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Igniting innovation: how managerial training drives patent propensity

Roberto Gabriele
University of Trento, Trento, Italy
Eleonora Pierucci and Marco Sforza
Roma Tre University, Rome, Italy, and
Oksana Tokarchuk
University of Trento, Trento, Italy

Abstract

Purpose – This study investigates the impact of managerial training on firms' innovation outcomes, focusing on how the "breadth" and "intensity" of training influence the likelihood of patent filings.

Design/methodology/approach – The analysis relies on a unique dataset that merges administrative training records from Fondirigenti – Italy's largest inter-professional fund for managerial training – with patent data from REGPAT and firm-level financial data from AIDA (the Italian section of Bureau van Dijk). To estimate the causal effects of training on innovation the study employs the Lewbel estimator using both endogenous and exogenous instruments. Additional analyses are conducted using probit models and Inverse Probability Weighting (IPW).

Findings – Results reveal a differentiated effect of training characteristics: the number of training programs attended by managers ("breadth") has a significant positive impact on the likelihood of patent filings, while the total hours of training ("intensity") does not. The positive association between training breadth and innovation is especially strong among smaller, less productive firms and those operating in supplier-dominated sectors.

Practical implications – Policymakers and firms should promote managers' training as a mean to igniting innovation, prioritizing the breadth of the scope of training opportunities over simply increasing training hours, especially when targeting innovation outcomes in smaller or less productive firms.

Originality/value – This is one of the first studies to causally link managerial training characteristics to firm-level innovation using a large-scale administrative dataset combined with patent and financial data, offering new insights into the nuanced effects of training "breadth" versus "intensity".

Keywords Managers training, Innovation, Patenting, Managers, Capabilities

Paper type Research article

1. Introduction

This paper aims to quantitatively assess the impact of upgrading managerial skills on the patent propensity of the firm. Knowledge management plays a potential role in the key task of integrating different forms of knowledge elicited from a variety of sources to spur innovation (Scarbrough, 2003). Specifically, training programs, as part of knowledge management practices, enhance the dynamic capabilities of a firm and contribute to its long-term investment in competitive advantage in human capital (Capozza and Divella, 2019). In fact, training is one of the antecedents of organizational learning, which, in turn, stimulates and improves the perception of the external environment and, consequently, stimulates innovation (Wang and Ellinger, 2011).

Hence, exposing managers to specialized training allows them, first, to detect possible business opportunities inside and outside of the firm's limits and, second, to think about mechanisms to protect their "new ideas" through patents, allowing future exploitation of such ideas and enhancement of the firm's competitive advantage.

The background of the study is the vast literature on firm-level innovation dynamics. Despite efforts of scholars, innovation determinants are still not fully understood

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(Teece, 2010). To contribute to this literature, this analysis relies on the concept of firm competencies and their evolution over time to shape dynamic capabilities, i.e. how firms adapt to changing market conditions and technological advancements (Teece, 2004). In turn, dynamic capabilities shape the firm's innovation decisions and processes.

The accumulation of knowledge stock and the consequent creation of managerial skills to manage and make decisions concerning innovation can be considered a crucial factor that helps build and upgrade the dynamic capabilities of a firm. In this respect, intellectual capital and its management play a key role. Granstrand (1998) emphasizes that management plays a pivotal role in acquiring, combining, and deploying resources in response to external business opportunities. Moreover, managerial competence itself is a meta-resource – one that is self-sustaining and continuously evolving. The co-evolution of technological advancements and managerial knowledge influences the direction of innovation and the firm's ability to generate new technologies.

Another strand of literature emphasizes the importance of human capital and competencies in innovation. In particular, the competencies of managers are among the most critical internal factors that may directly or indirectly affect the innovation activities of economic entities (Ahmad *et al.*, 2010; Galende and de la Fuente, 2003; Ko and Lu, 2010; Szczepańska-Woszczyna and Dacko-Pikiewicz, 2014; De Castro Gonçalves and da Silva Abbad, 2022).

Based on these premises, innovation research should explore how managerial competencies are developed, acquired, and sustained. Executive training serves as a crucial instrument for enhancing the expertise of management, particularly in terms of their strategic and operational capabilities. As such, well-designed training initiatives are among the most effective means of fostering managerial proficiency. Empirical evidence indicates that these programs significantly enrich a firm's knowledge assets and dynamic capabilities, thereby strengthening its capacity to formulate and execute strategic initiatives. Training investments contribute to continuous learning within organizations, leading to more innovation and greater organizational adaptability (Lau and Ngo, 2004). Managerial skills upgrading helps firms create new technologies and ideas, which can be protected and exploited through mechanisms like patents (Cantner *et al.*, 2011). For instance, a manager exposed to training in managing new digital technologies, who understands how to apply such technologies and reorganize part of the production process more efficiently, can decide to apply for a patent to shield the "new production process." In doing so, the manager enhances the dynamic capabilities and ensures the firm's future competitive advantage. These assumptions align with the view of managerial practices as one of the determinants of firm performance and innovation (Bloom and Van Reenen, 2010; Bloom *et al.*, 2019).

Extending prior studies, we analyze how the accumulation of managerial competencies – through its influence on established managerial practices – affects firms' patenting performance. In this respect, the Italian context, which is based on a backbone of small and medium companies, mainly from traditional sectors, with heterogeneous innovation performances, offers us an ideal laboratory to conduct the analysis. Hence, focusing on Italian firms and given the availability of information about managerial training (i.e. training programs for "dirigenti" activated by firms), we use the opportunity to test empirically hypotheses that give relevance to managerial training as a key factor in stimulating the patent propensity of firms.

This paper makes several contributions to the existing literature. First, it provides a novel focus on managerial training as a determinant of firm-level innovation performance, distinguishing between "breadth" and "intensity" of training.

Second, it employs a patent-based innovation output indicator, which offers a more robust and objective measure than self-reported innovation data.

Third, the analysis is based on a large sample of firms observed over an extended period, thus enhancing the generalizability and temporal relevance of the findings. Indeed, the empirical investigation is based on a unique dataset containing administrative data collected by Fondirigenti – the largest Italian interprofessional fund dedicated to financing managerial training – merged with patent data from REGPAT (OECD REGPAT, August 2022) and financial data from AIDA, the Italian section of Bureau van Dijk. Our dataset comprises a large sample of Italian firms active in a wide set of sectors, from traditional to more technology-intensive ones, for 2012–2018. The administrative nature of the Fondirigenti data provides a unique, fine-grained, and reliable representation of managers' training activities, otherwise not available through more standard survey sources. The sample built allows the investigation of heterogeneity of the effects across different Pavitt Sectors and size classes (See Appendix, Table A1).

The empirical strategy employs a combination of regression models to assess the impact of managerial training on firms' innovation performance. A probit model is used to investigate the relationship between training and patenting activity, while an Inverse Probability Weighted (IPW) regression addresses potential confounding factors and selection bias. To further account for endogeneity concerns, such as reverse causality and omitted variable bias, we implement a generated instrumental variable (IV) approach based on heteroskedasticity, following the methodology of Lewbel (2012). A notable strength of the paper is its exploration of heterogeneous effects, considering critical factors that may shape the innovation process, such as firms' sector of activity, size, and past performance.

The findings indicate a differentiated impact of training on innovation performance, depending on its dimensions. While the "breadth" of training – reflected in the number of distinct programs undertaken – has a positive and statistically significant effect on firms' innovation outcomes, the "intensity" of training – measured by the (per-capita) number of hours devoted to training – shows no significant association. This positive effect of training breadth is particularly evident among firms that are less productive, smaller in size, and those operating within supplier-dominated sectors. The heterogeneity in the effect across firm characteristics gives rise to policy implications, particularly the need to promote managerial training in those firms that stand to benefit the most – typically smaller firms equipped with limited internal capabilities.

The structure of the paper is as follows. Section 2 reviews the theoretical and empirical literature on the impact of training on firms' innovation performance and outlines the research hypotheses. Section 3 describes the dataset. Section 4 details the empirical strategy, with particular emphasis on the identification assumptions. Main results are presented in Section 5, while Section 6 provides discussion and concluding remarks.

