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RESEARCH ARTICLE

Digital adoption and human capital upscaling: a regional study of the manufacturing sector

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Abstract We study the effect of the diffusion of digitalization, measured as the level of expenditures in digital technologies, on labor demand within the manufacturing sector. We exploit unique information from a focus study of the quarterly survey of Unioncamere Piemonte (one of Italy's most industrialized and technologically advanced regions) to measure the extent to which planned digital technologies investments impact hiring propensity, differentiated by educational level. Based on a representative sample of non-micro firms, our findings suggest a positive relationship between digital investments and the probability of hiring highly educated workers, mainly driven by the demand for individuals with a post-secondary technical institute (ITS) diploma and post-MSc qualifications or a PhD in STEM fields. Conversely, we also find that digital investments negatively influence the probability of hiring low-educated individuals, primarily referring to the demand for workers with secondary education. Our results reveal firms' human capital upscaling dynamics powered by digitalization processes.

Plain English Summary Digitalization in Piedmont's manufacturing sector increases demand for highly educated workers, reshaping job dynamics and driving the need for human capital upscaling. Our study examines how digital investments impact Piedmont's workforce, revealing a preference for workers with advanced technical education while reducing demand for less-educated workers. We also found complementary and substitution effects across educational levels—while technology boosts demand for highly educated workers, there remains a need for diverse qualifications in roles less likely to be automated. To stay competitive, companies must focus on upscaling their workforce's human capital. Policymakers should develop education and training initiatives that support a broad range of qualifications, ensuring workers can adapt to the evolving digital economy and trying to reduce the negative externalities deriving from job polarization.

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1 Introduction

The relationship between digitalization and employment is one of the key topics in the public debate and on the agenda of many researchers around the world. The tension between opportunities and threats has brought many scholars and policymakers to investigate and discuss the mechanisms digital technologies generate in the economies and the labor markets. So far, we know that the literature is ambiguous, from a potential high labor-machine substitution according to some scholars—see Frey and Osborne (2017)—to more complex complementary effects—see Autor (2015). Indeed, we observe neither massive job layoffs nor significant dissemination of jobless factories. This is explained by the fact that digitalization (as well as the bulk of technological innovations), on the one hand, increases productivity, which, ceteris paribus, implies lower employment for the same output. However, on the other hand, it favors investments and training, which in turn demand higher employment (Weber, 2020). The net effect is still unclear, and this is already a takeaway because it suggests the need to dive into the type of technology and the complexity of firms' choices when they face a technological innovation: which technology is more suitable for a certain business process? How can this technology be combined with the current or future labor force? Along which margin, intensive or extensive, does this technology work? Especially, the last two questions point to the importance of looking at the composition of the labor force rather than the stock (Colombari et al., 2023). Existing evidence suggests that job growth trajectory is projected to increasingly favor workers with higher education, reinforcing the trend towards a more educated workforce in the digital era (Carnevale et al., 2013). However, it remains to be seen whether the demand for workers with high levels of education can complement or substitute for the demand for those with lower attainments. Although advanced technologies lead to a greater need for highly educated workers to maximize their implementation benefits (Brynjolfsson & Hitt, 2003; Fabiani et al., 2005), there are still no clear-cut answers regarding the impact on the entire distribution of educational demand and the intersection between different qualifications.

In this paper, we measure the relationship between investments in digital technologies and firms' hiring choices, focusing on their hiring propensity for workers' educational attainments. To do so, we leverage unique data on digital investments from a representative sample of manufacturing companies in Piedmont and employ a multi-layered empirical strategy based on two specifications of Probit models, a Tobit I model, and two versions of multivariate Probit model (i.e., a bivariate and a 6-variate form). Through this composite empirical approach, we are able to study the relationship of interest characterizing human capital in detail and focus on the choice of qualification composition of firms. Among educational categories, we can identify a group of workers in Italy who have qualifications from technical institutions known as Istituti Tecnici Superiori (ITS), which are the equivalent of Fachhochschule (FH) in German or University of Applied Sciences (UAS) in English. These institutions provide specialized education and training on practical and technological skills directly applicable to the industry. These professionals are crucial in manufacturing because they have the technical expertise and hands-on experience to operate, manage, and innovate with advanced manufacturing technologies. The presence of ITS graduates in the workforce can significantly improve a firm's ability to integrate digital technologies, thereby driving productivity and innovation effectively. Recognizing the importance of these professionals leads to a better understanding of how digital investments impact hiring practices and the specific value that different educational backgrounds bring to the industry.

Our results suggest that digital investments are not only positively related to firms' propensity to hire but also to the probability that they choose to hire highly educated workers. Moreover, this tendency seems stronger for specific categories of digital investments—in terms of the amount they plan to invest in 2021, suggesting a non-linear relationship. By performing multivariate Probit models, we allow the estimates to show potential substitution or complementary effects in demand for low and highly educated workers across all the educational levels we can identify. In other words, we can observe if firms' demand for workers with a specific level of schooling is associated with a higher or lower demand for individuals with different qualifications. Our analysis finds a complementary effect between digitalization and the demand for workers with tertiary education and a substitution effect between non-qualified workers and individuals with an ITS diploma. We also find a complementary effect between non-qualified workers and individuals with a Bachelor's or Master's degree in non-STEM fields.

