports investing in at least one of IoT, AR/VR, BDA, or ISU during the relevant three-year window, and zero otherwise. The second indicator captures investments in RT and equals one if the firm reports investing in robots during the previous three years. We also construct an interaction term (RT × EIT), equal to one when a firm invests in both categories. Given the availability of investment information, our main analysis focuses on the 2015, 2018, and 2022 waves. We compute changes in the two dimensions of firm hierarchy, O_{ft}, specifically the number of hierarchical layers L_{ft} and the average

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[21] For example, the 2018 wave contains information on firms that refer to the end of 2017 and, for some variables, to the period 2015-2017. The same lag applies to the other waves.

span of control B_{ft} over two periods: from the end of 2014 to the end of 2017, and from the end of 2017 to the end of 2021. These changes are related to investments undertaken during the corresponding three-year windows, 2015-2017 (reported in the 2018 wave) and 2019-2021 (reported in the 2022 wave). In a robustness check described in Section 3.4.4.1, we additionally exploit the 2010 wave to test for anticipatory effects. All control variables are measured in first differences, consistently with the dependent variables, and refer to the same time intervals. The temporal structure of the dataset is shown in Figure 1.

[Insert Figure 1 about here]

By merging the four available waves (2010, 2015, 2018, and 2022), we begin with an unbalanced panel of 76259 firms. Since information on investments in emerging technologies is available only in the 2018 and 2022 waves, our main analysis focuses on the 2015, 2018, and 2022 waves, while the 2010 wave is used exclusively for the anticipatory-effects robustness check. We implement a series of data-cleaning procedures, including the exclusion of firms that change regional location, inactive firms, and observations with extreme values in key variables. A detailed description of these procedures is provided in Online Appendix B.1. As specified in Equation (12), our baseline empirical model relates changes in hierarchical dimensions in the periods 2014-2017 and 2017-2021 to investments undertaken in 2015-2017 and 2019-2021, respectively. Estimation therefore requires firms to be observed in at least two consecutive waves among 2015, 2018, and 2022. After additionally excluding observations with missing values in the variables required for the empirical models (Equations 12 and 14), the final estimation sample consists of 19188 observations corresponding to 14793 firms.

3.3.2 Data on firm hierarchy and on emerging technologies

To operationalize the two primary dimensions of firm hierarchy, namely, the number of layers (L_{ft}) and the average span of control (B_{ft}), we use occupational data provided in the RIL survey. A layer (l) is defined as a group of employees with comparable knowledge set. The RIL database enables us to track the number of employees in four occupational categories consistently defined across survey waves: (i) managers, (ii) middle managers, (iii) clerical employees and white-collar workers, and (iv) blue-collar workers. Following Caliendo et al. (2015, 2020), and Pieri and Vatiero (2025), we classify and order these occupational categories into four hierarchical layers as follows:

- *layer* 1: Workers, including (iii) clerical and white-collar workers and (iv) blue-collar workers;
- *layer* 2: Middle managers, including employees in category (ii);

- *layer* 3: Managers, including employees in category (i);
- *layer* 4: Entrepreneur or owner, who is present in all firms (Caliendo and Rossi-Hansberg, 2012).

With this classification, we construct proxies for both the vertical and horizontal dimensions of firm hierarchy. We count the number of non-empty layers in each firm to measure the firm's depth (Colombo and Delmastro, 1999; Colombo and Delmastro, 2004; Colombo and Grilli, 2013; Caliendo et al., 2015; 2020):

$$L_{ft} = \text{number of non-empty layers in firm } f \text{ in year } t.$$

This count variable L_{ft} ranges from 1 (e.g., a one-layer firm or a self-employed individual, i.e., the entrepreneur) to 4 (i.e., the firm has at least one employee in each layer). To capture the horizontal dimension of hierarchy, we calculate the firm-level average span of control B_{ft} as follows. Using the number of employees in each layer, we compute the span of control for each layer B_{lft} as the number of subordinates in layer $l-1$ per supervisor in layer l. If layer l is empty, we divide the number of employees in layer $l-1$ by the number of supervisors in the next non-empty upper layer $(l+1)$, up to the entrepreneur layer, which is always non-empty. The firm-level average span of control is then given by:

$$B_{ft} = \frac{\sum_l B_{lft}}{L_{ft} - 1}$$

By construction, firms with $L_{ft} = 1$ have $B_{ft} = 0$, as firms consisting only of the entrepreneur have no subordinates and therefore a null span of control. In the baseline empirical analysis, we exclude these firms because they represent a peculiar case in which hierarchical structure is absent. However, in Section 3.4.4.2 we re-estimate the models including one-layer firms to verify that their exclusion does not drive the results. To assess the suitability of the RIL occupational classification for constructing proxies of hierarchical structure in Italian firms, we examine the distribution of firm size by number of organizational layers in Figure 2.

[Insert Figure 2 about here]

Firms with more layers tend to have more employees (Figure 2, panel A) and a higher turnover (Figure 2, panel B). These findings are consistent with both theory (e.g., Caliendo and Rossi-Hansberg, 2012) and empirical evidence from firms in France (Caliendo et al., 2015) and Portugal (Caliendo et al., 2020; Cooke et al., 2021).

We next describe how we construct the variables capturing firms' investments in ET. Using the information collected in the RIL survey on investments in specific Industry 4.0 technological areas, we define binary indicators capturing firms' investments in RT and EIT. Let RT_{ft} denote an indicator equal to 1 if firm f reports investments in robotics technologies in wave t, and 0 otherwise. Similarly, EIT_{ft} is defined as a binary variable equal to 1 if firm f reports investments in at least one emerging information technology (namely IoT, AR/VR, BDA, or ISU) and 0 otherwise. Finally, we construct the interaction term $RT_{ft} \times EIT_{ft}$, which identifies firms undertaking joint investments in both RT and EIT. Additional details on the questionnaire items used to construct these indicators are provided in Online Appendix B.2.1.

3.3.3 Descriptive analysis

Table 7 presents descriptive statistics comparing firms based on their investment status in emerging technologies, specifically no investments, investments in RT only, investments in EIT only and investments in both emerging technologies.[22]

[Insert Table 7 about here]

Without conditioning on other firm characteristics, firms that invested in EIT (columns 3 and 4) show a greater average increase in the number of hierarchical layers (+0.054 and +0.039, respectively) compared with firms that did not invest in EIT (columns 1 and 2). In contrast, firms that invested in RT (columns 2 and 4) show a smaller increase or even a reduction in the number of layers (-0.005 in column 2), relative to their counterparts not investing in RT (columns 1 and 3). This suggests that EIT investments may be associated with organizational deepening, while RT investments may be associated with a reduction in the number of hierarchical layers. Turning to changes in the span of control, firms that invested in both RT and EIT exhibit the largest increase in the average number of subordinates per supervisor (+1.323). In comparison, firms that did not invest in either technology show only a modest increase (+0.056). As for control variables, changes in workforce composition are heterogeneous by investment status. Firms that invested in EIT, either alone or in combination with RT, experienced the largest increases in the share of tertiary-educated employees (by 0.030 and 0.032, respectively), along with a relative increase in the share of workers receiving on-the-job training. These patterns suggest that investments in ET are often accompanied by workforce upgrading. The descriptive analysis also reveals substantial heterogeneity in the levels of firms' hierarchical dimensions. Firms that invested in both RT and EIT exhibit the highest average number

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[22] Online Appendix B.2.2 reports detailed definitions and summary statistics for all firm-level variables used in the empirical analysis.

of layers (3.067), followed by firms investing only in RT (2.709). Firms that did not invest in either technology show the lowest number of layers on average (2.344). The presence of managerial and middle-management layers is more common among firms that invested in emerging technologies. For instance, among firms investing in both RT and EIT, 50.4% have a managerial layer and 56.3% include middle managers. Differences in the span of control are most evident at the bottom of the hierarchy. For example, firms investing in both RT and EIT supervise, on average, 42.9 blue- and white-collar workers per supervisor, while firms that did not invest in emerging technologies supervise only 18.9.

It is important to note that firms investing in ET already exhibited different characteristics prior to the investment period ($t-1$). As shown by the (1-wave) lagged covariates included in the propensity score model, these firms were on average larger, more likely to invest in tangible and intangible assets, and had a greater share of employees in on-the-job training. They also had a lower reliance on temporary contracts, were more often led by CEOs with tertiary education, and were less likely to be family-owned. Furthermore, a higher share of these firms engaged in extraordinary transactions, had a union representative, and adopted a second-level wage bargaining scheme. These past differences underline the importance of accounting for the likelihood that the firm (i) does not invest in emerging technologies, (ii) invests only in robots, (iii) only in emerging information technologies, or (iv) in both, through the inverse probability weights, IPW_{ft}, defined in Section 3.2.

Figure 3 shows the standardized mean differences before applying IPW_{ft} and after. Values closer to zero indicate better covariate balance; the dashed lines at ± 0.25 represent the conventional threshold for acceptable imbalance (Imbens and Wooldridge, 2009).

[Insert Figure 3 about here]

There are substantial differences in observable characteristics (i.e., the pre-treatment variables used in the PS model) between firms that invest in emerging technologies (*RT*, *EIT*, or both) and those that do not. After applying the inverse probability weights, these differences are substantially reduced, indicating improved covariate balance. This improves the comparability of outcomes between treated and control firms. At the bottom of Figure 3, we also show previous-to-investment changes in the number of layers, in the span of control and in firm size. Reassuringly, prior to investment, firms were broadly similar in terms of changes in organizational depth, average span of control, and size suggesting comparable pre-trends between firms that invested in emerging technologies and those that did not.

Figure 4 shows the density of PSs for the four different values of the multivalued treatment variable. Each plot is categorized by the actual treatment value to which firms belong to. This figure provides an assessment of the condition of common support, which is one of the crucial requirements for estimating causal effects using IPWRA. Overall, the estimated PSs show a moderate degree of overlap across the groups, suggesting partial comparability of the distributions. Moreover, Figure 4 reveals that some PSs are near zero (top-right and bottom-right panel). These panels, which compare firms investing in only RT or in both technologies to the control group, display limited overlap in predicted probabilities, suggesting a weaker common support. For this reason, in a robustness check we will perform PS trimming (see Section 3.4.4.3), and we restrict the analysis to observations that fall within the region of common support.

3.4 Econometric results

3.4.1 OLS results: Firm-level analysis

Table 8 presents the OLS estimates of the effects of investing in emerging technologies on changes in the number of hierarchical layers within firms. The specification follows Equation (12).

[Insert Table 8 about here]

In columns (1) and (2), we separately introduce binary indicators for investment in RT and EIT, respectively. The coefficient estimate of RT investment is negative but not statistically significant, suggesting a potential larger reduction in the number of layers for firms that invest in RT compared with those that do not, though this effect lacks statistical precision. In contrast, EIT investment yields a positive and statistically significant coefficient estimate: firms that invest in EIT increase their number of layers by approximately 0.028 more than firms that do not invest in either technology. The magnitude of this effect corresponds to an additional change of about 1.075% (0.027/2.512 × 100) in the number of layers, relative to the sample average of 2.512 layers (see column 5, Table 7). This result is economically meaningful, considering that the average change in the number of layers in the sample is 0.030 (see column 5, Table 7). In column (3), we examine the impact of both independent and concurrent investments in RT and EIT using a multivalued treatment specification. The coefficient for firms investing in both technologies is 0.008 and not statistically significant, indicating no difference in the change in the number of layers relative to the baseline group (firms that invest in neither technology). A plausible explanation is that the opposing effects of the two technologies may cancel each other out, resulting in a null net impact. The separate effects within the same specification are consistent with the findings in columns (1) and (2), with investment in robots yielding a coefficient of -0.031 and investment in EIT yielding a coefficient of 0.028, the latter being statistically significant. At the bottom of column (3), we report marginal effects of investing in each technology. Specifically, we present: (i) the overall effect of switching from no investment to investing in RT (or

EIT); (ii) the effect of investing in RT (EIT) among firms that do not invest in EIT (RT); and (iii) the effect of investing in RT (EIT) among firms that do invest in EIT (RT). The overall marginal effect of EIT investment is 0.029, indicating an additional increase of 0.029 hierarchical layers relative to non-investing firms. This effect remains very similar (0.028) when EIT investments occur without concurrent investments in RT. However, when firms invest in both technologies, the marginal effect of EIT increases to 0.039, although this estimate is not statistically significant. In contrast, none of the marginal effects of RT investment are statistically significant, regardless of whether the firm also invests in EIT. Overall, OLS results suggest that firms investing in EIT tend to add additional layers of supervisors relative to firms that do not invest in EIT. By contrast, investments in robots are not significantly associated with a different path of change in the number of hierarchical layers compared with non-investing firms.

Table 9 shows the OLS estimates of the effects of emerging technologies on changes in firms' average span of control.

[Insert Table 9 about here]

In column (1), the coefficient on RT is 0.767, which is positive but not statistically significant. In column (2), investment in EIT is associated with a negative and statistically significant coefficient, indicating a reduction of 0.392 subordinate per supervisor in span of control relative to firms that do not invest in EIT. This corresponds to a 2.29% decrease relative to the average span of control for firms in the sample (-0.392/17.147 × 100). Given that the average change in span of control in the sample is 0.169, this reduction is relevant and suggests that EIT investment may be associated with narrower spans of control (see column 5, Table 7). Column (3) examines both independent and joint investments in RT and EIT. The coefficient for firms investing in both technologies is 0.567, not statistically significant. This may reflect offsetting effects, with RT potentially widening and EIT narrowing spans of control. When estimating the individual effects of each technology, results remain consistent with columns (1) and (2). At the bottom of column (3), we report marginal effects of investing in each technology. Specifically, we present: (i) the overall effect of switching from no investment to investing in RT (or EIT); (ii) the effect of investing in RT (EIT) among firms that do not invest in EIT (RT); and (iii) the effect of investing in RT (EIT) among firms that do invest in EIT (RT). The overall marginal effect of EIT investment is -0.425, indicating that EIT investment is associated with a reduction in the span of control relative to non-investing firms. This effect remains similar (-0.487) when firms invest in EIT without investing in RT. However, when firms invest in both technologies, the marginal effect of EIT becomes positive (0.469), although the estimate is not statistically significant. Turning to RT, the overall marginal effect is 0.557, which declines to 0.098 among firms that do not invest in EIT, with neither estimate being statistically significant. However, when firms invest in RT conditional on having invested in EIT, the marginal effect rises to 1.054, suggesting a potential complementary relationship: in firms that invest in EIT, RT may help expand the span of control by enabling managers to supervise larger teams more effectively. Overall, the OLS results suggest that while investments in EIT are associated with a reduction in the average span of control relative to firms that do not invest in EIT, investments in RT are associated with an increase in span of control only when combined with investments in EIT.

3.4.2 OLS results: Layer-level analysis

To investigate the effects at the layer level, we estimate the following empirical model:

$$\Delta O_{lft} = \beta_1 RT^{I}_{ft} + \beta_2 EIT^{I}_{ft} + \beta_3 RT^{I}_{ft} \times EIT^{I}_{ft} + \rho_1 RT^{I}_{ft} \times \theta_l + \rho_2 EIT^{I}_{ft} \times \theta_l + \rho_3 RT^{I}_{ft} \times EIT^{I}_{ft} \times \theta_l + \gamma_1 \Delta WEMP_{lft} + \Delta X'_{ft}\gamma + \theta_l + \Delta\tau_t + \alpha_j + \alpha_r + \Delta\varepsilon_{lft}. \quad (16)$$

O_{lft} refers to the two dimensions of the hierarchy at the layer level. In one case, l_{ft} is an indicator equal to one if layer l is non-empty (i.e., has more than zero employees) for firm f in year t, and zero otherwise, and Δl_{ft} measures whether a specific layer is created (value equal to +1), maintained (0) or eliminated (-1) from year $t-1$ to year t. In the other case, B_{lft} reflects the average number of subordinates in layer $l-1$ per supervisor in layer l, and ΔB_{lft} captures changes in the span of control at a given layer. In this specification, the regressors include indicators for investment in RT and in EIT, interacted with layer dummies (Blue & white collars = layer 1; Middle managers = layer 2; Managers = layer 3). The omitted category is layer 1 with no RT and no EIT investment. Coefficients on the layer dummies capture differences in organizational change for middle managers and managers relative to the baseline, while the interaction terms allow the effects of RT and EIT investments to vary across layers. The variable $WEMP_{lft}$ measures the share of female employees in each layer l, which is the only layer-level control variable available in our dataset. The vector ΔX_{ft} includes firm-level covariates in first differences, consistent with those used in Equation 12. We also control for layer fixed effects (θ_l), year fixed effects ($\Delta\tau_t$), industry fixed effects (α_j), and region fixed effects (α_r). The error term, $\Delta\varepsilon_{lft}$, is clustered at the firm level.[23] Results are reported in Table 10.

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[23] The RIL database collects information on investments in RT and EIT only at the firm level, without indicating which specific organizational layers are most related to these investments. Additionally, in Equation 16, only one covariate varies at the layer-firm-year level, while all other controls vary at the firm-year level. For these reasons, this analysis should be interpreted as descriptive evidence of how investments in emerging technologies may be associated with intra-firm changes across organizational layers, but we cannot rule out unobserved factors at the layer level that may be both correlated with changes regarding specific layers and investments in emerging technologies.

[Insert Table 10 about here]

Due to the presence of multiple interaction terms, and to aid interpretation, we present a series of figures that plot the marginal effects of investments in RT and EIT on Δl_{ft} or ΔB_{lft}, both unconditional and conditional on investment in the other technology. Figure 5 plots the marginal effects of investments in robots on the creation or elimination of different hierarchical layers, accounting for whether firms also invest in EIT.

[Insert Figure 5 about here]

For the managerial layer, investment in RT is associated with a higher likelihood of elimination, with a marginal effect of -0.036. Given the average value of the layer of managers in the sample is 0.253 (i.e., 25.3% of firms have a managerial layer; see column 5, Table 7), this corresponds to a 14.2% higher probability of elimination of the managers' layer for RT investors (-0.036/0.253 × 100 = -14.2), *ceteris paribus*. This effect becomes stronger (-0.052) when firms invest in RT alone and becomes weaker (-0.018) when firms invest also in EIT. For middle managers, RT investment shows the opposite pattern. The unconditional marginal effect is 0.032, indicating that firms investing in RT are more likely to add this layer. Considering that the sample mean for this layer is 0.262, the increase in the likelihood of adding this layer, amounts to about 12.2% (0.032/0.262 × 100 = 12.21). This effect is entirely driven by firms that invest in RT but not EIT, for which the marginal effect increases to 0.058. For blue- and white-collar employees, the marginal effects of RT investment are generally not statistically significant. When the firm invests in both RT and EIT, the marginal effect is 0.006. Given the high prevalence of this layer in the sample (mean = 0.997), this corresponds to a modest increase in the likelihood of adding this layer by 0.6% (0.006/0.997 × 100 = 0.60). Figure 6 shows the marginal effects of EIT investment on the creation or elimination of specific organizational layers.