2. Background literature and hypotheses development

2.1 Firms' knowledge, capabilities, and innovation

A significant strand of literature investigates the crucial relationship between employee training and organizational performance, largely adopting the Human Capital Theory and the Resource-Based View (RBV). Empirical evidence consistently demonstrates that training investments positively and significantly influence diverse outcomes, including profitability, productivity, and overall effectiveness (Aragón-Sánchez *et al.*, 2003; Úbeda García, 2005; Danvila Del Valle *et al.*, 2009; Danvila Del Valle and Sastre Castillo, 2009). The effectiveness of training is often associated with its specific delivery method (e.g. in-house on-the-job training) and its strategic alignment or "fit" with organizational goals (Becker and Gerhart, 1996; De Sáá-Pérez and García-Falcón, 2002). Overall, this body of research highlights the generalized economic and strategic value of human capital development through training, showing that its benefits may also unfold over time. Building upon this foundational work, the present study extends the analysis by focusing specifically on the impact of a specific training effort (namely, managerial training) on innovative performance – a critical yet less extensively explored dimension of organizational success.

A firm can be viewed as a repository of knowledge embedded in its business routines and processes, with its competencies composed of skills, experiences, and distinctive methods of operation. These competencies are the drivers of competitive advantage, which are inherently difficult to imitate, and must evolve over time to sustain competitive positioning. These dynamic capabilities are essential for firms to adapt to changing market conditions and technological advancements (Teece, 2004).

Managerial competence has been identified as a key determinant in fostering innovation within firms. According to Teece (2004), managerial skills, particularly in technology management, strategic decision-making, and organizational learning, are essential for building dynamic capabilities that enable firms to innovate and adapt to market changes. Teece's concept of "dynamic capabilities" emphasizes the ability of firms to integrate, build, and reconfigure resources in response to environmental shifts, with managerial competence being at the heart of this process. Grant (1996) further supports the argument that managerial competence is pivotal for effective knowledge management, a fundamental component of innovation. Competent managers can facilitate knowledge acquisition, integration, and application, thus enhancing a firm's innovation ability. The ability to make informed strategic decisions and effectively manage innovation processes ensures that firms are well-positioned to generate new products, services, and technologies that meet market needs. Lau and Ngo (2004) include management training as a key element of training-focused human resources (HR) practices that support innovation. Although not analyzed separately, it is recognized as essential for promoting a developmental culture, which mediates the relationship between HR systems and product innovation. Thus, training managers contributes indirectly to fostering innovation through cultural development. Training programs focusing on problem-solving, strategic thinking, and technological management are particularly effective in improving a firm's ability to generate new ideas and bring them to market. Furthermore, these training initiatives create an organizational climate conducive to innovation, where knowledge is constantly shared and new ideas are encouraged. The potential of managerial training in enhancing innovation capabilities is also supported by research from Powell and Houghton (2008), who argue that action learning helps SMEs address real business challenges through peer-based collaboration and reflection. This approach increases confidence, enhances strategic thinking, and leads to tangible outcomes, including developing new products and services. SMEs also form partnerships and adopt innovative practices that improve their business performance. Action learning emerges as a practical and inclusive method for driving innovation and growth in small enterprises. Cazeri *et al*. (2022) demonstrates that managerial training programs, particularly those focused on new technologies such as Industry 4.0, enhance innovation outcomes by equipping managers with the necessary skills to manage technological advancements. These training programs improve technological expertise and foster a culture of continuous learning and knowledge exchange, which is crucial for innovation. By upgrading technology management and innovation strategy competencies, managers are better equipped to identify valuable innovations, protect them through patents, and monetize these assets through licensing or collaboration with other firms. Therefore, the empirical evidence supports the causal link between training and firm innovation performance since training investments can positively influence innovation outcomes, particularly in product and process innovation. Dostie (2018), using longitudinal data from the Canadian Workplace and Employee Survey, finds that firms with higher training intensity over the entire firm's workforce – whether in classroom-based or on-the-job training – report a greater inclination toward introducing new or improved products and/or processes. Similarly, Sung and Choi (2014) highlights that training supports organizational learning, enhancing innovation, particularly when firms foster an innovative climate. Their study suggests that interpersonal and organizational learning practices mediate the training-innovation relationship. Rogers (2004) finds that managerial training can positively influence the introduction of new products or processes in manufacturing and non-manufacturing firms. In contrast, general training intensity does not significantly impact it. However, in small manufacturing firms, managerial training appears to negatively affect innovation, possibly due to a misalignment between training content and firms' immediate needs.

Against this backdrop, patenting activity appears to be closely tied to managerial competence and training. Indeed, intellectual property (IP) management skills are crucial for effectively managing patents and leveraging them for competitive advantage (Teece, 2004; Cantner *et al.*, 2011). Managerial training in IP management, patent strategy, and technology commercialization strengthens a firm's capacity to generate patents and safeguard its innovations, thereby supporting its long-term innovation strategy. Furthermore, it plays a crucial role in enhancing managerial competencies, which in turn boosts the firm's overall innovation capabilities. To deepen the reasons at the heart of the causal link between managerial training and patent activity, some studies focus on training's role in enhancing firms' absorptive capacity – the ability to recognize, assimilate, and apply new knowledge for innovation (Cohen and Levinthal, 1990). Boothby *et al.* (2010) shows that firms that integrate strategic training programs with new technology investments achieve greater productivity gains than those that adopt technology alone. Their findings suggest that training must align with technological capabilities to maximize its impact on innovation. Sheehan *et al.* (2023) extend this argument, showing that training investments enhance incremental and radical innovation, particularly in knowledge-intensive businesses, where continuous learning is essential.

The empirical literature can be broadly grouped along three main dimensions: the length of the time span considered, the measures of innovation employed, and the focus on either employee or managerial training.

Most empirical studies analyzing the relationship between training and innovation focus on periods before 2010, with relatively few studies examining more recent periods. Dostie (2018) uses longitudinal data from the Canadian Workplace and Employee Survey (WES) covering 1999–2006, while Sung and Choi (2014) utilizes data from 2004 and 2006, with innovation performance measured in 2006–2007. Similarly, McGuirk *et al.* (2015) analyzes data collected in 2009 to study innovation performance in 2007–2008, and Martínez-Ros and Orfila-Sintes (2012) examines the hospitality sector based on 2004, 2007, and 2010 data. One of the earliest studies, Rogers (2004), investigates Australian firms between 1994 and 1997, while Laplagne and Bensted (1999) focuses on Australian firms from 1990 to 1995. Although more recent studies such as Sheehan *et al.* (2023) examine data from 2013 and 2016, and Protogerou *et al.* (2017) use data collected in 2010–2011, the majority of the research on training and innovation has focused on pre-2010 periods. This temporal limitation suggests that empirical evidence may not fully reflect the rapid transformations in workplace learning, digitalization, and knowledge-based innovation in the last decade.

An aspect to be underlined is related to the measurement of innovation employed in the studies. Indeed, a firm's innovation level is often measured using self-reported indicators and objective patent data, though self-reported measures dominate empirical research. Most studies assess innovation subjectively, relying on manager or firm-level survey responses (Mendoza-Silva, 2021). For instance, Dostie (2018) and Martínez-Ros and Orfila-Sintes (2012) use binary self-reported innovation indicators, where firms indicate whether they introduced product, process, or organizational innovations. McGuirk *et al.* (2015) use manager-reported data to assess the presence of product, service, and process innovation. Rogers (2004) classifies firms as innovators (1) or non-innovators (0) based on self-reported changes in products, services, or processes. Protogerou *et al.* (2017) distinguish between innovation input (R&D expenditure as a share of turnover) and innovation output (product innovation radicalness categorized as "new to the firm," "new to the market," or "new to the world"). Meanwhile, Sheehan *et al.* (2023) uses structured survey scales to measure incremental and radical innovation, distinguishing between product/service modifications and entirely new products, services, or technologies. More rarely, some studies complement subjective innovation measures with objective indicators. For example, Sung and Choi (2014) combines self-reported product innovation data with patent registration records from the Korean Intellectual Property Office (KIPO).