The contribution of this paper lies in investigating the relationship between investments in digital technologies and hiring choices from multiple perspectives that still need to be addressed in the literature. Firstly, we are able to consider a set of advanced technologies and, secondly, discern between a comprehensive definition of worker educational attainments and the related demand of firms for each category of individuals. In this regard, we can identify six different levels of education (see Section 3), from workers with no qualifications to individuals with the highest attainable tertiary education. Our data also identifies workers with an ITS diploma, representing a category of technically specialized workers still almost unexplored in the literature. Moreover, since firms can simultaneously signal demand against multiple categories of individuals (by level of education)—which we refer to as mixed hiring strategies—we take this heterogeneity into account and observe whether the demand for specific categories of workers results in substitution or complementary demand for other workers with different qualifications.

The remainder of this paper is organized as follows. Section 2 presents a review of the literature. Section 3 describes the data used in the analysis and the descriptive statistics. The empirical methodology employed in this work is discussed in Section 4. The results of the study are presented in Section 5. Section 6 is dedicated to a more detailed discussion of the obtained results. Finally, Section 7 concludes the paper.

2 Digitalization and employment: a review of the literature

In this section, we present a review of the main literature dealing with digitalization (and technological innovation, in general) and its effect on employment. The section is structured to discuss the literature focus on employment with respect to skills and educational qualifications, highlighting their distinction. While education refers to formal qualifications obtained through schooling and higher education, skills pertain to specific competencies and abilities acquired through training and experience. Deming (2017) highlights this distinction, noting that while higher education often correlates with skill acquisition, the two are not synonymous. The rise of digitalization demands not only formal education but also continuous skill development, particularly in technical and problem-solving abilities. Sometimes, in the literature, the two are confused together.

Focusing on skills, research on digital technologies in manufacturing shows their complex impact on employment. Digitalization can displace routine and manual jobs but also creates opportunities for high-skilled workers. Studies highlight that technological advancements and automation increase demand for high-skilled labor, reduce the need for low-skilled workers, and cause job market polarization (Acemoglu and Restrepo, 2019; Autor et al., 2003; Bresnahan et al., 2002; Frey & Osborne, 2017; Graetz & Michaels, 2018; Nogueira & Madaleno, 2023). High-income cognitive jobs and low-income manual jobs are growing, while middle-income routine jobs are declining, with jobs requiring higher education and complex skills being less susceptible to automation.

Specific skills required in the digital age have also been examined. Research indicates that broadband internet and ICT investments enhance productivity primarily for high-skilled workers, increase demand for advanced technical skills, and influence hiring and personnel policies (Akerman et al., 2015; Cirillo et al., 2021; Falk & Biagi, 2017; Goos et al., 2014; Warning & Weber, 2018). Job polarization is further explained through routine-biased technological change and offshoring.

Other studies emphasize the need for policies addressing skill gaps exacerbated by technological advancements and measure the occupational vulnerability to labor-saving automation (Battisti et al., 2022; Mondolo, 2022; Montobbio et al., 2024). Overall, digitalization's impact on employment underscores the importance of higher education and advanced skills in mitigating job displacement risks.

This literature shows a polarization trend in labor markets. Digitalization increases demand for high-skilled labor through skill-biased technological change (SBTC), while automation reduces demand for workers performing routine jobs. However, low-skilled manual workers may see improved employment outcomes. IT investments complement skilled labor and enhance productivity when combined with advanced technical and cognitive abilities. Automation and AI replace routine tasks but create opportunities for those with advanced skills. Industrial robots and broadband internet drive demand for technically proficient workers. Digital technologies necessitate organizational changes that promote decentralized decision-making and teamwork. Certain occupations are more vulnerable to technological displacement, whereas those requiring advanced skills benefit from digital adoption. There is no clear distinction between skills developed through education and those gained through experience or vocational training, and research often overlooks specific skill sets impacted by various digital technologies. The reliance on different technological frameworks and data limitations hampers a broader understanding across industries and regions.

Another strand of the literature investigates the significant role that educational attainments play in how digitalization affects labor demand. Berman et al. (1994) provide early evidence of changes in the demand for skilled labor within US manufacturing, showing how shifts towards more skill-intensive production processes are associated with technological advancements. In this case, although the authors refer to skills, they examine shifts in labor demand explicitly considering educational levels such as college degrees. Carnevale et al. (2013) highlight that the fastest-growing occupations often require post-secondary education and specialized training but also emphasize the need for practical skills that can be immediately applied in the workplace. Employers are increasingly valuing specific skill sets over formal educational credentials alone. Fabiani et al. (2005) find that ICT adoption in Italian manufacturing is associated with a higher demand for high educational qualifications, highlighting the uneven impacts of digital technology adoption. Brynjolfsson and Hitt (2003) provide firm-level evidence on computing productivity using data from 527 large US firms over the period 1987–1994, demonstrating that IT investments significantly enhance productivity, especially when coupled with organizational changes that leverage these technologies. Bugamelli and Pagano (2004) provide context for understanding how regional industrial dynamics interact with technological investments. Specifically, they investigate barriers to ICT investment using firm-level data of Italian manufacturing firms, including the educational requirements of the workforce, emphasizing the role of educational qualifications in maximizing ICT adoption benefits.