[Insert Figure 6 about here]

For the managerial layer, the unconditional marginal effect is 0.009, implying a 3.56% increase in the likelihood of this layer being added (0.009/0.253 × 100 = 3.56). For middle managers, EIT investment has a positive and statistically significant effect: 0.017 unconditionally and 0.021 when not accompanied by RT investment. These correspond to increases of 6.49% and 8.01%, respectively, in the likelihood of adding a middle-management layer. The marginal effects on the layer of blue- and white-collars are negative, significant but small in magnitude. The unconditional marginal effect is -0.007, corresponding to a 0.70% higher likelihood in the elimination of the layer at the bottom of the hierarchy with respect to non-investing firms. This effect increases slightly to -0.008 for firms investing in EIT without also investing in RT.

Figures 7 and 8 present the marginal effects of investments in RT and EIT on changes in the span of control across different layers.

[Insert Figure 7 about here]

[Insert Figure 8 about here]

RT investment exhibits contrasting effects across the hierarchy. At the top, the number of managers per supervisor (in this case, the owner/entrepreneur) decreases by 0.272, and by 0.501 when firms do not also invest in EIT. Given an average of 3.234 managers per firm (see column 5, Table 7), this corresponds to an 8.41% reduction (0.272/3.234 × 100 = 8.41) in the number of managers per supervisor. No significant effect is observed for the number of middle managers per supervisor. At the bottom of the hierarchy, RT investment combined with EIT is associated with an increase of 1.925 blue- and white-collar employees per supervisor, although this effect is only mildly significant. Turning to EIT (Figure 8), investments are associated with a reduction in the number of both managers (-0.247 or -0.278, depending on the firm investing or not in RT) and middle managers (-0.254 or -0.249) per supervisor, while the span of control for blue- and white-collar employees remains statistically unaffected.

When viewed alongside the firm-level analysis, the layer-level results provide additional insights into how emerging technologies are associated with changes in organizational structure. The observed firm-level increase in the number of hierarchical layers following EIT investment appears to be driven primarily by the creation of managerial and middle-management layers. In contrast, the non-significant effect of RT investment at the firm level likely reflects offsetting dynamics: while RT increases the likelihood of adding a middle-management layer, it simultaneously raises the probability of eliminating the managerial layer, resulting in a “zero” net effect. Regarding the span of control, EIT investments are associated with a reduction of it, which is concentrated in the upper layers of the hierarchy, where the number of managers and middle managers per supervisor declines. Conversely, the modest increase in span of control observed for firms investing in RT (conditional of having invested also in EIT) is largely attributable to an expansion in the number of blue- and white-collar employees per supervisor at the bottom of the organizational structure.

3.4.3 RA and IPWRA results

This section presents the results of the RA and IPWRA models. Table 8 reports consistent results for the effect of emerging technologies on changes in the number of layers across both RA and IPWRA specifications. The marginal effect of investment in EIT is positive and statistically significant in both models and closely aligned with the OLS results. Under the IPWRA specification, the unconditional marginal effect of EIT investment is 0.034, indicating that firms investing in EIT add, on average, 0.034 more hierarchical layers than those that do not, *ceteris paribus*. This matches the RA estimate of 0.026. The effect appears to be primarily driven by firms that invest in EIT but not in RT (0.030). Among firms that also invest in RT, the marginal effect of EIT is higher in magnitude (0.098) but less precisely estimated. In contrast to the OLS results, investments in RT are associated with a higher reduction in the number of layers relative to firms that do not invest in RT. The IPWRA estimates show an unconditional marginal effect of -0.055 for RT, which becomes larger in magnitude (-0.087) when conditioning on no concurrent EIT investment. These findings are consistent with the RA marginal effects shown at the bottom of column (6). Overall, the evidence supports the OLS results that EIT investment is positively associated with deeper firm hierarchies, but also add that RT investment tends to flatten organizational structures. Importantly, these effects are mainly observed when firms invest in either RT or EIT alone. When firms invest in both technologies, the effects tend to cancel out, suggesting that the deepening effect of EIT may offset the flattening effect of RT.

Turning to changes in the average span of control (Table 9), both RA and IPWRA yield more conservative estimates compared with OLS, though the direction of the effects remains consistent. The marginal effect of EIT investment is negative across all specifications. Under IPWRA, the unconditional marginal effect is -0.262, suggesting that EIT investment reduces the average number of subordinates per supervisor. While this estimate is not statistically significant overall, the effect is mildly significant among firms that do not invest in RT (-0.453). The effect of RT investment is more nuanced. The unconditional IPWRA estimate is -0.008 and not significant. However, for firms that also invest in EIT, the marginal effect rises to 1.518 and becomes statistically significant. This result, which mirrors the OLS findings, suggests that RT may act as a complementary technology to EIT, enabling managers to supervise larger teams. This interpretation is reinforced by the marginal effect of EIT when firms also invest in RT, which rises to 2.482.

3.4.4 Robustness checks on IPWRA model

Tables 11-14 report a series of robustness checks for the IPWRA estimates. Each sub-section addresses a distinct methodological concern. First, we conduct additional tests on the direction of causality between investments in emerging technologies and changes in firms' hierarchy. Second, we perform checks aimed at addressing potential measurement issues and alternative sample definitions.

Third, we assess the sensitivity of our findings to violations of the overlap assumption and to alternative clustering structures of the error term (to cope with unmodeled correlation in investments and changes in firm hierarchy across firms belonging to the same industry and located in the same territory). Overall, the robustness checks confirm the reliability of our main findings.

3.4.4.1 Further tests on the direction of causality

Section 3.3.3 presents descriptive statistics suggesting that, prior to investment, firms were broadly similar in terms of changes in depth, average span of control, and size. While this evidence indicates comparable pre-trends, we provide a more rigorous test. Columns (1) of Tables 11 and 12 implement a lead specification by regressing current changes in firm hierarchy on future investments in RT and/or EIT.

[Insert Table 11 about here]

[Insert Table 12 about here]

Specifically, we regress changes in the number of layers and in the average span of control between 2014 and 2017 and between 2009 and 2014 on investments made in the subsequent periods 2019-2021 and 2015-2017, respectively. Investment information is drawn from the 2022 and 2018 waves of the RIL database, while firm-level controls (in first differences) are measured contemporaneously with the dependent variable. This test relies on the additional information from the 2010 wave and therefore reduces the number of observations. The absence of statistically significant coefficients indicates that future investments do not predict current organizational changes. This finding helps to rule out anticipatory effects, and it provides reassurance regarding the direction of causality.

We complement the lead specification with an additional test that focuses on firms switching their investment status between 2015-2017 and 2019-2021. Switching status is defined by comparing investment behavior recorded in the 2018 wave (covering 2015-2017) with that recorded in the 2022 wave (covering 2019-2021). This exercise is restricted to firms observed in both the 2018 and 2022 waves. For each technology, we compare firms that did not invest in the earlier period but invested in the later period (“switchers”) with firms that did not invest in either period (“controls”). We first estimate specifications including all firms that satisfy these conditions, regardless of their investment behavior in the other technology. We then estimate a more restrictive specification that isolates the effect of investing in a single technology by limiting the sample to firms that did not invest in the other technology in either period. Thus, this specification exploits cross-sectional variation in the 2022 wave while relying exclusively on pre-treatment characteristics measured in the 2018 wave.

The timing of the variables is therefore ordered: pre-treatment covariates are measured at the end of 2017, switching in investment behavior occurs between 2015-2017 and 2019-2021, and organizational changes are measured over 2017-2021. Compared with the pooled baseline specification, this design brings the analysis closer to a difference-in-differences interpretation, as identification exploits changes in firms' investment status over time. Consistent with our IPWRA framework, identification relies on conditional independence given pre-treatment covariates. We estimate three sets of models: (i) RT "switchers", (ii) EIT "switchers", and (iii) a multivalued treatment distinguishing no switch, RT-only switch, EIT-only switch, and joint RT+EIT switch.

Results, reported in Tables 11 and 12, are broadly consistent with the baseline IPWRA estimates. More specifically, columns (2) and (3) of Tables 11 and 12 focus on RT switchers, while columns (4) and (5) focus on EIT switchers. In each case, the first specification allows the investment path in the other technology to vary freely, whereas the second restricts the sample to firms that never invest in the other technology. For the change in the number of layers (Table 11), the estimated effects tend to be stronger when the sample is restricted to firms that do not invest in the other technology. This pattern is in line with the marginal effects reported in Table 8, where the impact of RT (EIT) on organizational depth is more pronounced among firms not simultaneously investing in EIT (RT). By contrast, for the change in the average span of control (Table 12), the effects are generally stronger when investment paths in the other technology are left unrestricted or when technologies are adopted jointly. This finding is consistent with Table 9, which highlights complementarities between RT and EIT in shaping the average span of control. Overall, the estimated effects under this design further strengthens the causal interpretation of our findings.

3.4.4.2 Robustness to measurement issues and sample definition

We next address the concern that observed changes in hierarchical structure may reflect internal promotions or simple replacement dynamics rather than genuine organizational restructuring. First, we restrict the sample to firms that (i) hired at least one employee during the year and (ii) exhibit total worker turnover strictly greater than excess turnover between the reference year and the preceding year, implying a non-zero net change in employment.[24] This restriction ensures that observed changes in hierarchical structure are associated with net employment adjustments, arising from worker entry or exit, rather than purely internal promotions, demotions, or replacement flows. Results, reported in

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[24] In the RIL data, hires and separations refer to worker flows occurring during the year preceding the survey. We reconstruct employment in the previous year using the identity $E_{y-1} \equiv E_y - H_y + S_y$, where H_y and S_y denote hires and separations in year y (the year prior to the survey wave). Total worker turnover is defined as $H_y + S_y$, while excess worker turnover is computed, following Burgess et al. (2000), as total turnover minus the absolute change in employment. By construction, the difference between total and excess turnover equals the absolute change in employment between $y - 1$ and y. Therefore, total turnover exceeds excess turnover whenever there is a non-zero net change in employment.

columns (1) and (3) of Table 13, are qualitatively consistent with the baseline IPWRA estimates presented in column (9) of Tables 8 and 9.

[Insert Table 13 about here]

Second, we re-estimate the IPWRA models including firms with a single organizational layer. This check addresses the possibility that excluding such firms might bias the results. One-layer firms are peculiar: they typically correspond to very small enterprises, in which the entrepreneur operates effectively as a self-employed worker. In these cases, the average span of control is equal to zero, and hierarchical structure is absent. Although these firms represent a relatively small share of the sample (about 7%), it is important to verify that their exclusion does not drive the results. As shown in Table 13 (columns 2 and 4), the inclusion of one-layer firms does not alter the sign, magnitude, or statistical significance of the coefficients. Thus, the baseline findings are not driven by the exclusion of these firms. In sum, the results remain stable both when we restrict attention to firms with net hiring and when we include one-layer firms.

3.4.4.3 Overlap and correlated shocks

In columns (1) and (4) of Table 14, we assess the sensitivity of our results to potential violations of the overlap assumption by applying asymmetric trimming of the PS, following the procedure proposed by Stürmer et al. (2010, 2021).

[Insert Table 14 about here]

Specifically, for each treatment category (k = 0, 1, 2, 3), as defined in Section 3.2, we compute the first percentile of the estimated propensity score among treated firms and exclude observations falling below this threshold. This approach mitigates the influence of observations with extreme weights or limited common support. This asymmetric trimming works well in reducing the potential bias when treatment group size is highly imbalanced.[25] The estimates from the trimmed sample are broadly consistent with the baseline results presented in column (9) of Tables 8 and 9, reinforcing the robustness of the IPWRA findings. In particular, the coefficients of EIT and RT investments remain in the same direction and comparable in magnitude, suggesting that the main findings are not driven by poor overlap or extreme IPW_{ft}.

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[25] As suggested by Yoshida et al. (2019), only the lower tail of the PS distribution needs to be trimmed. Trimming the upper tail is effectively implicit, because firms with a very high PS for one treatment category necessarily have very low PS values for the remaining categories, thus naturally excluding themselves from overlapping regions across groups.

As discussed in Section 3.2, while our baseline specifications cluster standard errors at the firm level, investment decisions and organizational changes may be correlated across firms operating in the same industry or geographic area. To address this concern, we examine the sensitivity of standard errors to alternative clustering structures that allow for correlated shocks among firms operating in the same sector and region. We cluster standard errors at the 2-digit NACE × NUTS2 level (columns 2 and 5) and at the industry (where industries are aggregated into three broad sectors, i.e. industry, construction, and services) × NUTS1 level (columns 3 and 6). With alternative clustering schemes, the treatment effects remain statistically significant at conventional levels, suggesting that our main results are not sensitive to a particular clustering structure.

4. Discussion and implications for managers and policymakers

In this section, we assess the extent to which our empirical findings align with our theoretical hypotheses and discuss implications for both firm management and policymakers.

On average, investments in EIT are associated with an increase in the number of organizational layers. Firms investing in EIT exhibit an increase of approximately 0.03 additional layers compared with non-investing firms, driven mainly by the addition of managerial and middle-management layers. At the same time, we observe that investments in EIT determine a higher contraction in the average span of control with respect to firms that do not invest in EIT, with supervisors overseeing roughly 0.26 fewer subordinates. This reduction is concentrated in the upper echelons of the hierarchy. However, if firms that invest in EIT also invest in RT, we observe that these firms increase their average span of control by 2.48 subordinates per supervisor more that firms that do not invest. Our evidence partially supports Hypothesis 1, which predicts an expansion of the span of control as a consequence of information-cost reductions induced by EIT. In fact, investments in EIT are positively associated with an additional increase in the average span of control when complemented with investments in RT, showing a complementary effect of the two technologies. In the absence of investments in RT, we observe a negative association between investments in EIT and changes in the firm’s average span of control. This suggests that EIT investments alone raise learning costs, determining greater costs than the benefits derived from improved information flows.

According to our findings, Hypothesis 3 is supported: the observed increase in hierarchical depth aligns with theoretical expectations, where variation in learning costs across layers drives hierarchical change. Overall, EIT investments reshape firm hierarchies by simultaneously reducing the span of control (in the absence of investments in RT) and increasing organizational depth, with learning costs playing a pivotal role in both dynamics and exerting their strongest effects in the upper echelons of the hierarchy.

For managers, these findings highlight that EIT investment is far from neutral with respect to organizational architecture. It becomes important to manage learning costs, especially given their impact on upper-tier roles. To mitigate extensive restructuring triggered by EIT, managers should implement mechanisms that facilitate knowledge acquisition and reduce learning burdens. Firms may face two practical options: hiring workers equipped with skills in emerging technologies or upgrading the skills of their existing workforce. OECD reports (2021, 2022) document the first strategy, namely the rising demand for new managerial and technical competencies accompanying the adoption of digital technologies. By contrast, a recent McKinsey Global Institute report (McKinsey Global Institute, 2024) suggests that, rather than hiring new employees with specialized technological skills, firms increasingly prefer to invest in reskilling their current workforce. This second approach allows them to manage the high learning costs involved while minimizing, insofar as possible, disruptions to established hierarchical structures.

From a policy perspective, since EIT investments tend to increase learning costs, public programs aimed at fostering digital transformation should be complemented by firm-level training initiatives to facilitate the organizational integration of EIT and mitigate potentially disruptive structural adjustments, particularly in managerial and middle-management layers, where our findings indicate the strongest effects of both depth and span of control. Accordingly, policymakers should design training schemes to help firms adapt to these new requirements associated with EIT. A well-known example in this direction is represented by several industry 4.0 programmes, such as Italy's "Piano Industria 4.0, Germany's "Qualifizierungschancengesetz", and France's "Plan d'Investissement dans les Compétences". These initiatives combine subsidies for the adoption of digital technologies with publicly co-funded training schemes aimed at reskilling both workers and managers in firms adopting emerging technologies.

Turning to investments in robots, we find that RT alone has little effect on the span of control; however, when combined with EIT, it leads to a substantial increase (+1.52 subordinates per supervisor) with respect to firms that do not invest in RT, thereby providing partial support for Hypothesis 2. These findings suggest that RT may enhance upper-level oversight, but its organizational impact emerges only when integrated with EIT. Moreover, RT investments alone reduce the number of organizational layers by approximately 0.06 to 0.09 layers more than firms that do not invest in RT, primarily due to the elimination of the top managerial tier, which could be partly replaced by RT (a form of "automation of management" *à la* Simon 1960). Given the reduction in depth, Hypothesis 4 is not supported. However, it is important to underline that this hypothesis posits that depth increases when two conditions are met: first, that investment in RT increases predictability, and second, a highly unrealistic condition that the knowledge base of an additional layer exceeds the combined knowledge bases of its upper and lower adjacent layers. Our interpretation of the observed reduction in depth is that the second condition does not hold. Additionally, we find that this flattening effect disappears when firms invest jointly in RT and EIT, consistent with offsetting organizational forces. These results again underscore the interdependences between the hierarchical effects of RT and EIT.

Therefore, managers should recognize that RT has the potential to reduce firm depth, particularly in the upper echelons. This result appears to extend beyond the national context examined in our study. For instance, Dixon (2020), shows that in Canada, robots are associated not only with an overall increase in firm-level employment, but also with a reduction in the number of managerial positions and a corresponding widening of the span of control for those managers who remain. Such evidence further challenges the long-standing expectation that new technologies would primarily substitute for physically intensive occupations, while leaving untouched those tasks requiring higher-order cognitive abilities such as problem solving and decision-making.

Given this, it is advisable for managers to invest in RT alongside EIT to mitigate the restructuring burdens, as investments in EIT can counterbalance RT's impact on both the span of control and organizational depth. Investing simultaneously in these emerging technologies allows firms to maintain balance and avoid excessive flattening that could impair managerial oversight or organizational coherence. In practice, leading firms such as Amazon[26] have already moved in this direction, implementing large-scale retraining initiatives in both EIT and RT to ensure that technological change is accompanied by proper investments in human capital.