Another relevant aspect emerging from the literature is that most studies focus on employee rather than managerial training, often evaluating the extent to which firms invest in workforce skill development to foster innovation. Several studies examine general employee training. For example, Dostie (2018) measures it as the proportion of employees receiving classroom or on-the-job training. Similarly, Martínez-Ros and Orfila-Sintes (2012) focus on whether firms have formal training plans. Sung and Choi (2014) assess corporate training by looking at training expenditure per employee and the extent of financial support for external education. Likewise, Protogerou *et al*. (2017) evaluate training based on the percentage of employees participating in formal programs. While most studies focus on employee training, a smaller subset of research emphasizes managerial training, recognizing its unique role in shaping strategic innovation decisions. McGuirk *et al*. (2015) investigate managerial training in small firms, showing that manager training significantly increases the likelihood of product, service, and process innovation. However, in larger firms, training primarily supports process innovation. Rogers (2004) also distinguishes managerial training from general employee training, finding that managerial training enhances innovation, whereas general training intensity does not significantly impact innovation. These findings suggest that while employee training contributes to applied innovation and process improvements, managerial training plays a strategic role in enhancing a firm's innovation capacity.

This distinction is crucial when innovation is measured through codified outputs, such as patents. Indeed, while employee training may enhance general problem-solving abilities or support incremental innovation at the operational level, it is less likely to directly influence patenting activity, which often requires formalized R&D processes, strategic vision, and resource orchestration. In contrast, managerial training plays a more pivotal role in this context. Managers are responsible for identifying innovative trajectories, allocating resources toward R&D, and navigating intellectual property strategies. As such, training that enhances managerial competencies – particularly in areas related to innovation management, strategic planning, and integration and organizational coordination – can have a strong and more direct impact on a firm's propensity to patent. As a result, managerial training may be particularly effective in enhancing the firm's ability to transform knowledge into codified, legally protectable forms such as patents.

The relative lack of studies on managerial training presents a gap in the literature that we also aim to fill by exploring the distinction between "breadth" and "intensity" of managers' training.

2.2 Hypotheses development

2.2.1 The relationship between managerial training and patent propensity. Managerial training is an essential driver of firm innovation; however, its role in fostering patent output remains debated. The extent to which firms implement managerial training programs and the intensity managers engage in training may influence patenting propensity differently. While some studies highlight a positive association between managerial training and corporate innovation success (Chen *et al*., 2015), others suggest that its effects are contingent on complementary factors such as R&D investments, technological expertise, and external collaborations (McGuirk *et al*., 2015). The extensive effort in managerial training – measured as the number of programs activated by a firm – is expected to affect patenting propensity positively. Indeed, the literature suggests that managers with broader training exposure enhance firms' strategic capabilities, enabling them to identify, protect, and commercialize innovative ideas through patents (Chen *et al*., 2015). Firms investing in more training programs may also foster a culture of innovation, providing managers with a diverse set of strategic tools to navigate competitive markets. Furthermore, Protogerou *et al*. (2017) emphasize that managerial human capital plays a pivotal role in shaping firm-level innovation performance, including patent filings, when integrated with knowledge management strategies. This suggests that firms with a broader portfolio of managerial training programs are more likely to build the strategic capabilities needed to increase their patenting output.

Conversely, increasing the intensity of managerial training – measured in terms of per capita training hours – may not have the same effect on patenting. Several studies indicate that training facilitates knowledge diffusion and learning processes, but its benefits on innovation may diminish over time (Dostie, 2018). Firms that invest heavily in training hours per manager may experience diminishing returns as managers reach a saturation point in knowledge absorption and application. Heubeck (2024) suggests that patenting requires combining managerial leadership and technological capabilities rather than simply increasing the number of training hours devoted to managerial development. Given that patenting is a resource-intensive process that requires strategic vision, technological investments, and external collaborations, the intensity of managerial training alone is unlikely to influence the propensity to patent significantly.

Thus, we propose the hypotheses:

H1a. Managerial training "breadth" (i.e. the number of training programs activated by the firm) affects a firm's propensity to patent.

H1b. Managerial training "intensity" (i.e. the number of per capita hours devoted to training) does not affect a firm's propensity to patent.

2.2.2 The relationship between managerial training, productivity, and patent propensity. Managerial training is crucial in enhancing firms' innovation capabilities, yet its effectiveness varies depending on firms' initial productivity levels. While highly productive firms may leverage managerial training to refine innovation strategies and optimize technological adoption, less productive firms may benefit from training to overcome structural inefficiencies and foster learning-based innovation. Best-performing firms, defined by their higher productivity levels, tend to have greater absorptive capacity, allowing them to extract more value from managerial training. Granstrand (1998) argues that managerial knowledge co-evolves with technological advancements, meaning that high-productivity firms are better positioned to translate managerial training into effective innovation outcomes. The ability to internalize new managerial skills and integrate them with existing technological capabilities allows these firms to accelerate knowledge recombination and the implementation of innovation strategies (Cantner *et al.*, 2009). Furthermore, Lau and Ngo (2004) highlight that firms with continuous learning cultures – more common among best-performing firms – foster more efficient knowledge exchange, enabling training to have a stronger impact on innovative capabilities. Training in these firms is not just about skill acquisition but about strategic knowledge application, where managers learn to navigate complex innovation environments and leverage training to drive technological adaptation and competitive differentiation.

Despite the advantages that best-performing firms derive from training, research also suggests that less-productive firms can enhance innovation capabilities through managerial training. These firms often face barriers to accessing external knowledge, lower absorptive capacity, and operational inefficiencies, which training can help mitigate (Lau and Ngo, 2004). By improving managerial decision-making and problem-solving skills, training allows firms in the lowest productivity quintile to develop innovation-oriented strategies despite initial resource constraints. Empirical evidence suggests that even firms with lower productivity can use training to stimulate innovation. Dostie (2018) finds that training fosters product and process innovation, particularly in firms that lack independent innovation capabilities. Similarly, Martínez-Ros and Orfila-Sintes (2012) show that firms with structured managerial training plans are more likely to engage in innovation, even when initial productivity levels are low. Moreover, Capozza and Divella (2019) emphasize that firms in emerging economies, often characterized by lower productivity and weaker innovation capacity, experience significant improvements in innovation when managerial training is effectively implemented. These findings suggest that while low-productivity firms may not have the same immediate capacity for innovation as high-productivity firms, training can still be a critical mechanism for fostering technological adaptation and incremental innovation. Thus, we propose the following hypothesis:

H2. Managerial training effectively fosters patenting within firms at both ends of the productivity spectrum – the highest and lowest performers.

2.2.3 Managerial training as a catalyst for innovation in small firms. The relationship between managerial training and innovation varies across firms, with small firms – often constrained by limited resources, external knowledge access, and absorptive capacity – facing more significant challenges in fostering innovation. However, managerial training can help bridge these gaps, equipping managers with the skills to improve decision-making, resource allocation, and innovation-oriented strategies (McGuirk *et al.*, 2015). The literature shows that managerial training significantly enhances innovation in small firms, particularly when aligned with broader strategic objectives. McGuirk *et al*. (2015) find that small firms investing in managerial training exhibit higher product and process innovation levels, especially when managers develop innovative human capital. Similarly, Rogers (2004) highlights that structured training programs are critical for small firms, enabling them to leverage external networks, adopt new technologies, and implement innovation-driven strategies. Moreover, Dostie (2018) emphasizes that on-the-job training is equally vital as formal training in fostering innovation, particularly in firms with lower initial innovation capabilities. Sung and Choi (2014) further argue that internal training investment increases firms' openness to innovation, with small firms particularly benefiting from training's role in developing an innovation-supportive culture. Managerial training also serves to overcome innovation barriers by strengthening firms' organizational learning capacities. Greenan and Napolitano (2024) find that firms with structured managerial training programs demonstrate higher innovation outputs, reinforcing that training fosters long-term innovation performance in firms with weaker initial innovation capabilities. Capozza and Divella (2019) further highlight that training enhances competitiveness, technological adaptation, and innovation potential in resource-constrained environments, such as small firms and emerging markets, allowing small firms to develop the strategic competencies needed to compete with larger, more innovative firms. We formulate the following hypothesis:

H3. The effect of managerial training on patenting is stronger for firms with lower inherent innovative capabilities, such as small firms.