The European Centre for the Development of Vocational Training (Cedefop, 2018) provides evidence that digital transformation in manufacturing necessitates a workforce equipped with high-level cognitive skills and advanced technical skills. Their findings suggest that vocational training and lifelong learning are essential in preparing workers for the demands of a digitalized labor market, discussing the educational requirements for skills needed in Industry 4.0. Colombari et al. (2023) examine the interplay between data-driven decision-making and digitalization in the automotive industries of Italy and the US, underscoring the sector-specific impacts of digitalization on the demand for higher educational qualifications. Still focusing on the last decade, when digital technologies have become the focal point, attention has shifted to their impact on the upskilling trend within firms. The significant innovation during this period lies in the functioning of software and hardware infrastructure, which extends beyond simple computerization of tasks to enable automated regulation of actions and processes, along with potentially unlimited data storage capacity. This wave of digitalization has led to profound transformations in labor markets, affecting job tasks at a granular level.

Consequently, some tasks have disappeared while new ones have emerged due to the adoption of digital technologies. At this point, some economists have raised the question: is this time different? Balsmeier and Woerter (2019) analyze Swiss firms and found that digitalization positively influences employment growth, particularly for firms investing in advanced digital technologies. Indeed, the positive effect of digitalization on upskilling is entirely driven by firms that employ machine-based digital technologies, such as robots, 3D printing, and IoT, and not from ERP or e-commerce platforms. They document increasing trends in the firms' human capital by differentiating between three levels of formal education (untrained workers with upper secondary education, trained workers with upper secondary education, and workers with professional tertiary education).

The effects of technological innovation on labor demand also extend to broader economic dynamics. Carbonero et al. (2023) analyze the fall of the labor income share in relation to technological change and hiring frictions, arguing that digitalization, while increasing productivity, can lead to a decline in the share of income accruing to labor, particularly for workers with lower educational qualifications. Piva and Vivarelli (2004) analyze the determinants of skill bias in Italy, identifying R&D, organizational changes, and globalization as key factors driving the demand for higher educational attainments. Vivarelli (2014) provides a survey of the economic literature on innovation, employment, and skills, offering insights into the complex interplay between technological advancements and labor market dynamics, emphasizing educational qualifications. Mustafa et al. (2022) examine the impact of digitalization trends on organizational structure, discussing how different organizational forms, such as bureaucracy, ambidexterity, and post-bureaucracy, respond to digital transformations.

Overall, this strand of the literature indicates that digitalization significantly increases the demand for workers with higher educational qualifications, such as college degrees and specialized training. Jobs requiring post-secondary education are among the fastest-growing in the digital age, as higher education provides the necessary knowledge and cognitive skills for adapting to technological changes. Higher educational levels enhance the effective use of digital technologies and help overcome barriers to ICT adoption, maximizing its benefits. Advanced qualifications also mitigate the negative effects of technological displacement, enabling smoother transitions into new roles created by technological advancements. However, while substantial research exists on the general impact of technological innovation, there are gaps in understanding how these effects vary by educational level and region. Educational groups usually consider a broad workforce class without entering into the sub-levels. In particular, regarding highly educated workers, the discussion on tertiary technical education (ITS, FH, and UAS) is limited.

In this context, a growing body of literature focuses on the role of ITS, FH, and UAS in digitalization and employment. The research suggests that combining research universities with applied technical institutions, such as UAS, can boost innovation output and foster innovation outside major innovation centers (Pfister et al., 2021), prepare the workforce with both technical skills and practical experience (Backes-Gellner et al., 2019), and contribute significantly to regional economic development (Lehnert et al., 2020), with heterogeneous impacts (Schlegel et al., 2022). FH and UAS, in particular, are involved in applied research that addresses real-world problems and enhances productivity through IT investments (Hackl, 2008). Research on ITS, focusing on the Italian case, indicates these institutions effectively address skill shortages in key sectors, particularly those related to ICT (Ballarino & Cantalini, 2019, 2020). Despite this, the literature still lacks empirical evidence linking technological innovation in general, and digitization in particular, with the demand for this category of workers.

Finally, we mention a few research works that focused on the relationship between technological change and human capital in small and medium-sized enterprises (SMEs) because it turned out that firm size significantly influences the complementarity between technology and skills. In this regard, Castro-Silva and Lima (2023) show that knowledge-intensive small firms have significant trouble retaining skilled workers compared to large firms, even when paying higher wages. Nevertheless, SMEs are recommended to invest in innovation and skilled labor because they prove to gain as large firms in the assimilation of digital technologies, especially to create new products (Hassan et al., 2024). By the same token, Bettiol et al. (2024) suggest that the labor productivity effect of digitalization in small firms is high (about 7%) but becomes negligible after two years. The evidence of these works highlights subtle dynamics within SMEs (e.g., innovation barriers, cost-related efficiency, integration intensity within the firm and with suppliers), which are worth understanding.

This paper aims to contribute to the strands of literature discussed above in three main ways. First, by providing empirical evidence on how planned digital technology investments influence hiring propensity, disentangling educational attainments in six levels, from non-qualified workers to individuals with a PhD in STEM fields. In this context, we are also able to focus on the demand for workers with an ITS diploma, emphasizing the role of technical qualifications in the manufacturing sector. Second, we focus on the Piedmont case, an Italian highly industrialized region, which has not yet been investigated in depth to the best of our knowledge. Finally, we analyze the complementary and substitution effects among the demands for workers with different educational levels to examine potential trends of human capital upscaling in firms' workforce. By addressing these gaps, this research contributes to a more comprehensive understanding of the relationship between digitalization and labor demand.