From a policy perspective, promoting investments in RT without encouraging its integration with EIT may lead to suboptimal organizational outcomes, such as unnecessary flattening of hierarchies that could undermine firm performance (Garicano and Hubbard, 2016). Public policies should support a coordinated technological investment strategy, emphasizing the complementarities between RT and EIT. By fostering this integration, policymakers can help firms leverage the benefits of ET, facilitating organizational restructuring that enhances productivity and adaptability rather than creating disruptive or less effective changes. Several illustrative cases, such as those in the United States (Atkinson et al. 2025) and in the United Kingdom (as documented by the Department for Science, Innovation and Technology, 2025), are consistent with this recommendation, as they combine public funding for training in RT with trainings initiatives in other emerging technologies.

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[26] See the relevant information on the corporate webpages of Amazon: https://www.aboutamazon.com/workplace/upskilling-commitments.

5. Concluding remarks

The literature in economics and management, beginning with the seminal contributions of Ronald Coase and Herbert Simon, has long emphasized the critical role of hierarchy in the efficient allocation of economic resources. Among these resources, knowledge occupies a particularly central position because it is the key driver of productivity, innovation and long-term economic growth. This paper advances the theory of knowledge-based hierarchies by conceptualizing hierarchy as a cognitive system designed to enhance the utilization of knowledge within organizations.

Our primary contribution is to integrate investments in EIT and RT into this conceptual framework. To the best of our knowledge, this study provides the first comprehensive theoretical framework that systematically develops hypotheses and explains the effects of EIT and RT on both dimensions of a firm's hierarchy: its depth and its span of control. In addition, this paper represents the first empirical attempt to test these hypotheses by examining how EIT and RT affect both hierarchical dimensions. Our results reveal a strong association between investments in emerging technologies and changes in hierarchical architectures. EIT exert a more pronounced influence than RT, while the impact of RT becomes stronger when combined with EIT. Importantly, these effects are particularly concentrated at the upper managerial tiers (managers and middle-management layers).

The implications are significant: organizational hierarchies may be substantially reshaped by investments in emerging technologies, precisely because hierarchy serve as a tool for improving the allocation of knowledge, and therefore adapts to the new conditions produced by EIT and RT. Managers and policymakers must thus understand the mechanisms through which EIT and RT transform hierarchies in order to make informed decisions about organizational design and governance.

Finally, this paper aims to serve as a springboard for pressing research questions in economics and organizational theory. For instance, since firms' hierarchies play a central role in shaping social inequalities (for example, wages tend to increase with higher layers[27]), it would be valuable to investigate whether, and to what extent, EIT and RT, through the restructuring of hierarchies, reinforce or mitigate such inequalities.

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[27] More generally, firms contribute significantly to gender, generational and ethnic disparities. OECD data indicate that, on average, women earn less than men and this gap also extends to corporate leadership (cf. Gender Equality, available at https://www.oecd.org/en/topics/gender-equality.html). Inequalities further manifest along age dimensions: Bianchi and Paradisi (2024) document a widening wage gap between older and younger workers in high-income economies. Finally, disparities persist along nativity lines: Lang and Lehmann (2012) provide evidence of sustained wage differentials and longer unemployment durations for minority workers relative to native workers, patterns consistent with labor market discrimination.

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Tables and Figures

Tables

Table 1. Our hypotheses and main empirical results.

Hypothesis	Theoretical prediction	Empirical finding	Theory-evidence alignment
Hp1 on EIT and span of control	Investments in EIT widen span of control when the sum of the changes in information costs and learning costs is negative.	Investments in EIT reduce span of control, especially in the upper hierarchical layers, and if firms do not invest in RT.	Hp1 is partially supported, when firms also invest in RT. *Explanation*: rejecting Hp1 (for firms not investing also in RT) implies that EIT raise supervisors' learning costs more than they lower information costs.
Hp2 on RT and span of control	Investments in RT widen span of control when predictability increases.	Investments in RT have no robust standalone effect; the span of control widens, especially at the base of the hierarchy, when investments in RT are coupled with investments in EIT.	Hp2 is partially supported. *Explanation*: predictability gains from RT materialize only when complemented by investments in EIT.
Hp3 on EIT and depth	Investments in EIT increase organizational depth when they shift relative learning costs in favor of individuals in the additional layer compared with their supervisors.	Investments in EIT increase the number of layers, mainly at the managerial and middle-management levels.	Hp3 is supported.
Hp4 on RT and depth	Investments in RT increase depth when predictability rises and the knowledge base of an additional layer exceeds the combined knowledge bases of its upper and lower layers.	Investments in RT alone reduce depth, especially at the managerial level. However, the flattening effect disappears when investments in RT are coupled with investments EIT, consistent with offsetting forces.	Hp4 is not supported. *Explanation*: rejecting Hp4 suggests that RT investments increased predictability, but the knowledge base of an additional layer does not exceed the combined knowledge bases of its adjacent layers.

Table 2. Assumptions on the effects of investments in emerging technologies on changes in information costs, learning costs, and predictability.

Emerging Technology	Effect on information costs (Δh)	Effect on learning costs (Δc_l)	Effect on predictability ($\Delta \lambda$)
EIT	Negative	Ambiguous	No effect
RT	No effect	No effect	Ambiguous

Table 3. Effects of investments in EIT on changes in the span of control (B_l)

Scenario	Hypothesized impacts of investments in EIT on		Predicted effect	Subject to condition:
	Δh	Δc_l		
A	$\Delta h < 0$	$\Delta c_l < 0$	Positive	
B	$\Delta h < 0$	$\Delta c_l > 0$	Positive	$(\Delta h + \Delta c_l) < 0$

Table 4. Effects of investments in RT on changes in the span of control (B_l)

Scenario	Hypothesized impacts of investments in RT on	Predicted effect
	$\Delta\lambda$	
C	$\Delta\lambda > 0$	Positive

Table 5. Effects of investments in EIT on changes in depth (L)

Scenario	Hypothesized impacts of investments in EIT on			Predicted effect	Subject to condition:	
	Δh	Δc_k	Δc_{k+1}			
D	$\Delta h < 0$	$\Delta c_k < 0$	$\Delta c_{k+1} < 0$	Positive	$\Delta c_k - \Delta c_{k+1} < \frac{\Delta c_k \cdot (\Delta h + \Delta c_k)}{\Delta c_{k-1}}$ and $\lvert\Delta c_k\rvert > \lvert\Delta c_{k+1}\rvert$	
E	$\Delta h < 0$	$\Delta c_k > 0$	$\Delta c_{k+1} > 0$	Positive	*E1.* $\Delta h + \Delta c_k > 0$ and $\Delta h + \Delta c_{k+1} > 0$	$\Delta c_k - \Delta c_{k+1} < \frac{\Delta c_k \cdot (\Delta h + \Delta c_k)}{\Delta c_{k-1}}$ and $\Delta c_{k+1} \geq \Delta c_k$
				Positive	*E2.* $\Delta h + \Delta c_k < 0$ and $\Delta h + \Delta c_{k+1} < 0$	$\Delta c_k - \Delta c_{k+1} < \frac{\Delta c_k \cdot (\Delta h + \Delta c_k)}{\Delta c_{k-1}}$ and $\Delta c_{k+1} > \Delta c_k$

Table 6. Effects of investments in RT on changes in depth (L)

Scenario	Hypothesized impacts of investments in RT on	Predicted effect	Subject to condition:
	$\Delta\lambda$		
F	$\Delta\lambda > 0$	Positive	$z_k > z_{k-1} + z_{k+1}$

Table 7 - Descriptive statistics

	(1) RT=0 & EIT=0	(2) RT=1 & EIT=0	(3) RT=0 & EIT=1	(4) RT=1 & EIT=1	(5) Total
Firm hierarchy dimensions (first diff.)					
Δ no. of layers	0.009	-0.005	0.054	0.039	0.030
Δ av. span of control	0.056	0.945	0.136	1.323	0.169
Firm characteristics (first diff.); outcome model: Eq.12, Eq. 13					
Δ% in firm size, %	0.004	0.102	0.065	0.090	0.036
Investments	0.338	0.761	0.606	0.890	0.486
Δ (pp) in emp., primary edu.	-0.023	0.007	-0.031	-0.041	-0.027
Δ (pp) in emp., secondary edu.	0.008	-0.014	0.002	0.009	0.005
Δ (pp) in emp., tertiary edu.	0.015	0.006	0.030	0.032	0.022
Δ (pp) in emp., <25 y.o.	-0.002	-0.012	0.000	-0.002	-0.001
Δ (pp) in emp., 25-34 y.o.	-0.035	-0.023	-0.029	-0.015	-0.031
Δ (pp) in emp., 35-49 y.o.	-0.042	-0.014	-0.038	-0.035	-0.040
Δ (pp) in emp., 50+ y.o.	0.080	0.049	0.067	0.052	0.073
Δ (pp) in emp. with on-the-job training	-0.011	-0.023	0.053	0.060	0.020
Δ (pp) in fixed-term contracts	0.002	0.019	0.007	0.006	0.005
Δ (pp) in female employees	-0.006	-0.009	-0.003	-0.008	-0.005
Firm hierarchy dimensions (levels)					
No. of layers	2.344	2.709	2.637	3.067	2.512
layer: managers (% of firms)	0.181	0.324	0.305	0.504	0.253
layer: middle managers (% of firms)	0.166	0.390	0.336	0.563	0.262
layer: blue- and white-collars (% of firms)	0.997	0.995	0.997	1.000	0.997
Av. span of control	15.081	26.977	18.228	26.082	17.147
No. of managers per supervisor (layer up - entrepreneur)	2.622	3.681	3.364	4.638	3.234
No. of middle managers per supervisor (layer up)	2.704	3.349	3.161	2.920	2.989
No. of BCs+WCs per supervisor (layer up)	18.880	37.014	25.138	42.880	23.046
Firm characteristics (levels; 1-wave lagged); PSM model: Eq. 14					
Firm size: 1-9 emp., lag	0.456	0.136	0.292	0.072	0.362
Firm size: 10-49 emp., lag	0.383	0.427	0.408	0.305	0.390
Firm size: 50-249 emp., lag	0.146	0.380	0.259	0.447	0.213
Firm size: 250+ emp., lag	0.014	0.056	0.041	0.176	0.035
Investments, lag	0.380	0.676	0.543	0.800	0.475
% of emp.,primary edu., lag	0.388	0.394	0.340	0.410	0.369
% of emp.,secondary edu., lag	0.501	0.466	0.514	0.459	0.504
% of emp.,tertiary edu., lag	0.111	0.140	0.147	0.131	0.128
% of emp. <25 y.o., lag	0.053	0.071	0.053	0.060	0.053
% of emp. 25-34 y.o., lag	0.215	0.223	0.221	0.213	0.218
% of emp. 35-49 y.o., lag	0.460	0.454	0.475	0.479	0.467
% of emp. 50+ y.o., lag	0.272	0.252	0.252	0.248	0.262
% of emp. on-the-job training, lag	0.374	0.441	0.431	0.461	0.403
% of fixed-term contracts, lag	0.073	0.066	0.066	0.060	0.069
% of female emp., lag	0.370	0.277	0.361	0.289	0.361
CEO edu.: compulsory, lag	0.219	0.211	0.154	0.141	0.187
CEO edu.: upper secondary , lag	0.526	0.451	0.511	0.449	0.515
CEO edu.: tertiary, lag	0.255	0.338	0.335	0.410	0.299
CEO age: 15-39 y.o., lag	0.061	0.066	0.055	0.041	0.057
CEO age: 40-49 y.o., lag	0.233	0.221	0.231	0.214	0.231
CEO age: 50-59 y.o., lag	0.351	0.362	0.359	0.341	0.354
CEO age: 60+ y.o., lag	0.355	0.352	0.355	0.404	0.358
Female CEO, lag	0.153	0.080	0.130	0.098	0.139
Industrial group, lag	0.110	0.221	0.179	0.332	0.153
Family firm, lag	0.871	0.742	0.806	0.734	0.834
Extraordinary transactions, lag	0.034	0.085	0.061	0.080	0.049
Union (RSA/RSU), lag	0.175	0.390	0.263	0.514	0.233
2nd-level wage barg. (prod.-linked), lag	0.038	0.136	0.087	0.254	0.071

Note: RIL database. This table reports descriptive statistics (unconditional averages) of the variables included in the outcome model (Eq. 12, Eq. 13) and those included in the propensity score model (Eq. 14).

Table 8 - Emerging technologies and the change (Δ) in the no. of layers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	RA	RA	RA	IPWRA	IPWRA	IPWRA
Inv. in RT=1	-0.015		-0.031	-0.049*		-0.108*	-0.012		-0.087**
	(0.016)		(0.042)	(0.028)		(0.059)	(0.028)		(0.043)
Inv. in EIT=1		0.027***	0.028***		0.027***	0.030***		0.027***	0.030***
		(0.008)	(0.008)		(0.008)	(0.008)		(0.008)	(0.009)
Inv. in RT = 1 & Inv. in EIT = 1			0.008			-0.010			0.011
			(0.018)			(0.031)			(0.031)
ΔX (firm controls)‡	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS1 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Het. effects of ΔX for each level of treatment	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Treatment model	No	No	No	No	No	No	Yes	Yes	Yes
#Observations	19188	19188	19188	19188	19188	19188	19188	19188	19188
#Firms	14793	14793	14793	14793	14793	14793	14793	14793	14793
Marg. eff. RT	-0.015		-0.026	-0.049*		-0.102***	-0.012		-0.055*
Marg. eff. RT (no EIT)			-0.031			-0.108*			-0.087**
Marg. eff. RT (yes EIT)			-0.020			-0.040			-0.019
Marg. eff. EIT		0.027 ***	0.029***		0.027 ***	0.026***		0.027 ***	0.034***
Marg. eff. EIT (no RT)			0.028 ***			0.030 ***			0.030 ***
Marg. eff. EIT (yes RT)			0.039			0.098			0.098*

Note: RIL database. All specifications include year, NUTS1 and industry fixed effects, where industries are aggregated into three broad sectors (industry, construction, and services) of the Italian economy. The vector of firm controls‡, in first differences, includes firm size (number of employees); the shares of employees by educational level and age group; the share of female employees; the share of employees receiving on-the-job training; and the share of employees with temporary contracts. The specification also includes a dummy for firms that made investments in tangible and intangible assets, as a proxy for changes in the stock of these assets. While in the OLS regression framework the variables included in the vector of firm controls are assumed to have the same effect both on investments in ETs and on changes firm organization, in the RA and IPWRA framework they are allowed to have heterogeneous effects. The IPWRA approach also estimates a treatment model, i.e., the probability of investing in RT or/and EIT as a function of predetermined firm characteristics, to compute the inverse probability weights. The reader is referred to Table B.4 in the Online Appendix for the coefficient estimates of the outcome model with all controls, and for the coefficient estimates of the treatment model. At the bottom we report marginal effects of investing in each technology. We show: (i) the overall effect of switching from no investment to investing in RT (or EIT); (ii) the effect of investing in RT (EIT) among firms that do not invest in EIT (RT); and (iii) the effect of investing in RT (EIT) among firms that do invest in EIT (RT). Cluster- (firm-) robust standard errors are reported in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table 9 - Emerging technologies and the change (Δ) in the average span of control

	(1) OLS	(2) OLS	(3) OLS	(4) RA	(5) RA	(6) RA	(7) IPWRA	(8) IPWRA	(9) IPWRA
Inv. in RT=1	0.767		0.098	0.674		-0.908	0.740		-1.417
	(0.553)		(1.326)	(0.883)		(1.791)	(0.578)		(1.233)
Inv. in EIT=1		-0.392*	-0.487**		-0.398*	-0.534**		-0.284	-0.453*
		(0.220)	(0.222)		(0.219)	(0.225)		(0.235)	(0.247)
Inv. in RT = 1 & Inv. in EIT = 1			0.567			0.654			1.065
			(0.619)			(1.060)			(0.687)
ΔX (firm controls)‡	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS1 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Het. effects of ΔX for each level of treatment	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Treatment model	No	No	No	No	No	No	Yes	Yes	Yes
#Observations	19188	19188	19188	19188	19188	19188	19188	19188	19188
#Firms	14793	14793	14793	14793	14793	14793	14793	14793	14793
Marg. eff. RT	0.767		0.557	0.674		0.167	0.740		-0.008
Marg. eff. RT (no EIT)			0.098			-0.908			-1.417
Marg. eff. RT (yes EIT)			1.054*			1.188			1.518**
Marg. eff. EIT		-0.392*	-0.425*		-0.398*	-0.402*		-0.284	-0.262
Marg. eff. EIT (no RT)			-0.487**			-0.534**			-0.453*
Marg. eff. EIT (yes RT)			0.469			1.562			2.482*

RIL database. All specifications include year, NUTS1 and industry fixed effects, where industries are aggregated into three broad sectors (industry, construction, and services) of the Italian economy. The vector of firm controls‡, in first differences, includes firm size (number of employees); the shares of employees by educational level and age group; the share of female employees; the share of employees receiving on-the-job training; and the share of employees with temporary contracts. The specification also includes a dummy for firms that made investments in tangible and intangible assets, as a proxy for changes in the stock of these assets. While in the OLS regression framework the variables included in the vector of firm controls are assumed to have the same effect both on investments in ETs and on changes firm organization, in the RA and IPWRA framework they are allowed to have heterogeneous effects. The IPWRA approach also estimates a treatment model, i.e., the probability of investing in RT or/and EIT as a function of predetermined firm characteristics, to compute the inverse probability weights. The reader is referred to Table B.5 in the Online Appendix for the coefficient estimates of the outcome model with all controls, and for the coefficient estimates of the treatment model. At the bottom we report marginal effects of investing in each technology. We show: (i) the overall effect of switching from no investment to investing in RT (or EIT); (ii) the effect of investing in RT (EIT) among firms that do not invest in EIT (RT); and (iii) the effect of investing in RT (EIT) among firms that do invest in EIT (RT). Cluster- (firm-) robust standard errors are reported in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table 10 - Layer-level OLS regressions: RT and EIT investments and changes in organizational layers