2.2.4 The role of managerial training for innovation across industry sectors. Managerial training plays a crucial role in fostering innovation across different industry sectors, but its effectiveness varies depending on the industry's reliance on other mechanisms for innovation. Firms in supplier-dominated and scale-intensive sectors may benefit more from managerial training in driving innovation. This may arise from differences in knowledge sources, innovation models, and how managerial decision-making influences technological advancements at the firm level. In supplier-dominated and scale-intensive industries– such as manufacturing, automotive, chemicals, and textiles – innovation is primarily driven by incremental learning, process optimization, and the absorption of external knowledge, rather than in-house R&D (Pavitt, 1984). These sectors depend heavily on learning-by-doing, supplier-led innovation, and continuous improvements in production processes, making managerial training especially effective in fostering innovation. Training enhances firms' absorptive capacity by equipping managers to identify, assimilate, and apply external knowledge to refine products and processes (Audretsch *et al.*, 2024). It also contributes significantly to process innovation and supply chain coordination. Unlike sectors focused on radical product innovation, firms in these industries often patent process innovations to boost efficiency and reduce costs (Toner, 2011). Managerial training helps firms codify and formalize these incremental improvements, leading to increased patenting. Furthermore, many firms in these sectors lack expertise in IP management, resulting in under-patenting relative to their innovation output (Greenan and Napolitano, 2024). Training equips managers with the necessary IP knowledge, strategic foresight, and negotiation skills to better navigate the patenting process and secure intellectual property rights. Conversely, in science-based and specialized supplier industries, such as pharmaceuticals, biotechnology, industrial machinery, and IT software, innovation primarily stems from in-house R&D and technological expertise rather than managerial decision-making (Pavitt, 1984). Firms in these industries employ highly specialized researchers and engineers responsible for generating patentable innovations. They also operate in high-appropriability contexts, where patenting is a central strategic activity, thereby reducing the influence of managerial training on patenting outcomes. Unlike supplier-dominated and scale-intensive industries, where managerial training helps formalize and systematize process innovations, science-based firms focus on radical product innovations, rendering process-oriented training less relevant. In such industries, patenting is primarily driven by scientific and technological discoveries rather than managerial strategies, and many of these firms possess well-established IP management teams, which further diminishes the role of managerial training in driving patent activity. Based on this, we propose the hypothesis:

H4. The effect of managerial training on firm-level patent propensity is stronger in sectors where innovation is primarily driven by learning economies, such as supplier-dominated and scale-intensive industries.

3. Data and descriptive statistics

We combine data from multiple sources to examine the relationship between managers' training and firms' innovative outcomes. The data on managers' training is sourced from administrative records provided by Fondirigenti, the largest inter-professional fund for financing managerial training in Italy. This information is then merged with patent data from REGPAT (OECD, 2022) and the Aida Bureau van Dijk database balance sheet data. In brief, to construct our dataset, we import and filter EPO application records to retain only those with Italian applicants. We harmonize individual identifiers using the HAN database and eliminate duplicate entries. We then construct a firm-level panel by aggregating patent-level variables based on unique applicant identifiers and priority years. Furthermore, we standardize firm-level patent data by creating normalized fields for company names and addresses, applying the harmonization procedures in line with those outlined in Lotti and Marin (2013). This process involves multiple string transformations to ensure consistent spelling and formatting. We apply similar cleaning procedures to a second dataset obtained from the AIDA business registry. Both datasets are lowercased and prepared for the matching process. Following the approach of Raffo (2015), we match firms based on tax codes, names, and address similarity, using defined thresholds for string similarity and Levenshtein distance. We select the final pairs matched according to refined similarity criteria to ensure the highest possible accuracy. Finally, we merged the data with the Fondirigenti archive using tax codes. The final sample consists of 70,695 firms observed from 2012–2018.

The dependent variable, i.e. firms' innovativeness, is a binary variable that takes the value of one if the firm has filed at least one patent application and zero otherwise. Patents lie further upstream in the innovation process. They are more closely linked to the enhanced analytical and strategic capabilities that managerial training is designed to develop, rather than to downstream outcomes such as the introduction of new products (Hagedoorn and Cloodt, 2003; Dziallas and Blind, 2019). While new product development generally reflects the use and commercialization of existing knowledge, patenting involves earlier, more knowledge-intensive stages such as identifying novel ideas, evaluating their strategic relevance, and securing intellectual property rights. These stages require strong judgment, foresight, and decision-making –competencies strengthened through managerial training. Focusing on patenting thus allows for a clearer assessment of how improved managerial skills influence a firm's innovative capacity, without the confounding effects of later-stage operational or market-driven factors.

Although patents may serve as an imperfect proxy for innovation – given that not all innovations result in patent filings and alternative innovation metrics exist – the literature widely recognizes patents as effective indicators of innovative activity. In particular, patent data have been shown to correlate strongly with other measures of innovation, such as the introduction of new products (Almeida *et al.*, 2011). Moreover, as noted by Banholzer *et al.* (2019), patents can capture product innovations, process innovations, or a combination of both (i.e. mixed patents).

Their study estimates that, at the European Patent Office (EPO), approximately 50% of patents are classified as product innovations, 12–15% as process innovations, and 35–38% as mixed (product and process-use) patents. Therefore, we use the presence of at least one patent as a proxy for innovation activity, which is the central focus of our analysis. We adopt a dichotomous variable to capture the transition from a non-innovative to an innovative state.

The main explanatory variables are: (1) the (log of) number of training programs initiated by the firm, and (2) the number of per-capita training hours. The first variable captures the breadth of the training. Each program can range from a single-topic class to courses covering multiple topics, and a firm may activate one or more programs for its managers. From Fondirigenti, we obtain information on the general topics covered by the training programs undertaken by participating firms. These programs provide participants (1) technical and managerial skills; (2) behavioral skills; (3) conceptual skills; and (4) leadership skills–the latter also encompassing topics related to decision-making, organization, and innovation. A substantial share of topics is directly relevant to innovation-related capabilities. For instance, “languages for business” appears in 58% of technical programs, “temporal” and “systemic perspective” modules account for 29% of conceptual programs, and “organization” and “innovation” together represent 58% of leadership programs. These themes are all instrumental in enhancing firms’ internal capabilities and innovative potential. Details on the most common topics covered in the programs are summarised in Appendix, Table A2.[1]. The second variable, i.e. the (log of) number of per-capita hours (in terms of the firm’s managers), measures the intensity of the training. Regardless of the number of training programs offered by the firm, this variable indicates whether the total number of hours contributes to the effectiveness of the programs. Finally, a set of firm-level control variables is selected to account for observable characteristics that may influence the firm’s innovativeness. These variables include: Total Factor Productivity [2], firm age, value added, number of employees, total liabilities, total intangible assets, and unit labor cost [3]. The latter two variables – intangible capital and unit labor cost – in addition to capturing the firm’s structural characteristics, also account for its intrinsic innovative capabilities. Intangible capital encompasses potential R&D expenditures [4], while unit labor cost serves as a proxy for workforce composition, thereby controlling for possible confounding factors related to inputs in the innovation production process.

Table 1 reports the variable descriptions and descriptive statistics for the entire sample. The innovative firms represent a very small fraction of the sample, being only 4% of the total,

Table 1. Variables description and statistics by innovative activity

Variable name	Mean		SD		Median	
Patent (1/0)	0.04		0.19		0.00	
	Patent = 0	Patent = 1	Patent = 0	Patent = 1	Patent = 0	Patent = 1
No. Training programs	0.11	0.28	0.45	0.79	0.00	0.00
Training hours (per capita)	0.11	0.08	4.38	0.39	0.00	0.00
Firm’s age	29.38	30.18	18.53	17.68	27.00	28.00
Employees	219.14	460.86	1,573.16	2,732.97	71.00	172.00
Value Added	20,851.65	41,348.93	153,891.90	156,665.80	5,345.15	14,844.16
TFP	158.78	166.24	500.06	94.87	116.43	145.47
Tot. Intangible assets	13,711.72	14,393.75	402,568.20	100,897.90	220.70	904.77
Unit Labour Cost	57.26	56.92	283.92	31.54	50.69	53.92
Total Liabilities	78,751.58	142,115.90	938,645.30	1,296,121.00	11,529.16	28,405.75
N. Obs	67,912	2,783	67,912	2,783	67,912	2,783

Note(s): Dependent variable shown at time *t*, all explanatory variables shown at time t−1

Source(s): Authors’ own work

and the evidence is consistent with the well-known picture of a non-innovative country such as Italy. When we compare the managerial training according to the innovativeness, we observe that the average number of training programs for innovating firms is much higher than those for non-innovating (0.28 against 0.11), but they train with lower intensity, i.e. they have a lower number of per capita hours (0.08 for innovating firms against 0.11 for non-innovating). When we condition the other variables on the dummy for patents, we obtain two similar subsamples for most of the variables considered. Looking at the mean, the firms are pretty homogeneous in terms of age (29 years for non-innovative against the 30 for patenting firms, on average), productivity (159 for the former against 166 for the latter), and unit labor cost (57 for both innovative and non-innovative firms). On the other hand, innovative firms show twice the values of non-innovative firms on the number of employees, value-added, intangibles, and liabilities. Therefore, innovative firms seem to be larger, in terms of employees, value-added, and assets (e.g. intangibles and liabilities), but not very different in terms of productivity, since they show a similar productive structure (i.e. TFP and unit labour cost). Moreover, innovative firms show a lower degree of variability (e.g. a lower standard deviation) for most of the variables (all but the age and the number of employees) with respect to non-innovative firms.