3 Data

The primary data source is represented by the survey *Indagine congiunturale sull'industria manifatturiera* of Unioncamere Piemonte, targeted at manufacturing firms in the Piedmont region. The data refers to the year 2021. The information was collected through a survey conducted in the first quarter of 2021, carried out on a representative sample of 1795 manufacturing firms belonging to different size classes and product sectors. The sample's representativeness is obtained through a stratification strategy of the universe of firms based on the number of active manufacturing companies from the Italian Business Register, operated by Unioncamere Piemonte. This stratification is subsequently used to calculate the weights we apply to our empirical strategy based on province, sector, and size. Table 13 shows the comparison between the sample of Unioncamere and the universe of manufacturing firms in Piedmont with respect to industry sector and province. The stratification strategy, combined with the inclusion of weights in the econometric regressions, ensures the sample's representativeness.

The dataset contains information on the structural characteristics of firms—size, location, etc.—and company performance (e.g., turnover, exports). The survey also has a specific digital focus developed on purpose by the paper's authors. This section concentrates on questions about the use of digital technologies, obstacles to digital innovation, investments in digital technologies, and cloud computing (CC). Additionally, it provides information on firms' recruitment choices based on educational level. The dataset also contains information related to previous years for some selected metrics, so encompassing data concerning not only the period of investigation (i.e., 2021) but also the years 2019 and 2020. Note that, only for the information related to past hiring choices, the survey asked for data on the three years before 2021, thus including aggregate data on hiring choices between 2018 and 2020.

The Unioncamere Piemonte dataset is enriched with AIDA accounting information to provide data on firms' revenues, EBITDA, and intangible assets in 2020. In the Appendix, Table 14 shows data construction related to Unioncamere Piemonte information, presenting survey questions and answers, type of variable, and time interval for each metric involved in the analysis. The table also presents the metrics from AIDA, their description, variable type, and time interval. In addition, Table 14 reports the resulting metrics deriving from the two datasets used in our analysis, specifying their use in the empirical models as dependent or independent variables.

In line with the literature, our focus is on non-micro firms, i.e., companies with at least ten employees. By excluding micro firms, the available observations are reduced from 1795 to 975. Of these 975 firms, AIDA accounting information was only accessible for 845. In particular, complete accounting information was unavailable for 124 small, 5 medium, and only 1 large company. In the Appendix, Table 15 presents the t-tests regarding the mean differences between the final sample and the pre-matching one. The results show that all the main variables from the Unioncamere Piemonte dataset included in the analysis do not have statistically significant differences, implying that the final dataset maintains its representativeness.

Table 1 shows the descriptive statistics of the metrics used in the analysis, concentrating on dummy and continuous variables. As explained in Section 4, we develop our analysis around two main samples. The first one is related to the full dataset composed of 845 firms. The second, instead, focuses only on the hiring firms. Indeed, out of 845 companies, only 345 planned to hire new workers in 2021. Table 1 presents the descriptive statistics related to all the dummy and continuous variables utilized in the empirical analysis for both samples. The information at our disposition includes a dummy regarding firms' propensity to hire in 2021, a dummy that captures the demand for highly educated workers (i.e., with tertiary education from Lv. 3—ITS diploma to Lv. 6—PhD or post-MSc qualification in STEM fields) regardless firms' demand for low-educated individuals and a dummy that, instead, takes the value 1 if firms plan to hire only highly educated workers. In addition, we also measure the share of highly educated workers demand, indicating the percentage of new assumptions that firms indicate with respect to workers with tertiary education. As a continuous variable for digital investments, we use a Principal Component Analysis strategy (PCA) to measure firms' digitalization over the period 2019-2021 (see Section 4.1). The data also includes infor-

Table 1 Descriptive statistics

	N	Mean	Median	SD	Min	Max
Propensity to hire in 2021	845	0.43	*NA*	*NA*	0.00	1.00
Highly educated workers demand	345	0.81	*NA*	*NA*	0.00	1.00
Only highly educated workers demand	345	0.49	*NA*	*NA*	0.00	1.00
% of highly educated demand	345	67.14	95.00	41.08	0.00	100.00
PCA - digital investments	845	0.53	−1.03	3.70	−9.92	9.48
	345	0.00	−0.11	2.42	−3.56	5.10
Employees	845	195.28	35.00	1,661.65	10.00	37,036.00
	345	127.00	49.00	372.67	10.00	5,254.50
Revenues (2020)	845	66,271.71	6,076.60	745,200.38	0.00	19,957,465.00
	345	64,487.18	8,332.81	424,218.68	0.000	7,255,557.00
EBITDA (2020)	845	2,725.73	434.58	38,622.38	−799,942.00	713,847.00
	345	6,274.50	678.69	41,267.42	−19,664.40	713,847.00
Outsourcing	845	0.38	*NA*	*NA*	0.00	1.00
	345	0.44	*NA*	*NA*	0.00	1.00
Past highly educated recruitment	845	0.65	*NA*	*NA*	0.00	1.00
	345	0.93	*NA*	*NA*	0.000	1.000
Past low-educated recruitment	845	0.51	*NA*	*NA*	0.00	1.00
	345	0.51	*NA*	*NA*	0.00	1.00
Exports (2021)	845	0.76	*NA*	*NA*	0.00	1.00
	345	0.80	*NA*	*NA*	0.00	1.00
Exports (2020)	845	0.77	*NA*	*NA*	0.00	1.00
	345	0.82	*NA*	*NA*	0.00	1.00
Intangible assets (2020)	345	14,777.30	79.09	160,821.72	0.00	2,872,677
Past digital investments	345	0.89	*NA*	*NA*	0.00	1.00