	(1) Creation/drop of each l	(2) Δ in span of control at each l
Inv. in RT	-0.008	0.019
	(0.008)	(1.517)
Inv. in EIT	-0.008***	0.186
	(0.002)	(0.250)
Inv. in RT=1 # Inv. in EIT=1	0.013*	1.905
	(0.008)	(1.878)
Inv. in RT=1 # Middle managers	0.066***	-0.030
	(0.026)	(1.606)
Inv. in RT=1 # Managers	-0.045	-0.521
	(0.030)	(1.566)
Inv. in EIT=1 # Middle managers	0.028***	-0.434
	(0.005)	(0.268)
Inv. in EIT=1 # Managers	0.014**	-0.464*
	(0.006)	(0.261)
Inv. in RT=1 # Inv. in EIT=1 # Middle managers	-0.068**	-1.985
	(0.029)	(1.964)
Inv. in RT=1 # Inv. in EIT=1 # Managers	0.021	-1.428
	(0.033)	(1.927)
Middle managers	-0.001	-0.164
	(0.003)	(0.159)
Managers	0.005	-0.182
	(0.004)	(0.155)
Δ in female emp. share in layer *l*	0.585***	0.125
	(0.012)	(0.281)
Constant	-0.001	0.240
	(0.003)	(0.166)
ΔX (firm controls)‡	Yes	Yes
Industry FEs	Yes	Yes
NUTS1 FEs	Yes	Yes
Year FEs	Yes	Yes
Adj.R-squared	0.126	0.033
#Layers	57564	57564
#Firms	14793	14793

Note: RIL (layer-level) database. All specifications include year, NUTS1 and industry fixed effects, where industries are aggregated into three broad sectors (industry, construction, and services) of the Italian economy. The dependent variables are (1) the change in the presence of each layer (creation/drop) and (2) the change in span of control within each layer, constructed as first differences between consecutive waves. The regressors include indicators for investment in RT and in EIT, interacted with layer dummies (Blue/White collars = layer 1, Middle managers = layer 2, Managers = layer 3). The omitted category is layer 1 with no RT and no EIT investment; coefficients on Middle managers and Managers are level differences relative to this baseline, while interaction terms capture how RT/EIT effects differ across layers. The vector of firm controls‡ (first differences) includes Δ log employment, the investment dummy (proxy for changes in tangible/intangible assets), changes in workforce composition (education shares, age shares), training, temporary contracts, and the change in the female share at the relevant layer. Cluster- (firm-) robust standard errors are reported in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table 11 - IPWRA model: Direction of causality and investment switchers; change (Δ) in the no. of layers

	(1) Lead ET inv.	(2) RT switchers (EIT: all paths)	(3) RT switchers (EIT: never invest)	(4) EIT switchers (RT: all paths)	(5) EIT switchers (RT: never invest)	(6) Joint RT-EIT switch (multivalued)
RT = 1 & EIT = 0, lead	0.049					
	(0.043)					
RT = 0 & EIT = 1, lead	0.018					
	(0.012)					
RT = 1 & EIT = 1, lead	-0.067					
	(0.051)					
RT switcher		-0.121**	-0.259***			
		(0.057)	(0.086)			
EIT switcher				0.033	0.037*	
				(0.021)	(0.022)	
RT-only switcher						-0.130
						(0.161)
EIT-only switcher						0.038*
						(0.022)
RT+EIT switcher						-0.321
						(0.236)
ΔX (firm controls)‡	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
NUTS1 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	No	No	No
Het. effects of ΔX for each level of treatment	Yes	Yes	Yes	Yes	Yes	Yes
Treatment model	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	8718	8232	817	3431	3276	3303
#Firms	6966	8232	817	3431	3276	3303

Note: RIL database. All specifications include both NUTS1 and industry fixed effects, where industries are aggregated into three broad sectors (industry, construction, and services) of the Italian economy. The vector of firm controls‡, in first differences, includes firm size (number of employees); the shares of employees by educational level and age group; the share of female employees; the share of employees receiving on-the-job training; and the share of employees with temporary contracts. The specification also includes a dummy for firms that made investments in tangible and intangible assets, as a proxy for changes in the stock of these assets. In column (1), the lead specification is estimated using the 2015 and 2018 waves. The 2010 wave enters only through lagged variables used to construct first-difference outcomes and controls for the 2015 observations. We regress changes in firm organization over 2009-2014 and 2014-2017 on subsequent (lead) investments in emerging technologies: investments made in 2015-2017 (recorded in the 2018 wave) and in 2019-2021 (recorded in the 2022 wave). Switching status is defined by comparing investment behavior in 2015-2017 (2018 wave) with investment behavior in 2019-2021 (2022 wave). Accordingly, columns (2)-(6) exploit cross-sectional variation in the 2022 wave, conditional on pre-treatment characteristics measured in the 2018 wave. Columns (2)-(3) focus on RT switchers and differ in the restrictions imposed on the EIT investment path (all paths in col. 2; restricted to never-investors in col. 3). Columns (4)-(5) mirror this strategy for EIT switchers, varying restrictions on the RT path (all paths in col. 4; restricted to never-investors in col. 5). Column (6) estimates a multivalued treatment model distinguishing no switch, RT-only switch, EIT-only switch, and joint RT+EIT switch. Cluster- (firm-) robust standard errors (equivalent to Huber/White/sandwich in columns 2-6) are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 12 - IPWRA model: Direction of causality and investment switchers; change (Δ) in the average span of control

	(1) Lead ET inv.	(2) RT switchers (EIT: all paths)	(3) RT switchers (EIT: never invest)	(4) EIT switchers (RT: all paths)	(5) EIT switchers (RT: never invest)	(6) Joint RT-EIT switch (multivalued)
RT = 1 & EIT = 0, lead	1.132					
	(1.356)					
RT = 0 & EIT = 1, lead	-0.089					
	(0.409)					
RT = 1 & EIT = 1, lead	-0.410					
	(1.243)					
RT switcher		1.801**	0.539			
		(0.868)	(2.337)			
EIT switcher				0.623	0.458	
				(0.490)	(0.488)	
RT-only switcher						-2.080
						(3.759)
EIT-only switcher						0.453
						(0.514)
RT+EIT switcher						10.035**
						(4.725)
ΔX (firm controls)‡	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
NUTS1 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	No	No	No
Het. effects of ΔX for each level of treatment	Yes	Yes	Yes	Yes	Yes	Yes
Treatment model	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	8718	8232	817	3431	3276	3303
# Firms	6966	8232	817	3431	3276	3303

Note: RIL database. All specifications include both NUTS1 and industry fixed effects, where industries are aggregated into three broad sectors (industry, construction, and services) of the Italian economy. The vector of firm controls‡, in first differences, includes firm size (number of employees); the shares of employees by educational level and age group; the share of female employees; the share of employees receiving on-the-job training; and the share of employees with temporary contracts. The specification also includes a dummy for firms that made investments in tangible and intangible assets, as a proxy for changes in the stock of these assets. In column (1), the lead specification is estimated using the 2015 and 2018 waves. The 2010 wave enters only through lagged variables used to construct first-difference outcomes and controls for the 2015 observations. We regress changes in firm organization over 2009-2014 and 2014-2017 on subsequent (lead) investments in emerging technologies: investments made in 2015-2017 (recorded in the 2018 wave) and in 2019-2021 (recorded in the 2022 wave). Switching status is defined by comparing investment behavior in 2015-2017 (2018 wave) with investment behavior in 2019-2021 (2022 wave). Accordingly, columns (2)-(6) exploit cross-sectional variation in the 2022 wave, conditional on pre-treatment characteristics measured in the 2018 wave. Columns (2)-(3) focus on RT switchers and differ in the restrictions imposed on the EIT investment path (all paths in col. 2; restricted to never-investors in col. 3). Columns (4)-(5) mirror this strategy for EIT switchers, varying restrictions on the RT path (all paths in col. 4; restricted to never-investors in col. 5). Column (6) estimates a multivalued treatment model distinguishing no switch, RT-only switch, EIT-only switch, and joint RT+EIT switch. Cluster- (firm-) robust standard errors (equivalent to Huber/White/sandwich in columns 2-6) are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 13 - IPWRA model: Robustness to measurement issues and sample definition

	(1) Firms with non-zero net employment change	(2) Including one-layer firms	(3) Firms with non-zero net employment change	(4) Including one - layer firms
	Dependent variable: ΔL_{ft}		Dependent variable: ΔB_{ft}	
Inv. in RT = 1 & Inv. in EIT = 0	-0.148***	-0.088*	1.897	-1.393
	(0.051)	(0.048)	(1.442)	(1.304)
Inv. in RT = 0 & Inv. in EIT = 1	0.033**	0.028***	-0.606	-0.435*
	(0.013)	(0.008)	(0.449)	(0.231)
Inv. in RT = 1 & Inv. in EIT = 1	-0.067	0.017	1.822	0.830
	(0.044)	(0.035)	(1.281)	(0.666)
ΔX (firm controls)‡	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
NUTS1 FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Het. effects of ΔX for each level of treatment	Yes	Yes	Yes	Yes
Treatment model	Yes	Yes	Yes	Yes
#Observations	9407	20621	9407	20621
#Firms	7851	16140	7851	16140

RIL database. Columns (1) and (3) restrict the sample to firms that (i) hired at least one employee in the last year and (ii) exhibit total worker turnover greater than excess turnover. This restriction ensures that worker flows reflect net employment changes rather than pure replacement dynamics. Columns (2) and (4) instead include firms with one organizational layer. All specifications include year, NUTS1 and industry fixed effects, where industries are aggregated into three broad sectors (industry, construction, and services) of the Italian economy. The vector of firm controls‡, in first differences, includes firm size (number of employees); the shares of employees by educational level and age group; the share of female employees; the share of employees receiving on-the-job training; and the share of employees with temporary contracts. The specification also includes a dummy for firms that made investments in tangible and intangible assets, as a proxy for changes in the stock of these assets. Cluster- (firm-) robust standard errors are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Table 14 - IPWRA model: Further checks

	(1) Trimming ps	(2) Cluster SE: NACE 2-digit x NUTS2	(3) Cluster SE: industry x NUTS1	(4) Trimming ps	(5) Cluster SE: NACE 2-digit x NUTS2	(6) Cluster SE: industry x NUTS1
	Dependent variable: ΔL_{ft}			Dependent variable: ΔB_{ft}		
Inv. in RT = 1 & Inv. in EIT = 0	-0.112***	-0.087**	-0.087*	0.936	-1.417	-1.417
	(0.043)	(0.043)	(0.053)	(0.944)	(1.297)	(2.082)
Inv. in RT = 0 & Inv. in EIT = 1	0.031***	0.030***	0.030***	-0.634**	-0.453*	-0.453**
	(0.010)	(0.008)	(0.007)	(0.309)	(0.248)	(0.224)
Inv. in RT = 1 & Inv. in EIT = 1	0.018	0.011	0.011	1.294	1.065	1.065
	(0.043)	(0.032)	(0.036)	(0.907)	(0.689)	(0.720)
ΔX (firm controls)‡	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
NUTS1 FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Het. effects of ΔX for each level of treatment	Yes	Yes	Yes	Yes	Yes	Yes
Treatment model	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	14149	19188	19188	14149	19188	19188
#Clusters	11436	1182	15	11436	1182	15

RIL database. In columns (1) and (4), we apply the trimming procedure proposed by Stürmer et al. (2011, 2021) to restrict the analysis to observations with propensity scores that fall within the region of common support between treated and untreated firms. In columns (2), (3), (5), and (6), we apply alternative clustering levels for the error term. All specifications include year, NUTS1 and industry fixed effects, where industries are aggregated into three broad sectors (industry, construction, and services) of the Italian economy. The vector of firm controls‡, in first differences, includes firm size (number of employees); the shares of employees by educational level and age group; the share of female employees; the share of employees receiving on-the-job training; and the share of employees with temporary contracts. The specification also includes a dummy for firms that made investments in tangible and intangible assets, as a proxy for changes in the stock of these assets. Cluster- (firm-) robust standard errors are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Figures

Figure 1 - Time structure of the RIL database

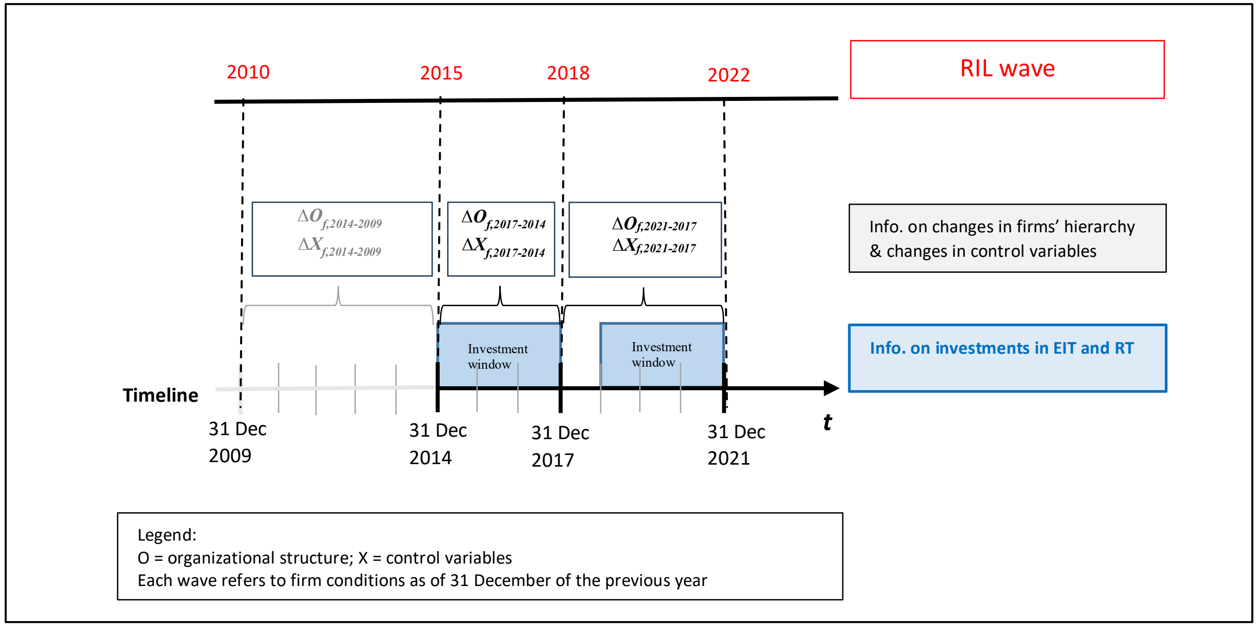
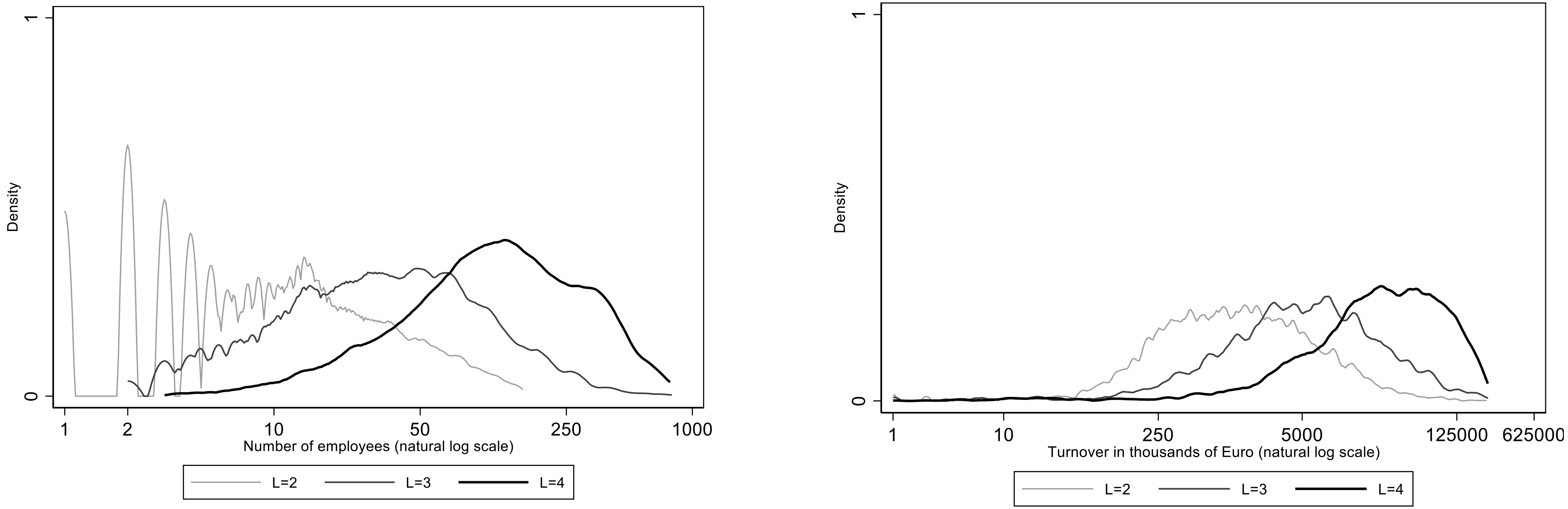