We focus on managerial training rather than employee training for conceptual and empirical reasons, given that our outcome variable – patenting – primarily reflects strategic decisions taken at the managerial level. Conceptually, managerial training is more directly linked to patenting activity. Trained managers are better positioned to identify innovation opportunities, allocate resources strategically, and navigate the formal processes of IP protection. Patents can serve multiple functions within a firm's innovation strategy – acting as defensive mechanisms, signaling tools, or vehicles for commercializing technological advancements. Managers typically make these strategic decisions, as the innovation process begins with high-level evaluation and a commitment of resources.

Empirically, two additional points motivate our focus. First, prior research often conflates training at different organizational levels, making it difficult to isolate the specific effects of managerial training on firm-level innovation outcomes such as patenting (Lau and Ngo, 2004). Our study addresses this gap by explicitly examining the distinct role of managerial training. Second, employee training is typically correlated with a range of observable firm characteristics – such as firm size, sector, or R&D intensity – which we include as controls. Although we do not model employee training directly, our empirical design captures its indirect effects through these covariates, enabling a more focused assessment of the relationship between managerial training and patenting.

4. Empirical analysis

4.1 Estimation strategy

The baseline empirical strategy is twofold. First, we employ a probit model to assess the impact of managerial training on firms' patenting activities. Second, to refine the comparison between firms that have received managerial training and those that have not – specifically, to address confounding and selection bias – we utilize the Inverse Probability Weighting (IPW) procedure. This approach allows us to balance the units in the sample, thereby providing more accurate estimates than the probit model.

Additionally, we acknowledge that endogeneity concerns may arise due to potential reverse causality and omitted variable bias. To mitigate this issue, we employ a generated instrumental variable based on sample heteroskedasticity (IVH), following the methodology outlined by Lewbel (2012) [5]. This approach uses both endogenous and exogenous instruments to evaluate the causal effect. The baseline equation is as follows:

$$Patents_{i,t} = \beta_0 + \beta_1 ManagerialTraining_{i,t-k} + \gamma \mathbf{F}_{i,t-k} + \sigma_s + \tau_t + \varepsilon_{i,t} \tag{1}$$

The dependent variable is the firm's innovativeness ($Patents_{i,t}$), which is measured using a dummy variable that takes the value of one for each year in which the firm filed at least one patent. The primary explanatory variable, *ManagerialTraining*, consists of the (log of) number of training programs ($LnNo\_Train_{i,t-k}$) and the (log of) number of per capita training hours ($LnHpc\_Train_{i,t-k}$). Both explanatory variables are lagged from $t-1$ to $t-3$ to mitigate simultaneity concerns. Additionally, a set of firm-level control variables is included in the vector **F**: firm age, value added, total intangible assets, unit labor cost, number of employees, total liabilities, and Total Factor Productivity (TFP). All control variables are expressed in natural logarithms and use the same time lags as the main explanatory variables. Time and sectoral fixed effects (at the NACE 2-digit level) are also included, and standard errors are clustered at the firm level.

Finally, to test the hypotheses, we examine the differentiated effects of training on subsamples defined by key variables of interest: quintiles of TFP, firm size, and Pavitt classes.

4.2 Identification strategy

Baseline estimates from the probit model may be biased due to reverse causality and omitted variable bias. Innovative firms tend to be, on average, larger, more productive, and have more resources. The increased complexity of these firms may incentivize access to training for managers, potentially creating a feedback loop that leads to endogeneity. To address these concerns, we first employ an IPW model to associate firms with similar characteristics, to reduce selection bias, and to balance the covariates used in the baseline probit model. Finally, we employ an instrumental variable approach based on the presence of heteroskedasticity in the sample (IVH), which combines an exogenous instrument with endogenous ones, following the methodologies outlined by Lewbel (2012) and Baum and Schaffer (2024).

Concerning the IPW, the weights are built accordingly to the following model:

$$\begin{aligned} Training_{i,t} &= \phi(NACE2_i, NUTS1_i, Size_i, Year_t) \\ &\Rightarrow \Pr\left(Training_{i,t} = 1 \middle| X\right) = \widehat{e}(T_i) \end{aligned} \tag{2}$$

The dependent variable $Training_{i,t}$ is a dummy variable taking the value one when the firm is engaged in at least one training program (and zero otherwise). This is a function of the sector of activity (*NACE*2, at the NACE 2-digit level); the NUTS-1 macro-region; the firm's size (in terms of number of employees, in three categories); and the year dummies. The function is estimated through a logit model. Then, we assign the weights according to the treatment status:

(1) $w_i = \frac{1}{\widehat{e}(T_i)}$ if $Training_{i,t} = 1$

(2) $w_i = \frac{1}{(1-\widehat{e}(T_i))}$ if $Training_{i,t} = 0$

Finally, the weights just defined are used to weight a linear probability model to associate firms having similar characteristics to mitigate the endogeneity concern.

The IVH approach combines an exogenous – traditional – IV, and some endogenous – heteroskedasticity-based — instrument. The exogenous IV is the weighted average (by the NACE 3-digit sector) of the per capita amount of funds available to firms for implementing training plans for their managers, measured in terms of employees. This funding is mandatory for affiliated firms and is determined by Fondirigenti, ensuring its exogeneity with respect to the firm. The endogenous instruments are generated as a function of the model's data. The variables are generated as a product of heteroskedastic errors: the higher the heteroskedasticity in the data, the larger the orthogonality of the product to the outcomes. According to Lewbel (2012), including these generated variables allows for control of unobserved common factors and corrects the endogeneity, eventually identifying the causal effect.

5. Results

5.1 Baseline model

The baseline results (Table 2) indicate a positive and significant effect of the number of training programs undertaken between periods $t-1$ and $t-3$ on the probability of a firm transitioning from a non-innovative to an innovative status. This effect is consistently observed across both standard probit, the inverse probability weighting (IPW), and the IV models (IV using heteroskedasticity, i.e. IVH). In particular, the number of training plans has a positive effect on patenting between 1.5 and 2% (columns 2 and 3, Table 2). In contrast, the total number of training hours does not significantly enhance the probability of innovating. The effect is even negative in the IPW model at time $t-1$. These findings suggest that the “breadth” of training programs, rather than the “intensity” measured by hours, offers the greatest benefit to a firm’s innovation performance (Dostie, 2018; Heubeck, 2024) [6].

To address the imbalance in the dependent variable, we also run a zero-inflated negative binomial (ZINB) model, which separately models (1) the likelihood of being a non-innovative firm (zero patents, about 96% of the sample) and (2) the number of patents filed by innovative firms. Even after accounting for the zero inflation, both the (log) number of training programs and (log) per capita training hours retain positive and statistically significant effects at the first and second lags. However, we refrain from interpreting these results in terms of patent counts, as the focus of our analysis is on the transition from a non-innovative to an innovative status. Therefore the ZINB estimates provide further robustness check to our analysis since the results confirm that the disproportionate share of non-innovative firms does not bias the key findings of the paper. Complete results are reported in Tables A3 and A4 in the Appendix and are completely consistent with our main findings.

To test hypotheses from H2 to H4, we split the sample according to (1) the quintiles of the productivity distribution, (2) the Pavitt classes, and (3) size classes. Tables 3–5 present the results for the instrumental variable estimation with the generated heteroskedasticity-based IV, which are discussed in detail in the following section.