mation related to the number of employees, revenues and EBITDA in 2020, a dummy indicating whether the firms outsource (part of) their production, and two additional dummies determining if firms hired low and highly educated workers in the period 2018-2020. We also have information related to exporting activities in 2020 and 2021, together with the amount of intangible assets in 2020. Ultimately, we measure firms' digitalization tendency through a dummy indicating whether the companies have spent a positive amount of money on digital technologies in 2020 or 2019.

Table 2 displays the sample distribution with respect to different subgroups of respondents, presenting the categorical variables involved in the analysis. Again, we distinguish between the full sample and the hiring firms sample. Regarding the industry sector, the sample depicts Piedmont's core manufacturing sector: most companies are allocated to the food, textile, metal, and mechanical sectors. Compared to OECD regions, Piedmont's economy is strongly based on manufacturing. It is identified as a moderate innovator region that performs within the top 40 EU Member State regions (Hollanders, 2021), ranking among the top 20 areas for employment in knowledge-intensive activities as a percentage of total employment in SMEs (OECD, 2021). It is also an upper-mid-income region, with a regional GDP per capita 17% higher than the OECD regional average and 2% higher than the OECD average overall in 2018 (OECD, 2022).

Regarding regional economic size, Piedmont is in the top 20% of OECD regional economies. Manufacturing in Piedmont has a higher economic relevance at the regional level with respect to the rest of the country: according to the last estimates of the Italian National Institute of Statistics (ISTAT), the manufacturing sector in Piedmont generates a value-added of

Table 2 Distribution of company characteristics—main categorical variables

	Full sample		Hiring firms sample	
	N	%	*N*	%
Industry sector				
Food	86	10.17	31	8.99
Textile, clothing, and footwear	104	12.31	33	9.57
Wood and furniture	20	2.37	5	1.45
Chemical, petroleum, and plastics	92	10.89	37	10.72
Metal	201	23.79	82	23.77
Electrical and electronic	51	6.04	24	6.96
Mechanical	137	16.21	69	20.00
Transportation equipment	40	4.73	18	5.22
Other industries	93	11.01	38	11.01
Jewelry	21	2.49	8	2.32
Total	*845*	*100*	*345*	*100*
Province				
Alessandria	113	13.37	43	12.46
Asti	66	7.81	25	7.25
Biella	84	9.94	32	9.28
Cuneo	99	11.72	41	11.88
Novara	121	14.32	52	15.07
Torino	224	26.51	100	28.99
Verbano-Cusio-Ossola	70	8.28	20	5.80
Vercelli	68	8.05	32	9.28
Total	*845*	*100*	*345*	*100*
Firm size				
10–49 employees (small)	528	62.49	173	50.14
50–249 employees (medium)	262	31.01	139	40.29
More than 250 employees (large)	55	6.50	33	9.57
Total	*845*	*100*	*345*	*100*
Digital investments in 2021				
€0	228	26.98	45	13.04
<€15K	216	25.56	85	24.64
€15k–€50k	186	22.01	82	23.77
€50k–€100k	94	11.12	60	17.39
€100k–€200k	49	5.80	30	8.70
> €200k	72	8.52	43	12.46
Total	*845*	*100*	*345*	*100*

25 billion euros, contributing to 22% of the total value added at the regional level, compared to the average of 19% in the regions of the North of Italy and 17% at the national level. Industry sector information, along with province and firm size, composes the basis for calculating the weights used in the empirical models. Ultimately, Table 2 also shows firms' distribution concerning digital investments in 2021, representing the main regressor used throughout the analysis in this paper.

The digital technologies considered in this work can be distinguished between hardware and software technologies. Table 3 displays the six technologies identified for which companies reported the planned investment amount in 2021. Table 4 displays firms' hiring choices by educational level in 2021 per class of digital investments.

Those companies that decide to recruit new employees (345 out of 845, without specifying the total number of people hired) indicate the distribution (in %) of the hiring choices per level of education. We identify six educational attainment levels: Lv. 1, non-qualified workers; Lv. 2, high school diploma; Lv. 3, ITS diploma; Lv. 4, Bachelor's or Master's degrees in non-STEM fields; Lv. 5, Bachelor's or Master's degrees in STEM fields; Lv. 6, post-MSc qualifications or PhD in STEM fields.

Specifically, Table 4 shows the average values of the percentages indicated by the companies per educational level with standard deviations in parentheses. This information is additionally categorized with respect to the six classes of digital investments planned in 2021. Note that while there are 345 out of 845 companies hiring in 2021, the same does not hold for digital investments. Indeed, Table 2 shows that, out of 845, 617 firms are planning to invest in digital technologies in 2021. This means that 272 firms investing in digital do not plan to recruit anyone in 2021.