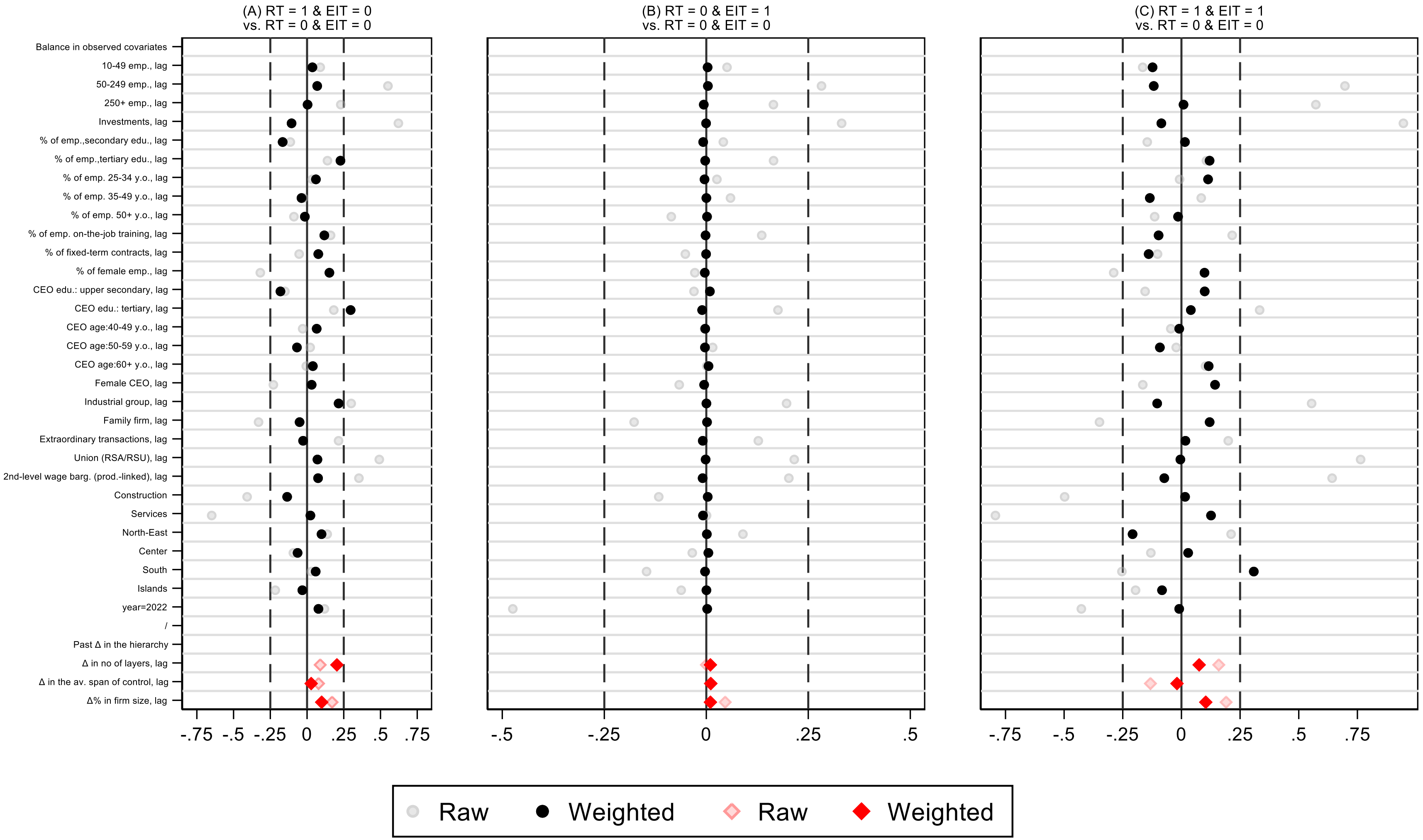
Figure 2 - Firm size distribution by number of layers



Panel A

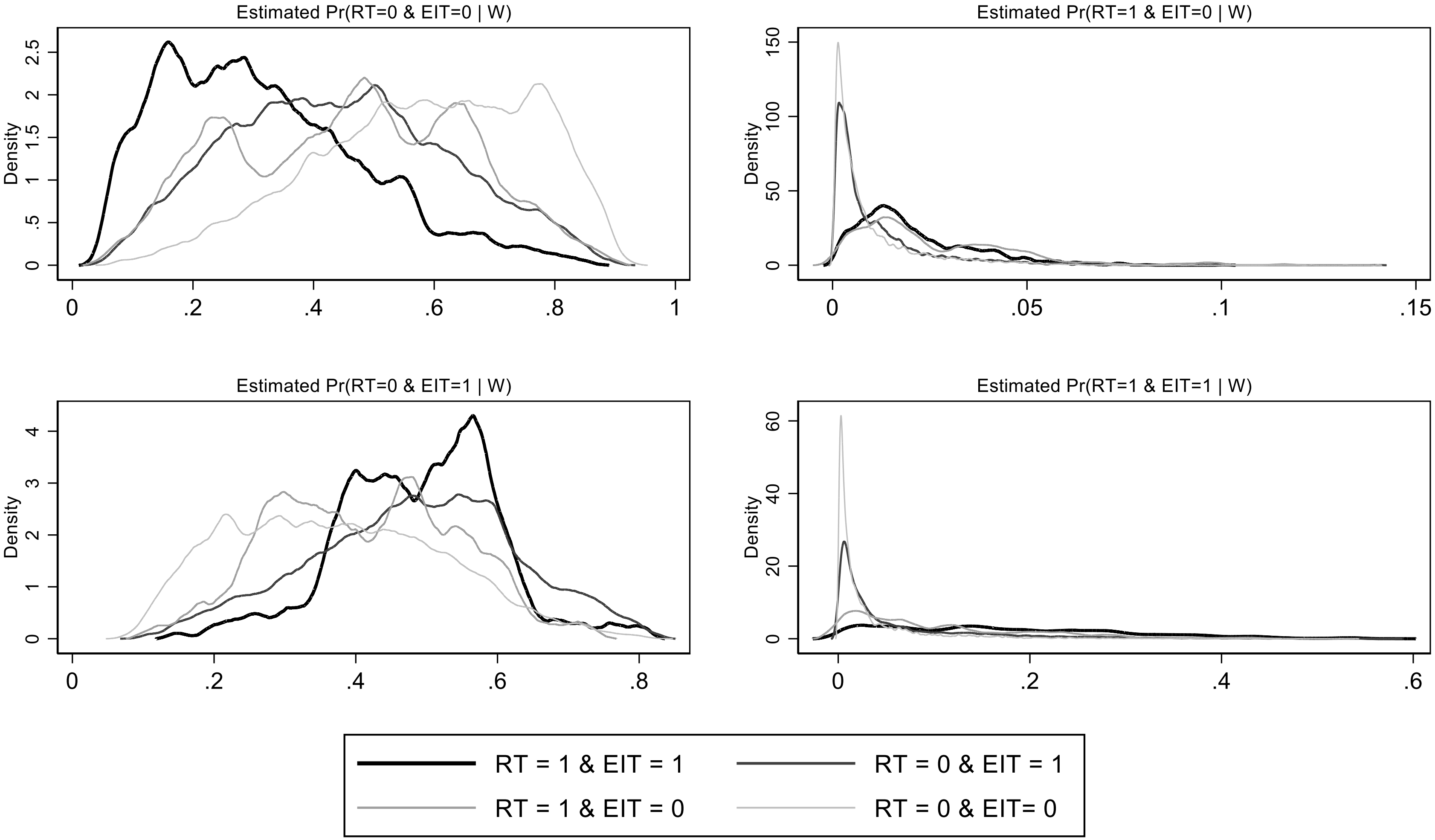
Panel B

Figure 3 - Covariate balance between treated and control firms: Standardized mean differences



Note: Points (●) denote the pre-treatment variables used in the propensity-score model, $\boldsymbol{W_{ft-1}}$; diamonds (◆) denote past changes in the number of layers, the average span of control, and firm size. For each covariate, light symbols refer to the raw sample (before applying IPW) and dark symbols refer to treated and control firms after propensity score re-weighting. Values closer to zero indicate better covariate balance; the dashed lines at ± 0.25 represent the conventional threshold for acceptable imbalance (Imbens and Wooldridge, 2009).

Figure 4 - Overlap of the propensity score distributions for each treatment category (indicated at the top of each panel)



Note: Kernel densities of the estimated propensity scores, shown separately the four treatment values: not investing in either technology (RT=0 and EIT=0); investing in RT only; investing in EIT only; investing in both technologies (RT=1 and EIT=1).

Figure 5 - Investments in RT and the creation/drop of each layer

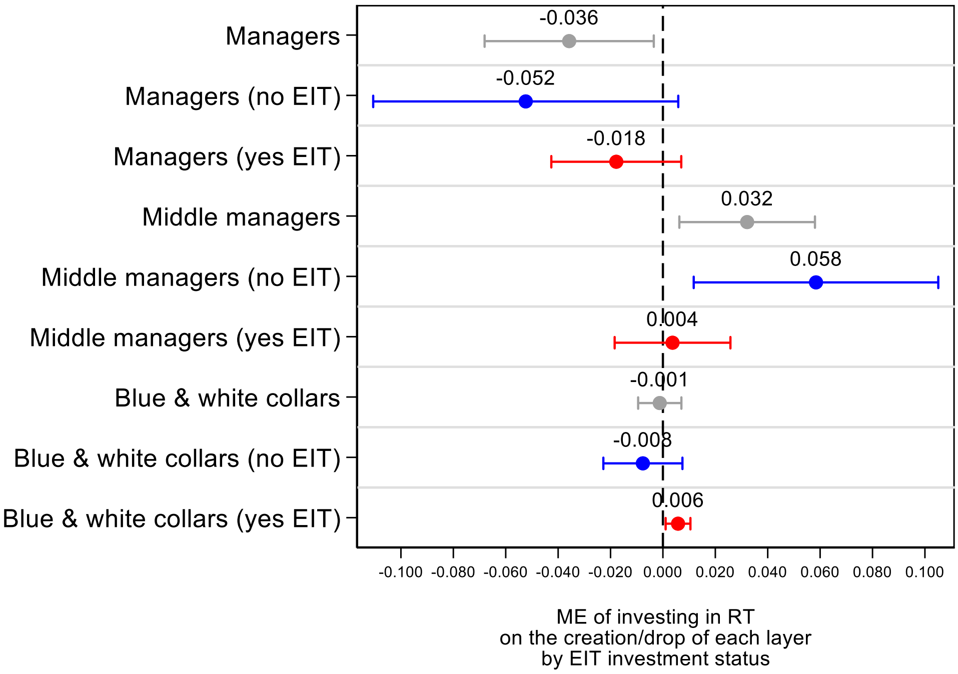


Figure 6 – Investments in EIT and the creation/drop of each layer

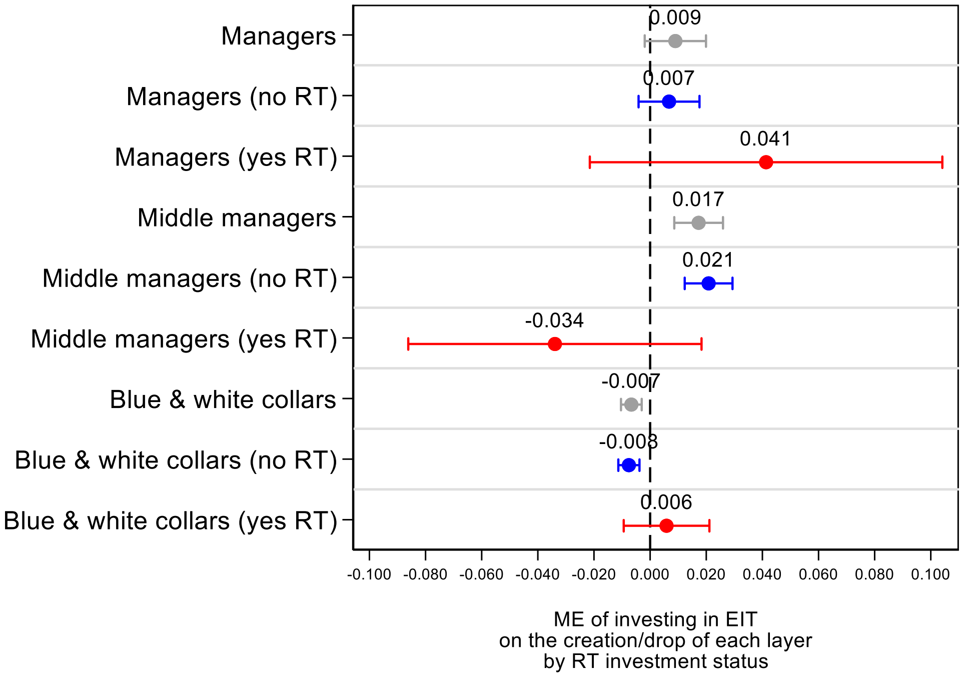


Figure 7 – Investments in RT and the change in span of control at each layer

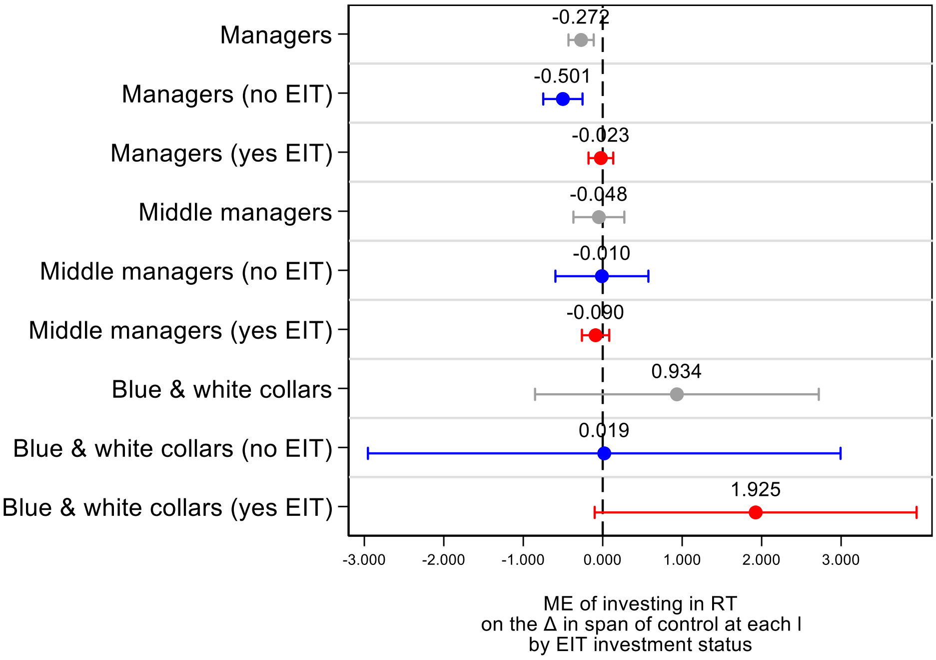
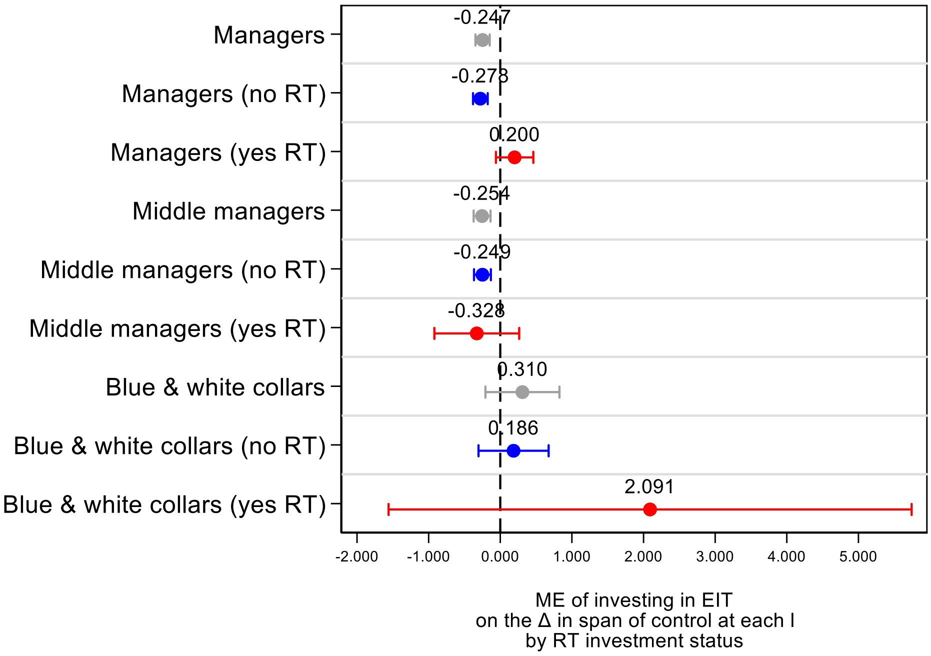


Figure 8 – Investments in EIT and the change in span of control at each layer



Firm hierarchy and emerging technologies

Additional Material - Online Appendix

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A. Theory

A.1.

In Section 2.2 of the article, we study the case in which a firm introduces an intermediate k-th layer between the workers' layer and the entrepreneur's layer. The firm will introduce this additional layer if net output with the k-th layer exceeds the net output without it. Analytically, this condition is:

$$\begin{aligned}
&Q \cdot \frac{1 - e^{-\lambda\cdot(z_E+z_k+z_w)}}{h \cdot (e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w})} - c_E \cdot z_E - B_E^3 \cdot c_k \cdot z_k - B_k^3 \cdot c_w \cdot z_w \\
&\qquad > Q \cdot \frac{1 - e^{-\lambda\cdot(z_E+z_w)}}{h \cdot e^{-\lambda\cdot z_w}} - c_E \cdot z_E - B_E^2 \cdot c_w \cdot z_w
\end{aligned}$$

This expression can be developed and simplified as follows.