Table 2. Baseline model – Results

		Probit (1)	IPW (2)	IVH (3)	Probit (4)	IPW (5)	IVH (6)
(ln) No. Training programs	$t-1$	0.0660*	−0.0021	0.0114***			
		(0.037)	(0.008)	(0.004)			
	$t-2$	0.1093***	0.0145*	0.0193***			
		(0.036)	(0.008)	(0.004)			
	$t-3$	0.1140***	0.0213**	0.0179***			
		(0.036)	(0.009)	(0.004)			
(ln) Training hours (p. c.)	$t-1$				−0.0577	−0.0120***	0.0010
					(0.050)	(0.004)	(0.004)
	$t-2$				0.0325	−0.0016	0.0068
					(0.044)	(0.006)	(0.004)
	$t-3$				−0.0052	0.0035	−0.0036
					(0.043)	(0.007)	(0.005)
Other controls		yes	yes	yes	yes	yes	yes
R-squared			0.029	0.054		0.028	0.052
Observations		68,021	67,859	70,695	68,021	67,859	70,695

Note(s): Robust standard errors in parentheses clustered at the firm level. Other controls include (lagged from $t-1$ to $t-3$, and in natural logarithm): Value Added, Firm’s age, Tot. Intangible assets, Total liabilities, Unit labour cost, Employees, TFP. Extended tables are reported in the Appendix. Sectoral fixed effects (NACE 2-digit) and year are always included. Lewbel IV (columns 3 and 6) includes an exogenous instrumental variable (see Section 4.2). Significance levels: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Source(s): Authors’ own work

Table 3. Heterogeneous effects by TFP quintiles

		q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
(ln) No. Training programs	t−1	0.0471***	−0.0017	0.0148*	0.0062	0.0155**					
		(0.009)	(0.010)	(0.009)	(0.009)	(0.006)					
	t−2	0.0338***	−0.0070	0.0320***	0.0147*	0.0133**					
		(0.009)	(0.010)	(0.009)	(0.009)	(0.007)					
	t−3	−0.0004	0.0038	0.0066	0.0166*	0.0261***					
		(0.010)	(0.011)	(0.010)	(0.010)	(0.007)					
(ln) Training hours (p. c.)	t−1						0.0227**	−0.0055	0.0028	−0.0003	0.0078
							(0.010)	(0.012)	(0.013)	(0.010)	(0.007)
	t−2						0.0062	0.0258*	0.0135	0.0049	0.0096
							0.009	(0.013)	(0.012)	(0.011)	(0.007)
	t−3						−0.0060	0.0039	0.0105	−0.0036	0.0063
							(0.010)	(0.015)	(0.013)	(0.011)	(0.007)
Other controls		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared		0.026	0.029	0.041	0.075	0.085	0.022	0.029	0.039	0.074	0.083
Observations		10,392	13,217	14,538	15,210	14,611	10,392	13,217	14,538	15,210	14,611

Note(s): IVH estimates. Other controls include (lagged from t−1 to t−3, and in natural logarithm): Value Added, Firm's age, Tot. Intangible assets, Total liabilities, Unit labour cost, Employees, TFP. Extended tables are reported in the Appendix. Sectoral fixed effects (NACE 2-digit) and year are always included. Lewbel IV includes an exogenous instrumental variable (see Section 4.2). Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01

Source(s): Authors' own work

Table 4. Heterogeneous effects by size classes

		1–49 (1)	50–249 (2)	250+ (3)	1–49 (4)	50–249 (5)	250+ (6)
(ln) No. Training programs	t−1	0.0310***	0.0136*	0.0122			
		(0.008)	(0.008)	(0.010)			
	t−2	0.0216***	0.0128*	0.0168*			
		(0.008)	(0.007)	(0.009)			
	t−3	0.0180**	0.0035	0.0136			
		(0.009)	(0.008)	(0.010)			
(ln) Training hours (p. c.)	t−1				0.0048	0.0021	−0.0001
					(0.004)	(0.008)	(0.012)
	t−2				−0.0013	0.0010	0.0263**
					(0.004)	(0.007)	(0.012)
	t−3				−0.0005	−0.0025	0.0012
					(0.005)	(0.007)	(0.012)
Other controls		yes	yes	yes	yes	yes	yes
R-squared		0.014	0.042	0.100	0.013	0.041	0.100
Observations		24,658	32,847	13,034	24,658	32,847	13,034

Note(s): IVH estimates. Other controls include (lagged from t−1 to t−3, and in natural logarithm): Value Added, Firm's age, Tot. Intangible assets, Total liabilities, Unit labour cost, Employees, TFP. Extended tables are reported in the Appendix. Sectoral fixed effects (NACE 2-digit) and year are always included. Lewbel IV includes an exogenous instrumental variable (see Section 4.2). Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01

Source(s): Authors' own work

5.2 Heterogeneous effects

In Section 2, we hypothesized that firms lagging behind in the productivity distribution may more largely benefit from managerial training. Such training strengthens a firm's ability to identify technological opportunities, adapt routines to enhance products and processes, and ultimately increases awareness of both the need and the potential to protect inventions through patents. Therefore, we split the sample based on the variables that define the productivity distribution (i.e. the quintiles of TFP). Table 3 reports the results for the IV models. Considering the number of training plans, a positive effect is observed even for firms in the fifth quintile; however, the effect is substantially stronger for firms in the first quintile. Furthermore, the most recent training hours per capita, specifically in periods $t-1$ and $t-2$, appear to have a significant impact on firms in the lowest quintiles. At the same time, no discernible effect is found for firms in the rest of the distribution. These results confirm our second Hypothesis (H2) regarding the beneficial effect of training for relatively weaker firms in terms of innovative capacity. Indeed, less productive firms often face substantial obstacles in accessing external knowledge, primarily due to limited absorptive capacity and various operational inefficiencies. These constraints can significantly impede their ability to learn from external sources and improve performance. However, training interventions have the potential to alleviate these issues by strengthening firms' capacity to assimilate and apply new knowledge (Lau and Ngo, 2004; Cantner *et al*., 2009; Martínez-Ros and Orfila-Sintes, 2012).

A similar rationale applies to firm size and the technological and knowledge dynamics of the industry in which a firm operates, as some sectors depend more heavily on external knowledge sources and organizational learning mechanisms. These factors may shape the extent to which training investments translate into innovation outcomes, particularly patenting. Table 4 presents the results of the IV models, disaggregated by firm size. The number of managerial training programs implemented by firms has a statistically significant effect on the likelihood of filing patents, particularly among smaller firms (i.e. those with 1–49 employees), where the effect is positive and significant. This suggests that in resource-constrained environments, such as small firms, enhanced managerial competencies may play a

Table 5. Heterogeneous effects by Pavitt taxonomy's classes

		SB (1)	SS (2)	SI (3)	SD (4)	SB (5)	SS (6)	SI (7)	SD (8)
(ln) No. Training programs	t−1	−0.0206*	0.0084	0.0251**	0.0163***				
		(0.011)	(0.011)	(0.010)	(0.006)				
	t−2	−0.0055	−0.0044	0.0370***	0.0267***				
		(0.011)	(0.011)	(0.010)	(0.006)				
	t−3	−0.0014	0.0140	0.0094	0.0283***				
		(0.011)	(0.012)	(0.010)	(0.006)				
(ln) Training hours (p. c.)	t−1					−0.0046	−0.0088	0.0078	0.0217***
						(0.011)	(0.011)	(0.011)	(0.008)
	t−2					0.0071	−0.0077	0.0143	0.0210***
						(0.011)	(0.011)	(0.012)	(0.008)
	t−3					−0.0093	−0.0065	0.0129	0.0024
						(0.010)	(0.012)	(0.012)	(0.008)
Other controls		yes	yes	yes	yes	yes	yes	yes	yes
R-squared		0.035	0.061	0.046	0.037	0.037	0.060	0.042	0.035
Observations		9,413	17,990	11,776	25,451	9,413	17,990	11,776	25,451

Note(s): IVH estimates. Pavitt classes: SB = Science-based; SS = Specialized suppliers; SI = Scale-intensive; SD = Supplier-dominated. Other controls include (lagged from t−1 to t−3, and in natural logarithm): Value Added, Firm's age, Tot. Intangible assets, Total liabilities, Unit labour cost, Employees, TFP. Extended tables are reported in the Appendix. Sectoral fixed effects (NACE 2-digit) and year are always included. Lewbel IV includes an exogenous instrumental variable (see Section 4.2). Significance levels: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Source(s): Authors' own work

more decisive role in initiating patent-relevant innovation processes (McGuirk *et al.*, 2015; Dostie, 2018; Sung and Choi, 2014). We also observe positive coefficients for medium-sized firms (column 4) and large firms (column 6), although statistical significance is more limited. Notably, for large firms, the number of training hours – as opposed to simply the number of programs – also exhibits a positive and significant effect, pointing to the importance of training intensity in larger and potentially more complex organizational settings. While training appears to foster patenting across different firm sizes, the magnitude of the effect is strongest among smaller firms, indicating that managerial training may be particularly impactful where formal innovation capabilities and structures are less developed, thus verifying our H3.