Table 4 provides valuable information in two main ways. On the one hand, firms show a concentration of interest in workers with an ITS diploma. Moreover, as expected, small firms tend to hire more workers with no qualifications and secondary education relative to medium and large firms, which favor workers with Bachelor's or Master's degrees and post-MSc qualifications or PhD in technical fields. On the other hand, despite the distribution exhibited by the average percentage levels, the standard deviations in parentheses reveal a sizable variability of these values, meaning that there are no standardized choice trends across companies.

We proceed with the distribution of digital investments in 2021 by categorizing firms based on their size. Figure 1 shows this distribution, dedicating a bar for each investment category for the full sample of firms. As expected, we can observe a *U-shaped* dynamics. Small firms tend to concentrate on low levels of investment, while the presence of large companies is more intense in the higher investment categories. Medium enterprises, instead, are more homogeneously distributed among the different categories, with a spike in the third investment range (i.e., €15k-€50k). We perform the same descriptive analysis restricting the attention to firms that intend to hire a positive number of workers in 2021. Figure 2 shows the three histograms of digital investment distributions per firm size. We can observe that, also in this case, the dynamics of the distributions along company sizes resemble the ones seen within the previous graph.

However, focusing only on hiring firms, there is a general tendency to invest more in digital technologies regardless of the companies' size. Significantly, the shares of firms reporting zero investments in digital equipment reduce noticeably with respect to Fig. 1.

Focusing on the hiring firms sample, the last descriptive statistics refers to firms' hiring choices per education category in 2021. Table 5 shows three different hiring strategies. First, companies that intend to hire only low-educated individuals, i.e., either workers with no qualifications (Lv. 1) or with a secondary school diploma (Lv. 2). Second, firms that want to hire highly educated workers, i.e., from Lv. 3 (workers with an ITS diploma) to Lv. 6 (workers with post-MSc qualifications or a PhD in STEM fields). We also acknowledge the presence of a third category of firms with mixed hiring strategies. These companies intend to hire a positive number of both low and highly educated workers in 2021. Table 5 displays the distribution of firms' hiring choices per education category and firms' size. It is worth noting that a relevant portion of companies intend to implement a mixed hiring strategy, regardless of the dimension. In particular, 25% to 39% of companies

Table 3 Digital technologies

Hardware (HW)	Software (SW)
Production monitoring sensors	Managerial software (ERP, CRM, SCM, etc.)
Digital motion control (inc. Robotics)	Business intelligence/data analytics software
Automated part tracking (APT) technologies	Blockchain

Table 4 Firm hiring choices per workers' educational attainments and digital investment class

Digital investment category	No qualifications Mean (SD)	High school Mean (SD)	ITS Mean (SD)	BA, MA (no STEM) Mean (SD)	BA, MSc (STEM) Mean (SD)	post-MSc or PhD (STEM) Mean (SD)	*N*
€0	27.67 (42.38)	25.56 (42.40)	35.38 (43.06)	1.87 (6.57)	8.24 (23.23)	1.29 (6.10)	45
<€15k	20.72 (38.44)	15.88 (31.18)	45.27 (43.43)	1.47 (6.85)	11.84 (24.11)	4.82 (17.77)	85
€15k–€50k	15.26 (32.58)	12.68 (27.61)	51.27 (39.23)	2.17 (7.93)	16.11 (28.17)	2.51 (9.63)	82
€50k–€100k	17.85 (32.57)	18.53 (30.92)	29.75 (35.90)	4.26 (11.53)	24.04 (32.71)	5.52 (16.30)	60
€100k–€200k	10.07 (27.01)	11.10 (25.32)	56.17 (37.32)	2.50 (8.07)	17.17 (23.84)	3.00 (8.26)	30
>€200k	4.86 (11.60)	11.88 (27.05)	33.33 (33.49)	9.60 (13.89)	30.95 (30.30)	9.37 (20.68)	43
Total	*16.92 (33.79)*	*15.94 (31.21)*	*42.17 (40.22)*	*3.28 (9.50)*	*17.35 (28.12)*	*4.34 (14.59)*	*345*

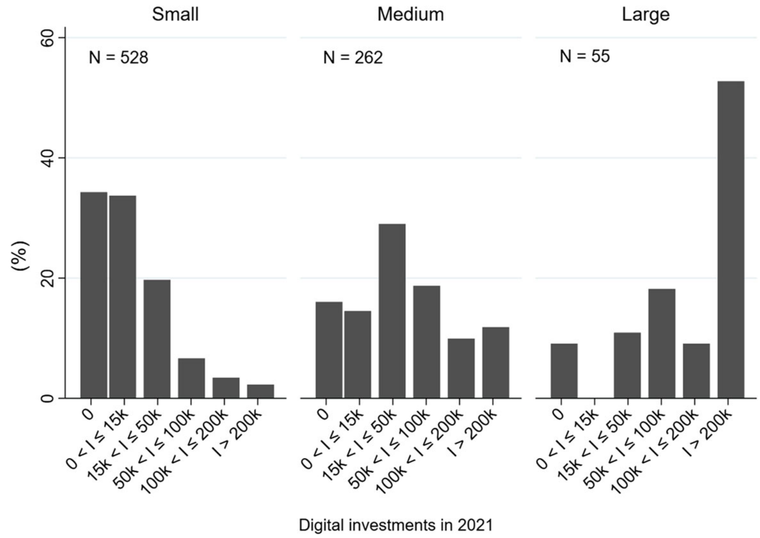

Fig. 1 Digital investments per firm size in 2021—full sample

indicated a positive percentage for both low and highly educated workers. The information presented in the table below is of particular interest to our research since it grounds the rationale for implementing multivariate models (more details in Section 4). Indeed, a multivariate approach enables the exploration of the internal connections between the demand for workers at different educational levels.