Both the left-hand and the right-hand side are rewritten using the least common multiple $\left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right) \cdot e^{-\lambda\cdot z_w}$.

$$\begin{aligned}
&\frac{Q \cdot e^{-\lambda\cdot z_w} - Q \cdot e^{-\lambda\cdot(z_E+z_k+2z_w)} - (c_E \cdot z_E) \cdot h \cdot \left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right) \cdot e^{-\lambda\cdot z_w} - (B_E^3 \cdot c_k \cdot z_k) \cdot h \cdot \left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right) \cdot e^{-\lambda\cdot z_w} - (B_k^3 \cdot c_w \cdot z_w) \cdot h \cdot \left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right) \cdot e^{-\lambda\cdot z_w}}{(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}) \cdot e^{-\lambda\cdot z_w}} \\
&> \frac{Q \ \cdot \left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right) - Q \cdot e^{-\lambda\cdot(z_E+z_w)} \cdot \left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right) - (c_E \cdot z_E) \cdot \left(h \cdot e^{-\lambda\cdot z_w}\right) \cdot \left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right) - (B_E^2 \cdot c_w \cdot z_w) \cdot \left(h \cdot e^{-\lambda\cdot z_w}\right) \cdot \left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right)}{(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}) \cdot e^{-\lambda\cdot z_w}}
\end{aligned}$$

Since the denominator is always positive, the inequality becomes:

$$\begin{aligned}
Q \cdot e^{-\lambda\cdot z_w} &- Q \cdot e^{-\lambda\cdot(z_E+z_k+2z_w)} - (c_E \cdot z_E) \cdot h \cdot e^{-\lambda\cdot(z_k+z_w)} - (c_E \cdot z_E) \cdot h \cdot e^{-\lambda\cdot 2z_w} \\
&- (B_E^3 \cdot c_k \cdot z_k) \cdot h \cdot e^{-\lambda\cdot(z_k+z_w)} - (B_E^3 \cdot c_k \cdot z_k) \cdot h \cdot e^{-\lambda\cdot 2z_w} - (B_k^3 \cdot c_w \cdot z_w) \cdot h \\
&\cdot e^{-\lambda\cdot(z_k+z_w)} - (B_k^3 \cdot c_w \cdot z_w) \cdot h \cdot e^{-\lambda\cdot 2z_w} \\
&> Q \ \cdot \left(e^{-\lambda\cdot z_k} + e^{-\lambda\cdot z_w}\right) - Q \cdot e^{-\lambda\cdot(z_E+z_w+z_k)} - Q \cdot e^{-\lambda\cdot(z_E+2z_w)} - (c_E \cdot z_E) \\
&\cdot \left(h \cdot e^{-\lambda\cdot(z_w+z_k)}\right) - (c_E \cdot z_E) \cdot \left(h \cdot e^{-\lambda\cdot 2z_w}\right) - (B_E^2 \cdot c_w \cdot z_w) \cdot \left(h \cdot e^{-\lambda\cdot(z_w+z_k)}\right) \\
&- (B_E^2 \cdot c_w \cdot z_w) \cdot \left(h \cdot e^{-\lambda\cdot(2z_w)}\right)
\end{aligned}$$

We factor out Q on the left-hand side and h on the right-hand side:

$$\begin{aligned}
Q \cdot &\left\{-e^{-\lambda\cdot(z_E+z_k+2z_w)} - e^{-\lambda\cdot z_k} + e^{-\lambda\cdot(z_E+z_w+z_k)} + e^{-\lambda\cdot(z_E+2z_w)}\right\} \\
&> h \\
&\cdot \left[(c_E \cdot z_E) \cdot e^{-\lambda\cdot(z_k+z_w)} + (c_E \cdot z_E) \cdot e^{-\lambda\cdot 2z_w} + (B_E^3 \cdot c_k \cdot z_k) \cdot e^{-\lambda\cdot(z_k+z_w)}\right. \\
&+ (B_E^3 \cdot c_k \cdot z_k) \cdot e^{-\lambda\cdot 2z_w} + (B_k^3 \cdot c_w \cdot z_w) \cdot h \cdot e^{-\lambda\cdot(z_k+z_w)} + (B_k^3 \cdot c_w \cdot z_w) \cdot e^{-\lambda\cdot 2z_w} \\
&- (c_E \cdot z_E) \cdot e^{-\lambda\cdot(z_w+z_k)} - (c_E \cdot z_E) \cdot e^{-\lambda\cdot 2z_w} - (B_E^2 \cdot c_w \cdot z_w) \cdot e^{-\lambda\cdot(z_w+z_k)} \\
&\left.- (B_E^2 \cdot c_w \cdot z_w) \cdot e^{-\lambda\cdot(2z_w)}\right]
\end{aligned}$$

On the right-hand side, we factor out $\left[e^{-\lambda\cdot(z_k+z_w)}+e^{-\lambda\cdot 2z_w}\right]$, which yields:

$$Q\cdot\left\{-e^{-\lambda\cdot(z_E+z_k+2z_w)}-e^{-\lambda\cdot z_k}+e^{-\lambda\cdot(z_E+z_w+z_k)}+e^{-\lambda\cdot(z_E+2z_w)}\right\}$$
$$>h\cdot\left(B_E^3\cdot c_k\cdot z_k+B_k^3\cdot c_w\cdot z_w-B_E^2\cdot c_w\cdot z_w\right)\cdot\left[e^{-\lambda\cdot(z_k+z_w)}+e^{-\lambda\cdot 2z_w}\right]$$

Namely:

$$\frac{Q\cdot\left\{-e^{-\lambda\cdot(z_E+z_k+2z_w)}-e^{-\lambda\cdot z_k}+e^{-\lambda\cdot(z_E+z_w+z_k)}+e^{-\lambda\cdot(z_E+2z_w)}\right\}}{\left[e^{-\lambda\cdot(z_k+z_w)}+e^{-\lambda\cdot 2z_w}\right]}$$
$$>h\cdot\left\{B_E^3\cdot c_k\cdot z_k+B_k^3\cdot c_w\cdot z_w-B_E^2\cdot c_w\cdot z_w\right\}$$

Using Equation (4) in the paper, we substitute: $B_E^3=\frac{e^{\lambda\cdot z_k}}{h+c_E}$, $B_k^3=\frac{e^{\lambda\cdot z_w}}{h+c_k}$, and $B_E^2=\frac{e^{\lambda\cdot z_w}}{h+c_E}$, which gives:

$$\frac{Q\cdot\left\{-e^{-\lambda\cdot(z_E+z_k+2z_w)}-e^{-\lambda\cdot z_k}+e^{-\lambda\cdot(z_E+z_w+z_k)}+e^{-\lambda\cdot(z_E+2z_w)}\right\}}{\left[e^{-\lambda\cdot(z_k+z_w)}+e^{-\lambda\cdot 2z_w}\right]}$$
$$>h\cdot\left\{\frac{e^{\lambda\cdot z_k}}{h+c_E}\cdot c_k\cdot z_k+\frac{e^{\lambda\cdot z_w}}{h+c_k}\cdot c_w\cdot z_w-\frac{e^{\lambda\cdot z_w}}{h+c_E}\cdot c_w\cdot z_w\right\}$$

After taking the least common multiple on the right-hand side and simplifying, we obtain:

$$\frac{Q\cdot\left\{-e^{-\lambda\cdot(z_E+z_k+2z_w)}-e^{-\lambda\cdot z_k}+e^{-\lambda\cdot(z_E+z_w+z_k)}+e^{-\lambda\cdot(z_E+2z_w)}\right\}}{\left[e^{-\lambda\cdot(z_k+z_w)}+e^{-\lambda\cdot 2z_w}\right]}$$
$$>h\cdot\frac{e^{\lambda\cdot z_k}\cdot c_k\cdot z_k\cdot(h+c_k)+e^{\lambda\cdot z_w}\cdot c_w\cdot z_w\cdot(c_E-c_k)}{(h+c_E)(h+c_k)}$$

This expression corresponds to the simplified form reported in Section 2.2 of the paper.

A.2.

In Section 2.4, we formulate four hypotheses. In the hypothesis 4, we express the left-side of inequality 6, which is $Q\cdot\frac{e^{-\lambda\cdot(z_{k+1}+z_k+z_{k-1})}+e^{-\lambda\cdot(z_{k+1}+2z_{k-1})}-e^{-\lambda\cdot(z_{k+1}+z_k+2z_{k-1})}-e^{-\lambda\cdot z_k}}{\left[e^{-\lambda\cdot(z_k+z_{k-1})}+e^{-2\lambda\cdot z_{k-1}}\right]}$ as $\frac{\Delta\lambda\cdot(z_k-z_{k-1}-z_{k+1})}{2}$ using a first-order Taylor series. For demonstrating that, assume that $\Delta\lambda\rightarrow 0^+$, namely that $\Delta\lambda$ approaches zero from the positive side. For $\Delta\lambda$ close to zero, we can approximate $e^{-\Delta\lambda\cdot z}$ using the first-order Taylor series expansion ($e^x\approx 1+x$) and rewrite the left-hand side of (6) as: $Q\cdot\frac{1-\Delta\lambda\cdot(z_{k+1}+z_k+z_{k-1})+1-\Delta\lambda\cdot(z_{k+1}+2z_{k-1})-1+\Delta\lambda\cdot(z_{k+1}+z_k+2z_{k-1})-1+\Delta\lambda\cdot z_k}{1-\Delta\lambda\cdot(z_k+z_{k-1})+1-\Delta\lambda\cdot 2z_{k-1}}$, which simplifies to $Q\cdot\frac{\Delta\lambda\cdot(z_k-z_{k-1}-z_{k+1})}{2-\Delta\lambda\cdot(z_k+3z_{k-1})}$. For small $\Delta\lambda$, we can approximate the denominator as a constant (≈ 2) and obtain $\frac{\Delta\lambda\cdot(z_k-z_{k-1}-z_{k+1})}{2}$.

B. Empirics

B. 1 The RIL survey: representativeness, composition in terms of industries, regions and firm size[1]

This paper uses data from the *Rilevazione Imprese e Lavoro* (RIL), a mandatory survey conducted by the National Institute for Public Policy Analysis (INAPP). The RIL survey is administered to a representative sample of Italian partnerships and limited liability companies of all size classes operating in the private, non-agricultural sector. The sample is stratified by firm size, industry, and geographical area. Firm size is defined using five categories based on the number of employees (0-4; 5-15; 16-49; 50-249; and 250 or more employees). Industry classification follows the NACE Rev.2 statistical classification, while geographic coverage is defined at the NUTS-2 regional level. The probability of inclusion in the sample is proportional to firm size, measured by total employment. The reference population is derived from the *Registro statistico delle imprese attive* (ASIA-Imprese), maintained by the Italian National Institute of Statistics (Istat). INAPP has conducted six survey waves to date, in 2005, 2007, 2010, 2015, 2018, and 2022. Each wave includes approximately 21,000 to 30,000 firms.

In this paper, we focus on the 2015, 2018, and 2022 waves of the survey, which include 30091, 30021, and 30120 firms, respectively. Our focus on these waves reflects the availability of information on emerging technologies (ET). Specifically, data on firms' investments in ET are collected only in the 2018 and 2022 waves. Since these investments constitute the key explanatory variables in our analysis of changes in firms' hierarchical organization, the empirical analysis necessarily relies on these waves. The longitudinal structure of the dataset is unbalanced: approximately 25% of firms are observed in two waves, and only about 10% appear in all three waves (2015, 2018, and 2022).

We implement a series of data-cleaning procedures. First, we exclude firms that changed regional location (NUTS-2) between 2014 and 2021 (804 observations), as well as firm-year observations referring to inactive firms (1,043 observations). Second, to mitigate the influence of extreme values, we trim observations above the 99th percentile of the overall distribution for the following variables: number of employees (883 observations), sales (725), average span of control (861), job turnover rate (711), and job excess turnover rate (784). As specified in Equation (12) in the paper, our baseline empirical model relates changes in hierarchical dimensions in the periods 2014-2017 and 2017-2021 to investments undertaken in 2015-2017 and 2019-2021, respectively. Estimation therefore requires firms to be observed in at least two consecutive waves among 2015, 2018, and 2022. After additionally excluding observations with missing values in the variables required for the empirical

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[1] Section 3.3 of the paper provides a brief description of the dataset; this appendix offers additional details on the survey design and sample structure.

models (Equations 12 and 14), the final estimation sample consists of 19188 observations corresponding to 14793 firms.

Table B1 compares the distribution of observations in the final estimation sample with that of the pooled RIL dataset across the 2015, 2018, and 2022 waves. Overall, the composition of the final sample closely mirrors that of the original RIL dataset in terms of sectoral, geographical, and firm-size distributions. Manufacturing firms are somewhat more represented in the final sample (41.06%) compared with the pooled RIL dataset (36.95%), while construction firms are slightly less represented (13.76% versus 15.53%), with services showing very similar shares across the two samples. From a geographical perspective, the final sample exhibits a higher representation of firms located in the North-West and North-East and a lower share of firms in the South and Islands, though the overall regional distribution remains broadly comparable. In terms of firm size, the final sample contains relatively fewer micro firms (1-9 employees) and a higher share of medium-sized firms (50-249 employees), reflecting the restrictions applied in the empirical analysis.

Table B1 - Distribution of observations by sector, region, and firm size: final sample versus pooled RIL dataset (2015, 2018, 2022)

Sector	Final sample (%)	RIL (2015, 2018, 2022; %)
Manufacturing, mining, quarrying	41.06	36.95
Construction	13.76	15.53
Services	45.18	47.52
Total	100.00	100.00
NUTS-1 regions		
North-West	29.07	26.04
North-East	27.58	24.45
Center	21.13	21.26
South	16.27	20.65
Islands	5.96	7.60
Total	100.00	100.00
Size class		
0	-	8.69
1-9 emp.	35.83	40.19
10-49 emp.	38.42	31.88
50-249 emp.	21.92	14.79
250+ emp.	3.83	4.46
Total	100.00	100.00
Observations	19188	89428

Despite these small differences, the final estimation sample retains a distribution across sectors, regions, and size classes that remains broadly consistent with the structure of the original RIL dataset.

B.2 Definition of variables and descriptive statistics

B.2.1 Data on investments in emerging technologies

Data on firms' investments in ET are collected only in the 2018 and 2022 waves of the RIL survey. The questionnaire gathers information on firms' investments in specific technological areas associated with Industry 4.0. As an illustration, in the 2022 wave firms were asked whether they had undertaken investments in selected technological areas during the period 2019-2021. Table B2 reproduces the wording of the questionnaire item used to elicit this information.

Table B2 - Question L3 (RIL questionnaire; 2022 wave): "*During the period 2019-2021, did the firm make investments in tangible or intangible assets, or purchase services, related to the following technological areas for use in its business activities?*"

Question	Technological area	Yes	No
L3a	Internet of Things (IoT) solutions and/or Augmented or Virtual Reality	☐	☐
L3c	Robotics	☐	☐
L3d	Cloud computing or Big Data Analytics	☐	☐
L3f	Cybersecurity or upgrading of existing IT systems	☐	☐

Note: (1) Only one response per row should be provided. (2) The question refers exclusively to investments or purchases of goods and services in technological fields related to Industry 4.0.

Below we report the definitions of the technological areas as provided in the questionnaire.

- *Internet of Things (IoT)* refers to devices that communicate in real time with other devices, updating their operating routines. These systems rely on enabling technologies such as sensor networks and radio-frequency identification (RFID).
- *Augmented Reality (AR)* and *Virtual Reality (VR)* refer to technologies that enhance or simulate human sensory perception through digitally generated information, typically transmitted electronically and often manipulated through software. Interaction may occur through mobile devices, personal computers equipped with webcams or sensors, or specialized devices for vision (e.g., head-mounted displays), hearing (earphones), and manipulation (gloves), which add multimedia information to the perceived environment.
- *Robotics* includes next-generation industrial robots and service robots designed to work alongside humans and perform specialized tasks. These robots are typically computer-controlled and programmable along three or more axes. They may be fixed or mobile and are widely used in industrial automation (e.g., robotic welding, laser cutting, spray painting). Collaborative robots can operate autonomously in complex environments requiring interaction with people, objects, or

other devices (e.g., construction, cleaning, transport, surveillance, security). This category also includes other equipment controlled by computerized systems or managed through sensors and interconnection technologies.

- *Cloud computing* refers to access to software, computing power, and memory capacity through remote servers.
- *Big Data Analytics* refers to technological systems that allow firms to store, process, and transmit very large volumes of data using advanced storage and analytical tools.

In the empirical analysis (Section 3.3.2), we group technological areas L3a, L3d, and L3f into a broader category of emerging information technologies (EIT). Investments in robotics (L3c) are instead treated as a separate technological category. Firms reporting investments in both categories are classified as joint investors.

Figures B1-B3 provide a descriptive overview of how investments in ET, including RT and EIT, are distributed across firms in the RIL dataset (waves 2018 and 2022), according to sector, geographical (NUTS-1) location, and firm size. Across all dimensions, most firms report no investment in ET, although the incidence of investment varies systematically across groups. Sectoral differences are particularly pronounced: firms in manufacturing, mining, and quarrying display the highest diffusion of both RT and EIT investments, while construction firms exhibit the lowest investment incidence. Service-sector firms occupy an intermediate position, with relatively limited investment in robots but a higher incidence of EIT investments. Geographical differences are more moderate. Investments in both technologies are slightly more common in the northern NUTS-1 regions, particularly in the North-West and North-East, while firms located in the South and the Islands show lower adoption rates. Firm size emerges as the most salient dimension: the likelihood of investing in either technology increases markedly with firm size. Large firms (250+ employees) display the highest incidence of both EIT and RT investments and are also more likely to invest in both technologies simultaneously, whereas very small firms rarely report such investments. These descriptive patterns are consistent with official statistics on the diffusion of digital technologies among Italian firms. For instance, Istat (2024) shows that investments in digital technologies are more widespread among larger firms and that the most common areas of investment include cybersecurity, cloud computing, and ICT-related training. Similarly, analyses based on Istat data reported by the OECD (2022) highlight that adoption rates of digital technologies are uneven across sectors and territories, with more advanced technologies (such as automation, simulations of interconnected machines, or 3D printing) being more concentrated in manufacturing activities, while adoption rates are generally higher in the northern regions of the country than in the Centre and the South. Moreover, the same evidence shows that technology adoption increases strongly with firm size, reflecting both scale economies in technology adoption and the greater availability of complementary capabilities among larger firms. Overall, the patterns observed in the RIL data are therefore broadly in line with the stylized facts documented in the official statistics on digital transformation in the Italian economy.