Finally, we further explore our H4 by splitting the sample according to the Pavitt taxonomy, with the results reported in Table 5. The impact of managerial training is positive and statistically significant for firms in supplier-dominated sectors, which also show a significant association between training hours and patenting activity at the 1% significance level (column 8). This effect is particularly strong for supplier-dominated firms, which typically lack in-house R&D capabilities and rely more heavily on external sources of knowledge and learning-by-doing for innovation. For these firms, managerial training likely enhances the ability to recognize, absorb, and strategically utilize external knowledge, thereby supporting engagement with formal innovation outputs such as patents (Audretsch *et al.*, 2024; Greenan and Napolitano, 2024).

Firms in scale-intensive sectors also exhibit a positive effect of managerial training, specifically with respect to the number of training programs undertaken in the recent past. This suggests that even in industries where innovation depends on incremental improvements and process optimization, investments in managerial competencies can contribute to innovation-related outcomes – potentially by improving internal coordination, strategic planning, and the ability to manage complex innovation processes. Overall, these results confirm that the relationship between managerial training and patenting varies across sectoral regimes. The effects are most pronounced in sectors where firms are structurally more dependent on learning mechanisms and external knowledge flows.

To check the robustness of the results, we exclude from the sample the firms operating in the regions of southern Italy. Here, data may lack representativeness, due to a lower number of firms participating in Fondirigenti. The small number of firms of the sample operating in the south – larger and more productive – may be outliers, altering the main results, and then we test the baseline models excluding them. As shown in Table 6, the results remain robust in sign and magnitude. The number of training plans is effective in enhancing the patent activity of the firms, with the coefficients showing the same magnitude as the baseline (Table 6, column 2). In contrast, the training hours continue to show no significant effects (column 4).

6. Discussion and conclusions

This paper sheds light on the role of managers in upgrading their competencies to manage the evolution of the landscape in which the firm operates, driven by changing market conditions and technological progress (Hitt *et al.*, 1998).

The empirical analysis confirms that the “breadth” of managerial training is effective in enhancing the firm’s patenting propensity. In particular, managerial training in more recent periods has a strong positive and significant effect, while no effect is observed for training “intensity”. When we split the sample according to firms’ size in terms of productivity and number of employees, we also find a positive effect for firms on the lower end of the size distribution, both in terms of productivity and number of employees.

Managerial training plays a crucial role in supporting the development of dynamic capabilities, which are particularly important for firms of different sizes in adapting to increasingly complex and rapidly changing environments. For small enterprises, such training may enhance managers’ ability to identify internal and external opportunities and consider strategic responses accordingly. These could include, for example, the use of patenting as a

Table 6. Robustness – Excluding firms from southern regions

		Full sample (1)	Excluding south (2)	Full sample (3)	Excluding south (4)
(ln) No. Training programs	t−1	0.0114***	0.0092**		
		(0.004)	(0.004)		
	t−2	0.0193***	0.0170***		
		(0.004)	(0.004)		
	t−3	0.0179***	0.0165***		
		(0.004)	(0.005)		
(ln) Training hours (p. c.)	t−1			0.0010	0.0009
				(0.004)	(0.005)
	t−2			0.0068	0.0071
				(0.004)	(0.005)
	t−3			−0.0036	−0.0039
				(0.005)	(0.005)
Other controls		yes	yes	yes	yes
R-squared		0.054	0.054	0.052	0.052
Observations		70,695	65,445	70,695	65,445

Note(s): IVH estimates. Other controls include (lagged from t−1 to t−3, and in natural logarithm): Value Added, Firm's age, Tot. Intangible assets, Total liabilities, Unit labour cost, Employees, TFP. Extended tables are reported in the Appendix. Sectoral fixed effects (NACE 2-digit) and year are always included. Lewbel IV includes an exogenous instrumental variable (see Section 4.2). Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01

Source(s): Authors' own work

means to safeguard valuable practices, processes, or products. In larger firms, managerial training may contribute to a more informed and strategic use of intellectual property tools, not only to support innovation but also for defensive purposes, such as preserving competitive advantages and reducing exposure to imitation or infringement. Finally, we examine the technological opportunities within the sectors in which the firms operate. The effect of training is positive – both for "breadth" and "intensity" – for firms in supplier-dominated sectors, where learning opportunities primarily come from external sources. A similar effect is observed for firms operating in scale-intensive sectors.

This evidence underscores the value of managerial training in strengthening firms' innovative capabilities, highlighting its potential as a critical lever for enhancing both innovation and productivity. These issues are particularly pressing for Italian firms, where the dynamics of innovation and productivity remain persistently sluggish, regardless of firm size, age, or sector. Many firms struggle to adopt new technologies, upgrade organizational practices, or fully leverage knowledge assets – challenges that are often compounded by limited managerial competencies. Although referred to a specific country, our analysis shed light on an understudied policy tool, namely managerial training, which may enhance firms' innovativeness in contexts with similar characteristics of national and sectoral innovation systems. Indeed, several Mediterranean countries share features comparable to Italy's: a large proportion of small firms, low patenting intensity, and a production structure concentrated in traditional sectors. We therefore believe that the evidence drawn from this rich and reliable data source may offer valuable insights for policymakers seeking to design innovation policies in comparable economic environments.

From a managerial perspective, our findings indicate that investments in managerial training are a strategic lever for enhancing firm innovation performance. The positive association between training and innovation outcomes supports the view that human capital development and innovative capability function as complementary assets. This implication is particularly salient for small firms, where managerial competencies often represent a critical bottleneck. In such contexts, strengthening managers' skills can substantially improve organizational efficiency and productivity. These mechanisms also help explain why smaller firms may find it worthwhile to allocate financial resources to managerial training despite tighter budget constraints.

Public policy support for managerial training – especially when targeted at small and medium-sized enterprises (SMEs) and those operating in industries with scarce external knowledge flows or weak innovation networks – could serve as a powerful instrument to foster catch-up growth. By equipping managers with the skills to recognize technological opportunities, allocate resources more strategically, and implement effective innovation processes, such interventions can help unlock latent potential within firms. Over time, this can contribute to narrowing the gap between lagging firms and those at or near the productivity frontier and revitalizing the broader innovation ecosystem.

This study advances the existing literature by uncovering the role of managerial training in fostering innovation, while also disentangling its effects across different types of firms. It draws on an accurate administrative database containing unique information on training activities, merged with objective measures of innovation performance – specifically patent data – rather than relying on self-reported indicators, which are often subject to bias and comparability issues. However, some limitations have to be acknowledged. First, while patent data provide a more standardized and verifiable proxy for technological innovation, they may fail to capture important non-patentable forms of innovation, particularly in services, marketing, and organizational processes. Future research could address this limitation by combining codified and objective measures, such as patent data, with complementary indicators capable of capturing more tacit or non-codified forms of innovation, thereby enabling a more holistic understanding of firms' innovative activities.

Second, more granular information on managerial training, combined with data on the share of managers participating in specific programs, would allow to better disentangle which types of training are most effective in enhancing firms' innovation performance. In line with this observation, distinguishing between on-the-job and in-classroom training would make it possible to assess the relative contribution of experiential learning versus formal instruction, thereby improving future empirical analyses.