Overall, employing a multivariate model will provide a more comprehensive understanding of the relationships between investment in digital technologies, the demand for workers by level of education, and potential internal connections across different educational levels. Therefore, the presence of mixed hiring choices, as shown in Table 5, supports the empirical strategy defined in the following section.

4 Empirical strategy

This paper is based on a multi-layered empirical approach. The methodological sequence is organized as follows. Firstly, we exploit the information about digital investments from 2019 to 2021 to obtain a single continuous variable through a PCA approach. We use this variable within a standard Probit model environment to get a first glimpse of the relationship between

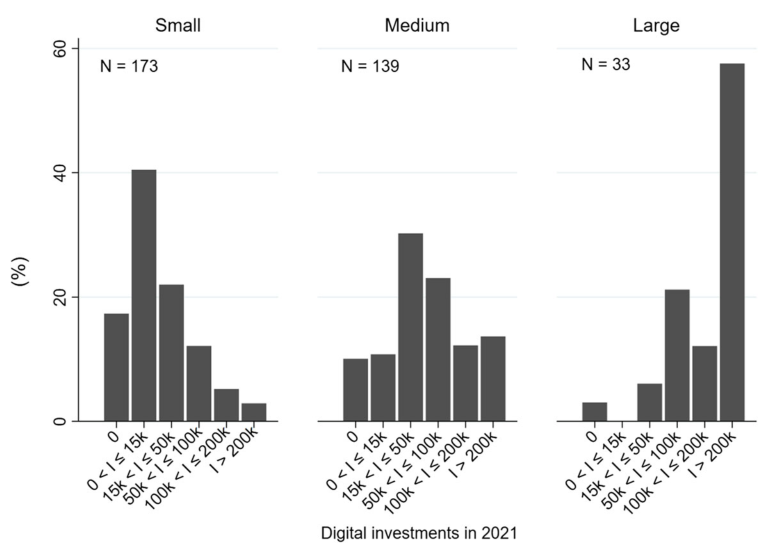

Fig. 2 Digital investments per firm size in 2021—hiring firms sample

Table 5 Firms hiring choices per education category

Firm size	Low education	High education	Mixed qualifications	*Total*
Small	50	79	44 *(58.49%)*	173
Medium	13	72	54 *(73.43%)*	139
Large	1	19	13 *(85.94%)*	33
Total	64	170	111 *(67.14%)*	345

Note: The values in parentheses within *Mixed qualifications* column indicate the average proportions of highly educated workers demanded

digital investments and the demand for new workers by educational level. Subsequently, we implement again a Probit model, focusing on the digital investments planned for 2021. We have built three dependent variables for these first two empirical exercises, all in dichotomous format. The first dummy—firms' propensity to hire—takes the value 1 if the firms want to recruit at least one new worker. The second dummy—firms' demand for highly educated workers—equals 1 if firms indicate a positive demand for workers with tertiary education (i.e., with at least an ITS diploma), regardless of whether firms also demand low-educated individuals (i.e., firms with mixed hiring strategies).

The third dummy—firms' demand for *only* highly educated workers—becomes equal to 1 if firms have positive demand only for workers with tertiary education, indicating no interest for low-educated workers (i.e., individuals with no qualification or with secondary education), not allowing mixed hiring strategies. Every model specification involves a reformulation of the dependent variable, each of which aims at capturing the relationship under analysis from a different perspective, focusing on the human capital intensity adopted by the companies.

Focusing on the demand for highly educated workers (i.e., the second dependent variable formulation), we expand the analysis through a Tobit I model by exploiting a left-censored continuous dependent variable capturing the demand for new workers with high educational levels. In this case, the continuous variable measures the percentage of recruitment that firms allocate to workers with tertiary education. Finally, we implement two versions of multivariate Probit models to investigate how digitalization influences the demand for low and highly educated workers (bivariate case) and the demand for each of the six educational levels we are able to identify (6-variate case). Figure 3 shows the flow chart that traces each step of the empirical strategy implemented in this research, indicating the dependent variables used in each context together with the digitalization metrics involved. For each step of the analysis, the figure also displays the sample used ($N = 845$ refers to the full sample, while $N = 345$ indicates the hiring firm subsample).

Sections 4.1, 4.2, and 4.3 present the empirical models performed in this paper. In addition, Table 16, in the Appendix, shows the correlation coefficient matrix, indicating no multicollinearity issues. The main regressors, i.e., the continuous digital investment variable obtained through PCA and the categorical digital investment variable, do not show high correlations with other variables. In addition, to ensure the robustness of our findings, we conducted additional analyses to address potential sample selection concerns. Importantly, our sampling process is exogenous to firms' decisions regarding digital investment and hiring, minimizing the risk of selection bias. Recognizing potential selection issues when focusing on the 345 hiring firms, we reran the regressions on the full sample of 845 firms. The results remained consistent, with no significant differences in relationships or significance levels. We also applied the Heckman model in the first step of the analysis, although it may not be necessary due to the exogeneity of the sampling process, finding no evidence of sample selection affecting our results.[1] Furthermore, as presented in Table 2 of Section 3, our descriptive statistics indicate that the two samples do not differ remarkably, further supporting the validity of our approach.