Figure B1 - Percentage of firms investing in emerging technologies by industry; final sample (19188 observations)

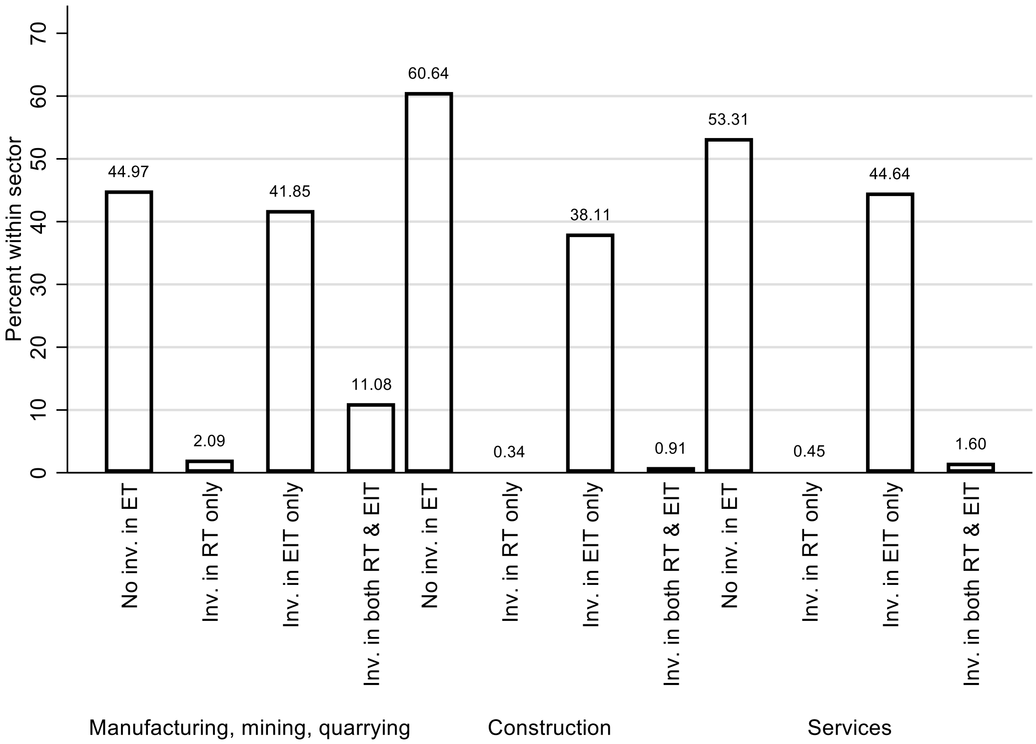


Figure B2 - Percentage of firms investing in emerging technologies by NUTS-1 region; final sample (19188 observations)

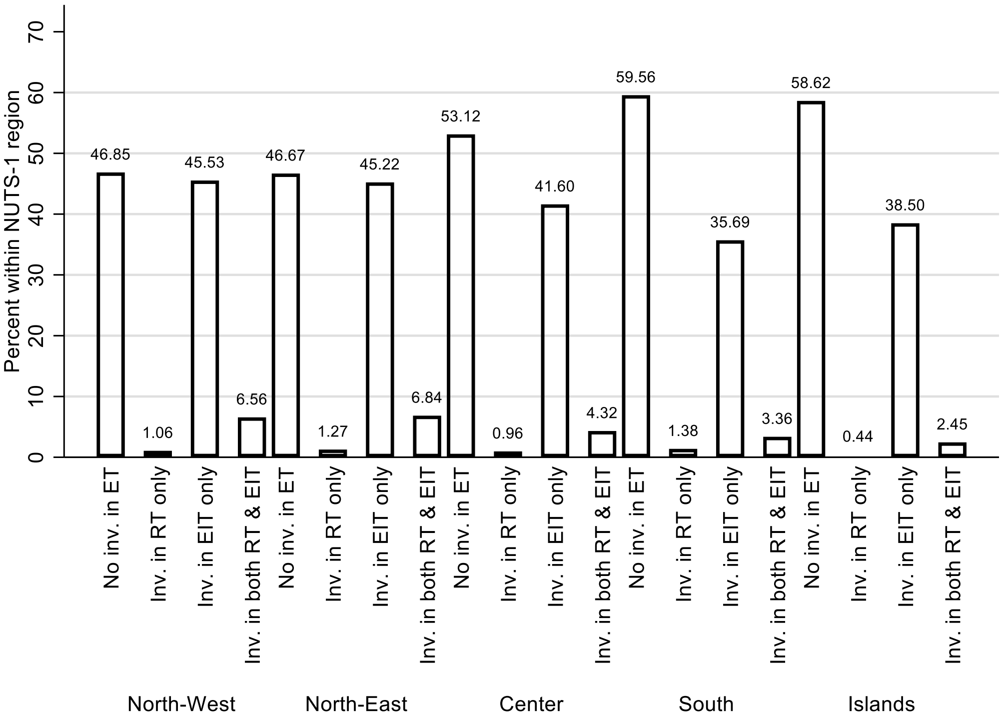
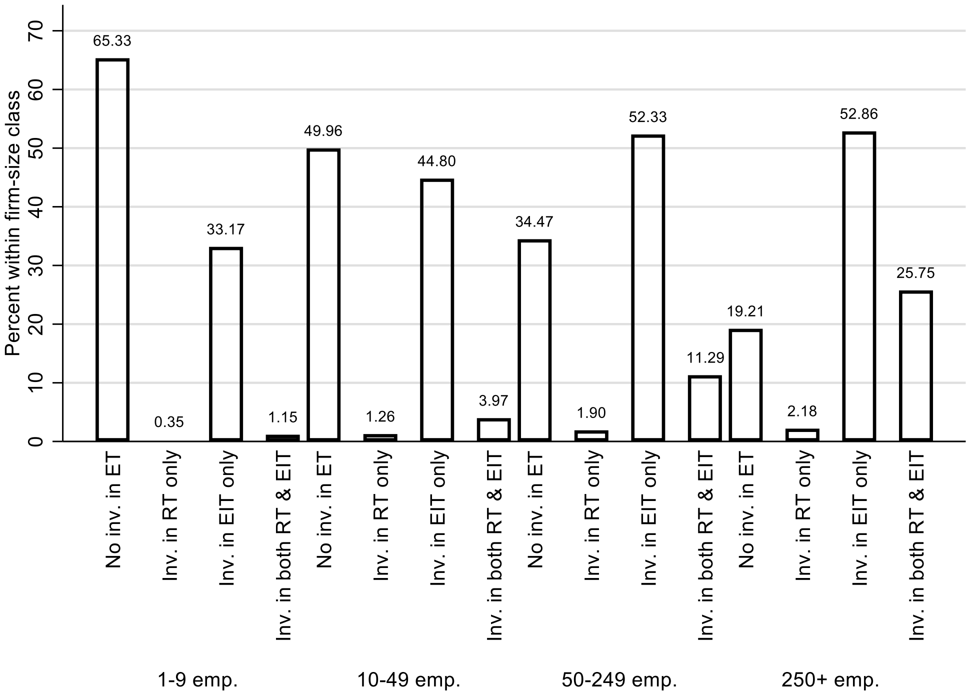


Figure B3 - Percentage of firms investing in emerging technologies by firm size; final sample (19188 observations)



B.2.2 Control variables

Table B3 reports descriptive statistics for the variables capturing firm characteristics and organizational structure used in the empirical analysis, and provides their definitions. The statistics are computed on the final sample (19188 observations).

Table B3 – Definitions and descriptive statistics on firm characteristics; final sample

Variable	Definition	Mean	SD	Min	Max
Δ no. of layers	Change in the number of active hierarchical layers between two consecutive survey waves.	0.030	0.515	-2.000	2.000
Δ av. span of control	Change in the firm's average span of control between two consecutive survey waves.	0.169	14.679	-149.000	143.222
Δ% in firm size	Change in the logarithm of total employment between two consecutive survey waves.	0.036	0.426	-5.296	4.277
Investments	Dummy equal to one if the firm made investments in tangible or intangible assets, and zero otherwise.	0.486	0.500	0.000	1.000
Δ (pp) in emp., primary edu.	Change in the share of employees with primary education between two consecutive survey waves.	-0.027	0.312	-1.000	1.000
Δ (pp) in emp., secondary edu.	Change in the share of employees with secondary education between two consecutive survey waves.	0.005	0.334	-1.000	1.000
Δ (pp) in emp., tertiary edu.	Change in the share of employees with tertiary education between two consecutive survey waves.	0.022	0.199	-1.000	1.000
Δ (pp) in emp., <25 y.o.	Change in the share of employees younger than 25 between two consecutive survey waves.	-0.001	0.129	-1.000	1.000
Δ (pp) in emp., 25-34 y.o.	Change in the share of employees aged 25-34 between two consecutive survey waves.	-0.031	0.236	-1.000	1.000
Δ (pp) in emp., 35-49 y.o.	Change in the share of employees aged 35-49 between two consecutive survey waves.	-0.040	0.290	-1.000	1.000
Δ (pp) in emp., 50+ y.o.	Change in the share of employees aged 50 or more between two consecutive survey waves.	0.073	0.250	-1.000	1.000
Δ (pp) in emp. with on-the-job training	Change in the share of employees receiving on-the-job training between two consecutive survey waves.	0.020	0.504	-1.000	1.000
Δ (pp) in fixed-term contracts	Change in the share of employees with fixed-term contracts between two consecutive survey waves.	0.005	0.168	-1.000	1.000
Δ (pp) in female employees	Change in the share of female employees between two consecutive survey waves.	-0.005	0.164	-1.000	1.000
No. of layers	Number of (non-empty, i.e. >0 employees) hierarchical layers in the firm, where hierarchical layers are defined as it follows: *l4*: Entrepreneur/owner; *l3*: managers; *l2*: middle managers; *l1*: white collars & blue collars	2.512	0.737	2.000	4.000
layer: managers (% of firms)	Dummy equal to one if the firm has at least one manager, and zero otherwise.	0.253	0.435	0.000	1.000
layer: middle managers (% of firms)	Dummy equal to one if the firm has at least one middle manager, and zero otherwise.	0.262	0.440	0.000	1.000
layer: blue- and white-collars (% of firms)	Dummy equal to one if the firm has at least one blue- or white-collar worker, and zero otherwise.	0.997	0.053	0.000	1.000
Av. span of control	Average firm number of subordinates in layer *l-1* per supervisor in the adjacent non-empty superior layer (*l*)	17.147	21.668	1.000	155.000
No. of managers per supervisor (layer up - entrepreneur)	Number of managers supervised by the entrepreneur	3.234	4.311	1.000	73.000
No. of middle managers per supervisor (layer up)	Number of middle managers supervised by the nearest higher active layer.	2.989	4.841	0.091	121.000
No. of BCs+WCs per supervisor (layer up)	Number of blue- and white-collar workers supervised by the nearest higher active layer.	23.046	30.865	0.027	460.000
Firm size: 1-9 emp., lag	Dummy equal to one if, in the previous wave, the firm had 1-9 employees.	0.362	0.481	0.000	1.000
Firm size: 10-49 emp., lag	Dummy equal to one if, in the previous wave, the firm had 10-49 employees.	0.390	0.488	0.000	1.000
Firm size: 50-249 emp., lag	Dummy equal to one if, in the previous wave, the firm had 50-249 employees.	0.213	0.409	0.000	1.000
Firm size: 250+ emp., lag	Dummy equal to one if, in the previous wave, the firm had 250 or more employees.	0.035	0.183	0.000	1.000
Investments, lag	Dummy equal to one if the firm made investments in tangible or intangible assets in the previous wave.	0.475	0.499	0.000	1.000
% of emp.,primary edu., lag	Share of employees with primary education in the previous wave; %	0.369	0.333	0.000	1.000
% of emp.,secondary edu., lag	Share of employees with secondary education in the previous wave; %	0.504	0.314	0.000	1.000
% of emp.,tertiary edu., lag	Share of employees with tertiary education in the previous wave; %	0.128	0.213	0.000	1.000
% of emp. <25 y.o., lag	Share of employees aged <25 years in total employment in the previous wave; %	0.053	0.112	0.000	1.000
% of emp. 25-34 y.o., lag	Share of employees aged 25-34 years in total employment in the previous wave; %	0.218	0.222	0.000	1.000
% of emp. 35-49 y.o., lag	Share of employees aged 35-49 years in total employment in the previous wave; %	0.467	0.254	0.000	1.000
% of emp. 50+ y.o., lag	Share of employees aged 50+ years in total employment in the previous wave; %	0.262	0.236	0.000	1.000
% of emp. on-the-job training, lag	Share of employees receiving on-the-job training in the previous wave.	0.403	0.420	0.000	1.000
% of fixed-term contracts, lag	Share of employees with fixed-term contracts in total employment; %	0.069	0.145	0.000	1.000
% of female emp., lag	Share of female employees in total employment; %	0.361	0.310	0.000	1.000
CEO edu.: compulsory, lag	The firm's top manager has attained (in the previous wave) compulsory education; dummy	0.187	0.390	0.000	1.000
CEO edu.: upper secondary , lag	The firm's top manager has attained (in the previous wave) secondary education; dummy	0.515	0.500	0.000	1.000
CEO edu.: tertiary, lag	The firm's top manager has attained (in the previous wave) tertiary education; dummy	0.299	0.458	0.000	1.000
CEO age: 15-39 y.o., lag	The firm's top manager (in the previous wave) is aged 15-39 years; dummy	0.057	0.232	0.000	1.000
CEO age: 40-49 y.o., lag	The firm's top manager (in the previous wave) is aged 40-49 years; dummy	0.231	0.422	0.000	1.000
CEO age: 50-59 y.o., lag	The firm's top manager (in the previous wave) is aged 50-59 years; dummy	0.354	0.478	0.000	1.000
CEO age: 60+ y.o., lag	The firm's top manager (in the previous wave) is aged 60+ years; dummy	0.358	0.479	0.000	1.000
Female CEO, lag	The firm's top manager (in the previous wave) is female; dummy	0.139	0.346	0.000	1.000
Industrial group, lag	Dummy equal to one if the firm belonged to an industrial group in the previous wave, and zero if it was stand-alone.	0.153	0.360	0.000	1.000
Family firm, lag	Dummy equal to one if the firm was family-owned in the previous wave, and zero otherwise.	0.834	0.372	0.000	1.000
Extraordinary transactions, lag	Dummy equal to one if the firm was involved in extraordinary transactions in the previous wave, and zero otherwise.	0.049	0.215	0.000	1.000
Union (RSA/RSU), lag	Firm has workers' union representation; dummy	0.233	0.423	0.000	1.000
2nd-level wage barg. (prod.-linked), lag	Firms has activated a second (firm)-level bargaining scheme, linked to levels of production or productivity; dummy	0.071	0.258	0.000	1.000
Number of hires in year *y*		6.673	20.291	0.000	585.000
Total worker turnover in year *y*	(no. of hires + no. of separations in *y*)	12.363	36.510	0.000	1151.000
Excess worker turnover in year *y*	(no. of hires + no. of separations in *y*) - |Δ employment in *y*|	9.043	31.897	0.000	1150.000

B.3. Tables not included in the main text

Tables B4 and B5 report the full set of coefficients for the models presented in Tables 8 and 9 in the main text, respectively. Table B4 refers to the models in which the dependent variable is the change in the number of hierarchical layers, whereas Table B5 refers to those in which the dependent variable is the change in the average span of control. In the paper, Tables 8 and 9 focus on the coefficients of primary interest, namely those associated with investments in emerging technologies and their interactions, while omitting the estimates for firm-level control variables and, in the IPWRA specifications, the coefficients of the treatment model, in order to save space. Tables B4 and B5 provide these complete estimation results, including all coefficients associated with the control variables in the outcome equations and those from the treatment model used to compute the inverse probability weights.

Table B4 - Emerging technologies and the change (Δ) in the no. of layers: firm controls' and treatment model's coefficients