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(The Appendix follows overleaf)

Appendix

Table A1. Sample composition

	No. firms	Percent
Pavitt class		
Science based	9,413	14.56
Specialised suppliers	17,990	27.84
Scale and information intensive	11,776	18.22
Suppliers dominated	25,451	39.38
Total	64,630	
Size class (no. empl.)		
1–49	24,658	34.96
50–249	32,847	46.57
250+	13,034	18.48
Total	70,539	

Total composition by combined Pavitt-size classes

Pavitt/Size	1–49	50–249	250+	*Total*
Science based	5.24%	6.47%	2.85%	14.56%
Specialised suppliers	10.26%	13.11%	4.42%	27.84%
Scale and information intensive	5.24%	9.47%	3.51%	18.22%
Suppliers dominated	13.90%	18.18%	7.34%	39.38%
Total	34.96%	46.57%	18.48%	

Note(s): Sample composition refers to the estimation sample derived from the baseline model
Source(s): Authors' own work

Table A2. Summary of topics covered within program categories

Category	Topic	Share
Technical and Managerial	Languages for business	58%
	Organization and human resources	7%
	Safety	7%
	Strategy	5%
Behavioral	Communication	41%
	Interpersonal relationships	32%
	Negotiation	20%
	Autonomy	7%
Conceptual	Problem solving	34%
	Temporal (or strategic) perspective	17%
	Systemic perspective	12%
	Logical-analytical	10%
Leadership	Decision-making	35%
	Integration/organization	33%
	Innovation	25%
	Propensity to risk	7%

Note(s): First four topics covered for each category of training programs activated by Fondirigenti. The share in the third column refers to the number of programs activated covering the specific topic (second column) on the total number of programs of the category (first column)
Source(s): Authors' own work

Table A3. Zero-Inflated Negative Binomial model

	w/Residuals Count (1)	Inflate (2)	Without residuals Count (3)	Inflate (4)	w/Residuals Count (5)	Inflate (6)	Without residuals Count (7)	Inflate (8)
Firm's age		0.087		0.093		0.086		0.092
		(0.074)		(0.074)		(0.071)		(0.071)
Avg. Wage		−0.236*		−0.235*		−0.239**		−0.238**
		(0.125)		(0.125)		(0.121)		(0.121)
Employees		−0.295***		−0.299***		−0.304***		−0.308***
		(0.037)		(0.037)		(0.035)		(0.035)
Dummy ATECO	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Training plans (t-1)	−4.085		0.246***					
	(3.189)		(0.084)					
Training plans (t-2)	3.370		0.187**					
	(3.359)		(0.084)					
Training plans (t-3)	3.665		0.077					
	(3.497)		(0.089)					
Training hours (t-1)					−4.013		0.505***	
					(3.072)		(0.160)	
Training hours (t-2)					2.346		0.435***	
					(3.014)		(0.149)	
Training hours (t-3)					5.081		0.192	
					(3.581)		(0.160)	
Residuals IV t-1	4.337				4.532			
	(3.196)				(3.087)			
Residuals IV t-2	−3.192				−1.922			
	(3.368)				(3.026)			
Residuals IV t-3	−3.594				−4.904			
	(3.502)				(3.586)			
Firm's age (t-1)	−9.382**		−9.264**		−9.336**		−10.040**	
	(4.622)		(4.450)		(4.518)		(4.453)	

(*continued*)

Table A3. Continued

	w/Residuals Count	Inflate	Without residuals Count	Inflate	w/Residuals Count	Inflate	Without residuals Count	Inflate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm's age (t-2)	13.972**		13.725**		13.983**		14.859**	
	(6.893)		(6.649)		(6.743)		(6.656)	
Firm's age (t-3)	−4.704**		−4.535*		−4.739**		−4.909**	
	(2.394)		(2.315)		(2.342)		(2.317)	
Value added (t-1)	0.905		1.063		1.111		0.872	
	(1.408)		(1.402)		(1.423)		(1.411)	
Value added (t-2)	0.639		0.583		−0.080		0.600	
	(1.950)		(1.939)		(1.999)		(1.947)	
Value added (t-3)	−0.971		−1.087		−0.400		−0.949	
	(1.329)		(1.314)		(1.360)		(1.320)	
Tot. Intangibles (t-1)	0.104***		0.108***		0.109***		0.110***	
	(0.024)		(0.024)		(0.024)		(0.024)	
Tot. Intangibles (t-2)	0.065**		0.062**		0.051*		0.061**	
	(0.029)		(0.029)		(0.030)		(0.029)	
Tot. Intangibles (t-3)	0.005		0.008		0.021		0.010	
	(0.023)		(0.022)		(0.024)		(0.023)	

Source(s): Authors' own work

Table A4. (continued) Zero-Inflated Negative Binomial model

	w/Residuals Count (1)	Inflate (2)	Without residuals Count (3)	Inflate (4)	w/Residuals Count (5)	Inflate (6)	Without residuals Count (7)	Inflate (8)
Avg. Wage (t-1)	0.441**		0.413**		0.421**		0.400*	
	(0.214)		(0.208)		(0.212)		(0.208)	
Avg. Wage (t-2)	−0.228		−0.150		−0.170		−0.160	
	(0.239)		(0.233)		(0.234)		(0.233)	
Avg. Wage (t-3)	0.135		0.221		0.099		0.196	
	(0.205)		(0.180)		(0.206)		(0.181)	
Employees (t-1)	−0.059		−0.222		−0.385		−0.054	
	(1.173)		(1.166)		(1.196)		(1.174)	
Employees (t-2)	−0.677		−0.615		0.074		−0.622	
	(1.605)		(1.594)		(1.662)		(1.601)	
Employees (t-3)	0.607		0.798		0.226		0.686	
	(1.103)		(1.091)		(1.139)		(1.096)	
Tot. Liabilities (t-1)	0.156		0.165*		0.160		0.165*	
	(0.098)		(0.098)		(0.098)		(0.098)	
Tot. Liabilities (t-2)	0.031		0.020		0.001		0.015	
	(0.126)		(0.125)		(0.126)		(0.125)	
Tot. Liabilities (t-3)	−0.290***		−0.275***		−0.286***		−0.281***	
	(0.100)		(0.096)		(0.098)		(0.096)	
TFP (t-1)	−0.601		−0.740		−0.826		−0.557	
	(1.407)		(1.402)		(1.425)		(1.410)	
TFP (t-2)	−0.596		−0.572		0.133		−0.596	
	(1.947)		(1.937)		(2.003)		(1.944)	
TFP (t-3)	0.904		1.032		0.327		0.900	
	(1.325)		(1.312)		(1.361)		(1.317)	
Constant	−1.588***	4.822***	−1.597***	4.849***	−1.513***	4.937***	−1.509***	4.962***
	(0.136)	(0.599)	(0.135)	(0.598)	(0.134)	(0.585)	(0.133)	(0.583)
Dummy ATECO	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Alpha	1.468***		1.463***		1.403***		1.398***	
	(0.115)		(0.114)		(0.115)		(0.114)	
Observations	70,682	70,682	70,682	70,682	70,682	70,682	70,682	70,682

Note(s): Model in columns 1–2 and 5–6 is augmented with the first-stage residual inclusion, while model in columns 3–4 and 7–8 do not include residuals. The inflation factor (zero generating process) is reported in "Inflate" (columns 2, 4, 6, and 8), while "Count" (columns 1, 3, 5, 7) reports the coefficients on the dependent variable. Sector and time dummies included in all specifications. Significance levels: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Source(s): Authors' own work

Notes

1. If some degree of misclassification exists, it would likely be of a classical nature, leading to attenuation of estimated effects. Therefore, our results should be interpreted as conservative: the true impact of managerial training on innovation outcomes is probably stronger than our estimates indicate.
2. Total Factor Productivity has been estimated using the Levinsohn and Petrin (2003) methodology.
3. This variable is obtained by dividing total direct personnel costs by the number of employees.
4. Under Italian accounting standards, firms are not required to report R&D expenditures separately; consequently, such spending is included within the total intangible capital stock.
5. For other papers studying innovation and using the Lewbel methodology, see: Agostino *et al*. (2025), Bogliacino *et al*. (2018).
6. As a robustness check, we also address the concern that unobserved shocks might jointly influence both the dependent and explanatory variables – namely, patenting and training. To mitigate this issue, we augmented the benchmark specification (the probit model) by adding an additional set of controls: the interaction between sector and year dummies. This inclusion enables us to capture sector-specific business cycle dynamics that could simultaneously affect firms' innovative activities (i.e. patenting), their training decisions, and other explanatory variables. Results are consistent with those of the benchmark specification and are available from the authors upon request.

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Corresponding author
Eleonora Pierucci can be contacted at: eleonora.pierucci@uniroma3.it