	(1)	(2)		(3)			(4)	(5)		(6)			(7)	(8)				(9)						
	OLS	RA		IPWRA			OLS	RA		IPWRA			OLS	RA				IPWRA						
	_	OME0	OME1	OME0	OME1	TME1	_	OME0	OME1	OME0	OME1	TME1	_	OME0	OME1	OME2	OME3	OME0	OME1	TME1	OME2	OME3	TME2	TME3
Δ% in firm size	0.194***	0.189***	0.383***	0.190***	0.304***		0.192***	0.175***	0.220***	0.183***	0.200***		0.192***	0.172***	0.689***	0.216***	0.331***	0.176***	0.633***		0.196***	0.227***		
	(0.010)	(0.010)	(0.072)	(0.010)	(0.089)		(0.010)	(0.012)	(0.018)	(0.015)	(0.019)		(0.010)	(0.012)	(0.133)	(0.018)	(0.071)	(0.014)	(0.120)		(0.019)	(0.080)		
Investments	0.016**	0.015**	0.037	0.016**	0.005		0.007	0.011	0.002	0.011	0.007		0.008	0.011	0.237***	0.004	-0.006	0.012	0.265***		0.010	-0.016		
	(0.008)	(0.008)	(0.043)	(0.008)	(0.066)		(0.008)	(0.011)	(0.012)	(0.012)	(0.012)		(0.008)	(0.011)	(0.085)	(0.012)	(0.049)	(0.013)	(0.079)		(0.013)	(0.084)		
Δ (pp) in emp., secondary edu.	0.034***	0.034***	-0.005	0.035***	0.061		0.033***	0.032**	0.037*	0.028*	0.030		0.033***	0.028*	0.316**	0.047**	-0.088	0.025	0.371**		0.043*	0.003		
	(0.012)	(0.013)	(0.070)	(0.013)	(0.107)		(0.012)	(0.014)	(0.021)	(0.017)	(0.022)		(0.012)	(0.015)	(0.157)	(0.022)	(0.076)	(0.018)	(0.161)		(0.023)	(0.128)		
Δ (pp) in emp., tertiary edu.	0.138***	0.140***	0.121	0.139***	0.181		0.136***	0.163***	0.094***	0.145***	0.082**		0.136***	0.167***	-0.056	0.092**	0.145	0.149***	-0.137		0.086**	0.396*		
	(0.022)	(0.022)	(0.105)	(0.023)	(0.203)		(0.022)	(0.027)	(0.036)	(0.030)	(0.039)		(0.022)	(0.027)	(0.182)	(0.037)	(0.126)	(0.030)	(0.210)		(0.040)	(0.235)		
Δ (pp) in emp., 25-34 y.o.	0.065**	0.063**	0.015	0.063**	-0.037		0.065**	0.042	0.099**	0.028	0.089*		0.065**	0.036	0.574	0.107**	-0.139	0.021	0.495*		0.093*	0.068		
	(0.030)	(0.030)	(0.175)	(0.031)	(0.272)		(0.030)	(0.036)	(0.048)	(0.043)	(0.048)		(0.030)	(0.036)	(0.350)	(0.049)	(0.194)	(0.043)	(0.285)		(0.050)	(0.387)		
Δ (pp) in emp., 35-49 y.o.	0.116***	0.108***	0.208	0.106***	0.099		0.116***	0.094**	0.148***	0.077*	0.113**		0.116***	0.090**	0.536	0.138***	0.106	0.067	0.413		0.104**	0.054		
	(0.030)	(0.031)	(0.149)	(0.032)	(0.215)		(0.030)	(0.037)	(0.049)	(0.044)	(0.048)		(0.030)	(0.037)	(0.364)	(0.051)	(0.158)	(0.045)	(0.367)		(0.051)	(0.305)		
Δ (pp) in emp., 50+ y.o.	0.158***	0.144***	0.447***	0.140***	0.549*		0.158***	0.147***	0.171***	0.109**	0.151***		0.158***	0.142***	0.554	0.143***	0.411**	0.101**	0.449		0.127**	0.620		
	(0.032)	(0.033)	(0.164)	(0.034)	(0.289)		(0.032)	(0.039)	(0.051)	(0.046)	(0.050)		(0.032)	(0.039)	(0.339)	(0.053)	(0.184)	(0.047)	(0.346)		(0.053)	(0.401)		
Δ (pp) in emp. with on-the-job training	-0.011	-0.010	-0.023	-0.010	-0.008		-0.012	-0.021**	-0.001	-0.014	0.003		-0.012	-0.019*	-0.020	0.000	-0.013	-0.012	0.031		0.006	-0.059		
	(0.008)	(0.008)	(0.035)	(0.008)	(0.052)		(0.008)	(0.010)	(0.012)	(0.012)	(0.012)		(0.008)	(0.010)	(0.080)	(0.013)	(0.039)	(0.012)	(0.075)		(0.013)	(0.072)		
Δ (pp) in fixed-term contracts	0.005	0.002	0.044	0.003	-0.030		0.007	0.015	-0.009	-0.001	0.020		0.007	0.014	-0.135	-0.017	0.065	-0.001	-0.096		0.023	-0.346		
	(0.024)	(0.024)	(0.135)	(0.024)	(0.229)		(0.024)	(0.027)	(0.043)	(0.038)	(0.041)		(0.024)	(0.027)	(0.228)	(0.044)	(0.172)	(0.039)	(0.226)		(0.042)	(0.234)		
Δ (pp) in female employees	-0.058**	-0.049**	-0.474**	-0.049**	-0.687**		-0.059**	-0.040	-0.103**	-0.038	-0.091*		-0.059**	-0.034	-0.373	-0.092*	-0.457	-0.030	-0.722***		-0.086*	-0.154		
	(0.023)	(0.023)	(0.232)	(0.024)	(0.312)		(0.023)	(0.025)	(0.049)	(0.032)	(0.047)		(0.023)	(0.025)	(0.336)	(0.049)	(0.285)	(0.032)	(0.258)		(0.047)	(0.357)		
10-49 emp., lag						1.020***						0.444***								1.055***			0.420***	1.256***
						(0.119)						(0.040)								(0.224)			(0.040)	(0.139)
50-249 emp., lag						1.709***						0.938***								1.543***			0.860***	2.305***
						(0.129)						(0.056)								(0.257)			(0.058)	(0.150)
250+ emp., lag						2.356***						1.402***								1.616***			1.158***	3.255***
						(0.173)						(0.118)								(0.408)			(0.126)	(0.209)
Investments, lag						0.660***						0.489***								0.525***			0.457***	1.001***
						(0.078)						(0.034)								(0.158)			(0.035)	(0.090)
% of emp.,secondary edu., lag						0.046						0.529***								0.299			0.546***	0.363**
						(0.130)						(0.057)								(0.284)			(0.058)	(0.149)
% of emp.,tertiary edu., lag						0.396*						1.038***								1.106***			1.071***	0.974***
						(0.205)						(0.091)								(0.391)			(0.092)	(0.235)
% of emp. 25-34 y.o., lag						-0.976***						-0.175								-1.298**			-0.147	-0.961**
						(0.344)						(0.161)								(0.610)			(0.164)	(0.408)
% of emp. 35-49 y.o., lag						-1.165***						-0.048								-1.594***			-0.012	-1.034***
						(0.296)						(0.145)								(0.563)			(0.149)	(0.346)
% of emp. 50+ y.o., lag						-1.867***						-0.173								-2.019***			-0.104	-1.867***
						(0.321)						(0.151)								(0.606)			(0.155)	(0.372)
% of emp. on-the-job training, lag						0.061						0.265***								0.116			0.272***	0.241***
						(0.081)						(0.039)								(0.187)			(0.040)	(0.092)
% of fixed-term contracts, lag						-0.653**						-0.265**								-0.755			-0.232**	-0.772**
						(0.270)						(0.115)								(0.631)			(0.117)	(0.302)
% of female emp., lag						-0.203						-0.110*								-0.422			-0.120**	-0.245
						(0.144)						(0.060)								(0.315)			(0.061)	(0.161)
CEO edu.: upper secondary, lag						-0.027						0.209***								-0.201			0.205***	0.147
						(0.096)						(0.045)								(0.189)			(0.046)	(0.110)
CEO edu.: tertiary, lag						0.087						0.253***								-0.110			0.241***	0.296**
						(0.111)						(0.054)								(0.224)			(0.055)	(0.125)
CEO age:40-49 y.o., lag						-0.154						-0.082								-0.331			-0.088	-0.159
						(0.162)						(0.074)								(0.314)			(0.076)	(0.185)
CEO age:50-59 y.o., lag						-0.154						-0.045								-0.330			-0.050	-0.131
						(0.156)						(0.072)								(0.301)			(0.073)	(0.179)
CEO age:60+ y.o., lag						-0.134						-0.017								-0.537*			-0.036	-0.056
						(0.159)						(0.073)								(0.308)			(0.074)	(0.182)
Female CEO, lag						-0.008						-0.017								-0.340			-0.029	0.043
						(0.111)						(0.047)								(0.263)			(0.048)	(0.123)
Industrial group, lag						0.134						0.093*								-0.149			0.064	0.238**
						(0.092)						(0.055)								(0.220)			(0.057)	(0.104)
Family firm, lag						0.273***						0.177***								-0.138			0.131**	0.446***
						(0.092)						(0.052)								(0.195)			(0.054)	(0.104)
Extraordinary transactions, lag						-0.073						0.165**								0.345			0.211***	0.017
						(0.120)						(0.078)								(0.261)			(0.080)	(0.142)
Union (RSA/RSU), lag						-0.016						-0.057								0.069			-0.057	-0.076
						(0.085)						(0.047)								(0.185)			(0.048)	(0.097)
2nd-level wage barg. (prod.-linked), lag						0.224**						0.359***								0.167			0.323***	0.472***
						(0.098)						(0.075)								(0.244)			(0.079)	(0.116)
Constant		0.010	-0.001	0.010	0.060	-2.240***		-0.002	0.027*	-0.001	0.021	-0.631***		-0.003	-0.090	0.027*	0.028	-0.004	-0.080	-2.361***	0.018	0.099	-0.714***	-2.433***
		(0.010)	(0.047)	(0.010)	(0.079)	(0.349)		(0.013)	(0.015)	(0.015)	(0.015)	(0.172)		(0.013)	(0.107)	(0.015)	(0.052)	(0.016)	(0.080)	(0.652)	(0.016)	(0.120)	(0.176)	(0.408)
Industry FEs	Yes	Yes		Yes			Yes	Yes		Yes			Yes	Yes				Yes						
NUTS1 FEs	Yes	Yes		Yes			Yes	Yes		Yes			Yes	Yes				Yes						
Year FEs	Yes	Yes		Yes			Yes	Yes		Yes			Yes	Yes				Yes						
#Observations	19188	19188		19188			19188	19188		19188			19188	19188				19188						
#Firms	14793	14793		14793			14793	14793		14793			14793	14793				14793						

Note: RIL database. All specifications include year, NUTS1 and industry fixed effects, where industries have been aggregated in three broad sectors (industry, construction, and services) of the Italian economy. While in the OLS regression framework the variables included in the vector of firm controls are assumed to have the same effect both on investments in ETs and on changes firm organization, in the RA and IPWRA framework they are allowed to have heterogeneous effects. The IPWRA approach also estimates a treatment model, i.e., the probability of investing in RT or/and EIT as a function of predetermined firm characteristics, to compute the inverse probability weights. Cluster- (firm-) robust standard errors are reported in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table B5 - Emerging technologies and the change (Δ) in the average span of control: firm controls' and treatment model's coefficients

	(1)	(2)		(3)			(4)	(5)		(6)			(7)	(8)				(9)						
	OLS	RA		IPWRA			OLS	RA		IPWRA			OLS	RA				IPWRA						
	_	OME0	OME1	OME0	OME1	TME1	_	OME0	OME1	OME0	OME1	TME1	_	OME0	OME1	OME2	OME3	OME0	OME1	TME1	OME2	OME3	TME2	TME3
Δ% in firm size	9.288***	9.322***	8.088***	9.425***	8.638***		9.315***	9.279***	9.378***	9.593***	8.986***		9.312***	9.331***	6.019	9.376***	8.813***	9.845***	10.466***		9.068***	8.217***		
	(0.409)	(0.417)	(1.942)	(0.430)	(1.052)		(0.409)	(0.533)	(0.615)	(0.601)	(0.628)		(0.409)	(0.534)	(5.118)	(0.645)	(1.848)	(0.600)	(3.334)		(0.659)	(1.136)		
Investments	-0.129	-0.111	-0.749	-0.144	-0.833		0.039	0.059	0.059	0.019	0.148		-0.008	0.050	-0.304	0.051	-1.379	-0.025	-2.075		0.021	-0.248		
	(0.209)	(0.212)	(1.245)	(0.220)	(1.209)		(0.214)	(0.301)	(0.308)	(0.415)	(0.273)		(0.215)	(0.304)	(2.430)	(0.318)	(1.449)	(0.424)	(1.967)		(0.292)	(1.599)		
Δ (pp) in emp., secondary edu.	0.108	0.040	1.457	0.054	1.196		0.113	-0.301	0.781	-0.034	0.537		0.111	-0.267	-0.947	0.596	2.611	-0.025	-4.117		0.327	2.806		
	(0.330)	(0.332)	(2.091)	(0.352)	(2.373)		(0.330)	(0.378)	(0.603)	(0.546)	(0.520)		(0.330)	(0.375)	(6.099)	(0.628)	(2.148)	(0.557)	(5.215)		(0.553)	(3.108)		
Δ (pp) in emp., tertiary edu.	-0.988*	-1.306**	4.037	-1.115*	-0.463		-0.960	-1.609**	0.016	-0.729	0.001		-0.964	-1.683**	1.409	-0.594	4.779	-0.847	6.987*		-0.463	-1.945		
	(0.599)	(0.578)	(4.378)	(0.614)	(3.270)		(0.599)	(0.653)	(1.106)	(0.889)	(0.970)		(0.599)	(0.657)	(5.395)	(1.056)	(5.429)	(0.916)	(4.133)		(0.983)	(3.961)		
Δ (pp) in emp., 25-34 y.o.	-0.571	-0.412	-4.222	-0.558	-1.051		-0.548	0.063	-1.559	-0.077	-1.057		-0.562	0.245	-16.371*	-1.566	-1.087	0.151	-9.769		-1.219	-1.071		
	(0.720)	(0.722)	(4.788)	(0.782)	(3.726)		(0.720)	(0.723)	(1.418)	(1.068)	(1.077)		(0.720)	(0.719)	(8.906)	(1.462)	(5.712)	(1.073)	(7.413)		(1.204)	(4.775)		
Δ (pp) in emp., 35-49 y.o.	-1.137	-0.962	-4.523	-1.052	-1.803		-1.117	-0.738	-1.765	-1.134	-1.119		-1.130	-0.511	-19.001*	-1.764	-1.142	-0.676	-12.472		-1.244	-0.928		
	(0.799)	(0.804)	(4.261)	(0.867)	(3.376)		(0.799)	(0.826)	(1.522)	(1.263)	(1.204)		(0.798)	(0.820)	(9.928)	(1.588)	(4.876)	(1.277)	(9.557)		(1.342)	(4.332)		
Δ (pp) in emp., 50+ y.o.	-0.825	-0.553	-7.395	-0.576	-4.339		-0.828	-0.666	-1.105	-0.582	-0.694		-0.830	-0.481	-15.274	-0.704	-6.047	-0.190	-6.779		-0.464	-7.580		
	(0.842)	(0.845)	(5.118)	(0.914)	(3.866)		(0.842)	(0.875)	(1.596)	(1.369)	(1.276)		(0.842)	(0.870)	(10.779)	(1.649)	(5.885)	(1.432)	(9.257)		(1.407)	(4.691)		
Δ (pp) in emp. with on-the-job training	-0.102	-0.178	1.118	-0.144	-0.909		-0.090	-0.416*	0.308	-0.428	0.057		-0.090	-0.498**	3.994	0.278	0.663	-0.449	1.335		0.026	-2.015		
	(0.211)	(0.211)	(1.167)	(0.222)	(1.065)		(0.211)	(0.250)	(0.348)	(0.377)	(0.299)		(0.211)	(0.250)	(2.569)	(0.353)	(1.322)	(0.386)	(2.236)		(0.315)	(1.635)		
Δ (pp) in fixed-term contracts	0.894	0.819	3.804	0.810	3.000		0.875	0.900	0.849	1.687	0.161		0.876	0.828	7.027	0.758	2.722	1.501	5.469		0.106	2.751		
	(0.629)	(0.631)	(4.354)	(0.662)	(3.824)		(0.629)	(0.659)	(1.243)	(1.039)	(1.015)		(0.630)	(0.660)	(7.127)	(1.267)	(5.620)	(1.070)	(4.959)		(1.068)	(5.062)		
Δ (pp) in female employees	0.564	0.462	6.013	0.447	7.604**		0.567	0.102	1.499	-0.794	0.771		0.579	0.014	7.311	1.438	5.418	-0.976	13.043**		0.758	1.223		
	(0.601)	(0.601)	(5.783)	(0.634)	(3.808)		(0.601)	(0.697)	(1.088)	(1.270)	(0.856)		(0.601)	(0.698)	(9.531)	(1.096)	(6.739)	(1.276)	(6.107)		(0.900)	(3.679)		
10-49 emp., lag						1.020***						0.444***								1.055***			0.420***	1.256***
						(0.119)						(0.040)								(0.224)			(0.040)	(0.139)
50-249 emp., lag						1.709***						0.938***								1.543***			0.860***	2.305***
						(0.129)						(0.056)								(0.257)			(0.058)	(0.150)
250+ emp., lag						2.356***						1.402***								1.616***			1.158***	3.255***
						(0.173)						(0.118)								(0.408)			(0.126)	(0.209)
Investments, lag						0.660***						0.489***								0.525***			0.457***	1.001***
						(0.078)						(0.034)								(0.158)			(0.035)	(0.090)
% of emp.,secondary edu., lag						0.046						0.529***								0.299			0.546***	0.363**
						(0.130)						(0.057)								(0.284)			(0.058)	(0.149)
% of emp.,tertiary edu., lag						0.396*						1.038***								1.106***			1.071***	0.974***
						(0.205)						(0.091)								(0.391)			(0.092)	(0.235)
% of emp. 25-34 y.o., lag						-0.976***						-0.175								-1.298**			-0.147	-0.961**
						(0.344)						(0.161)								(0.610)			(0.164)	(0.408)
% of emp. 35-49 y.o., lag						-1.165***						-0.048								-1.594***			-0.012	-1.034***
						(0.296)						(0.145)								(0.563)			(0.149)	(0.346)
% of emp. 50+ y.o., lag						-1.867***						-0.173								-2.019***			-0.104	-1.867***
						(0.321)						(0.151)								(0.606)			(0.155)	(0.372)
% of emp. on-the-job training, lag						0.061						0.265***								0.116			0.272***	0.241***
						(0.081)						(0.039)								(0.187)			(0.040)	(0.092)
% of fixed-term contracts, lag						-0.653**						-0.265**								-0.755			-0.232**	-0.772**
						(0.270)						(0.115)								(0.631)			(0.117)	(0.302)
% of female emp., lag						-0.203						-0.110*								-0.422			-0.120**	-0.245
						(0.144)						(0.060)								(0.315)			(0.061)	(0.161)
CEO edu.: upper secondary, lag						-0.027						0.209***								-0.201			0.205***	0.147
						(0.096)						(0.045)								(0.189)			(0.046)	(0.110)
CEO edu.: tertiary, lag						0.087						0.253***								-0.110			0.241***	0.296**
						(0.111)						(0.054)								(0.224)			(0.055)	(0.125)
CEO age:40-49 y.o., lag						-0.154						-0.082								-0.331			-0.088	-0.159
						(0.162)						(0.074)								(0.314)			(0.076)	(0.185)
CEO age:50-59 y.o., lag						-0.154						-0.045								-0.330			-0.050	-0.131
						(0.156)						(0.072)								(0.301)			(0.073)	(0.179)
CEO age:60+ y.o., lag						-0.134						-0.017								-0.537*			-0.036	-0.056
						(0.159)						(0.073)								(0.308)			(0.074)	(0.182)
Female CEO, lag						-0.008						-0.017								-0.340			-0.029	0.043
						(0.111)						(0.047)								(0.263)			(0.048)	(0.123)
Industrial group, lag						0.134						0.093*								-0.149			0.064	0.238**
						(0.092)						(0.055)								(0.220)			(0.057)	(0.104)
Family firm, lag						0.273***						0.177***								-0.138			0.131**	0.446***
						(0.092)						(0.052)								(0.195)			(0.054)	(0.104)
Extraordinary transactions, lag						-0.073						0.165**								0.345			0.211***	0.017
						(0.120)						(0.078)								(0.261)			(0.080)	(0.142)
Union (RSA/RSU), lag						-0.016						-0.057								0.069			-0.057	-0.076
						(0.085)						(0.047)								(0.185)			(0.048)	(0.097)
2nd-level wage barg. (prod.-linked), lag						0.224**						0.359***								0.167			0.323***	0.472***
						(0.098)						(0.075)								(0.244)			(0.079)	(0.116)
Constant		-0.138	0.803	-0.131	1.709	-2.240***		0.131	-0.321	-0.067	-0.314	-0.631***		0.173	-2.275	-0.556	1.708	0.049	-0.963	-2.361***	-0.440	1.326	-0.714***	-2.433***
		(0.242)	(1.412)	(0.255)	(1.609)	(0.349)		(0.309)	(0.381)	(0.439)	(0.346)	(0.172)		(0.309)	(3.024)	(0.400)	(1.617)	(0.457)	(2.175)	(0.652)	(0.373)	(1.995)	(0.176)	(0.408)
Industry FEs	Yes	Yes		Yes			Yes	Yes		Yes			Yes	Yes				Yes						
NUTS1 FEs	Yes	Yes		Yes			Yes	Yes		Yes			Yes	Yes				Yes						
Year FEs	Yes	Yes		Yes			Yes	Yes		Yes			Yes	Yes				Yes						
#Observations	19188	19188		19188			19188	19188		19188			19188	19188				19188						
#Firms	14793	14793		14793			14793	14793		14793			14793	14793				14793						

Note: RIL database. All specifications include year, NUTS1 and industry fixed effects, where industries have been aggregated in three broad sectors (industry, construction, and services) of the Italian economy. While in the OLS regression framework the variables included in the vector of firm controls are assumed to have the same effect both on investments in ETs and on changes firm organization, in the RA and IPWRA framework they are allowed to have heterogeneous effects. The IPWRA approach also estimates a treatment model, i.e., the probability of investing in RT or/and EIT as a function of predetermined firm characteristics, to compute the inverse probability weights. Cluster- (firm-) robust standard errors are reported in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *,**

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