4.1 PCA strategy and standard Probit model

The first empirical exercise relates to the implementation of a PCA strategy. PCA is the most popular strat-

[1] The results related to these additional checks are available upon request.

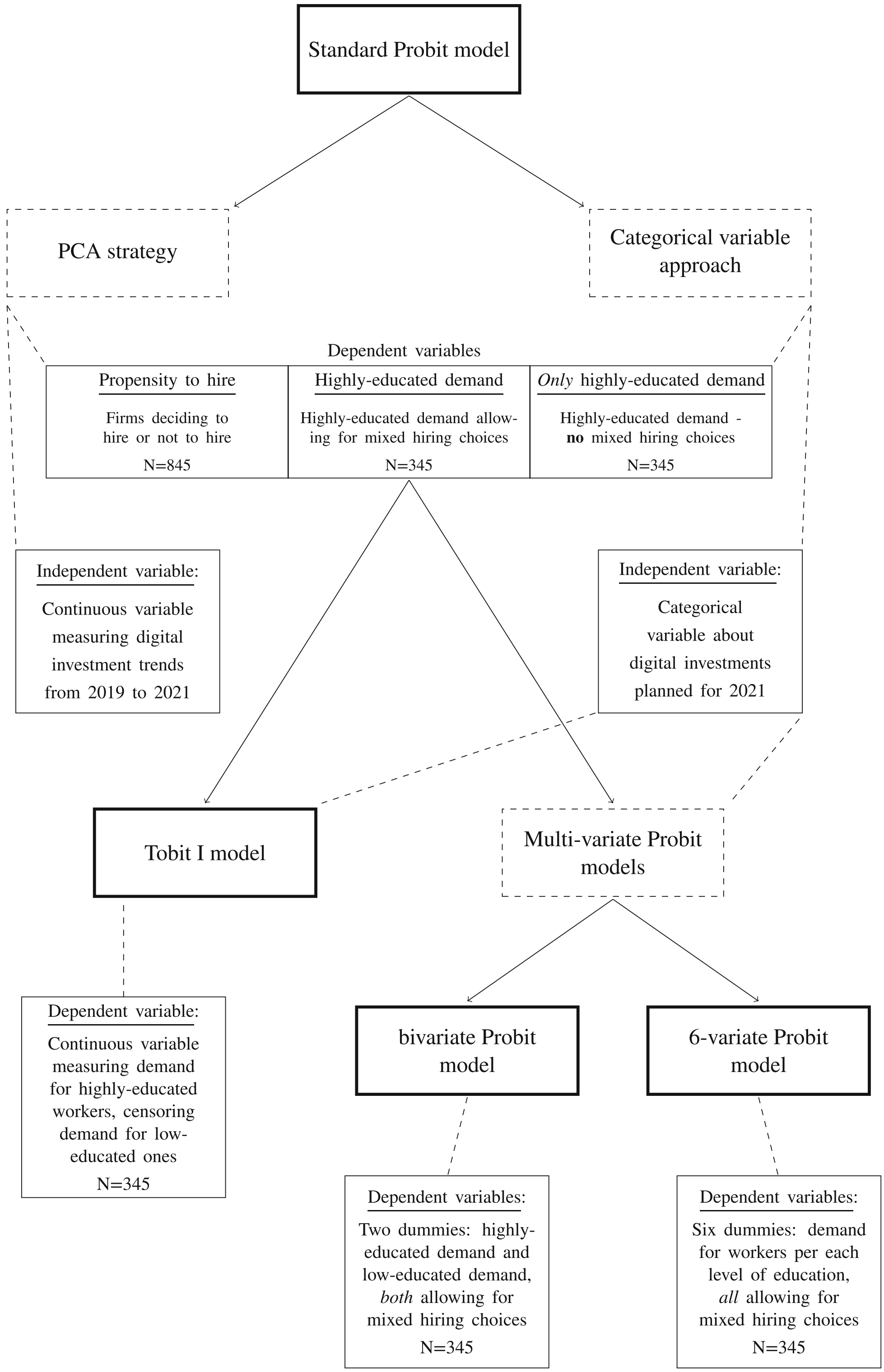

Fig. 3 Empirical strategy—flow chart

egy for implementing data dimensionality reduction. Specifically, PCA involves identifying a linear combination of variables that provides maximum variability (Hotelling, 1933). The new variables obtained through this linear combination are known as principal components (PCs), which are uncorrelated and arranged in order of decreasing variance. The purpose of using PCA for dimensional reduction is to identify k factors in dataset X with p variables, where $k < p$ (Zelterman, 2015).

In the context of our analysis, we implement PCA to obtain a single variable that can measure firms' digital investment choices in three years (i.e., 2019, 2020, and 2021). In such a way, from three different categorical variables, one for each year, we gather one continuous variable that traces the investment paths of manufacturing firms. We use this variable within three Probit model specifications as the main regressor. As anticipated above, each specification is characterized by an appropriate dependent variable that aims to capture a specific perspective of the human capital intensity of the firms. In the first case, we analyze the propensity of the firms to hire new workers for the full sample of 845 firms. Accordingly, the covariate $Hiring\ Propensity_i$ takes the value 1 when companies intend to hire a positive number of new workers in 2021, regardless of workers' educational level. Equation 1 shows the Probit model specification.

$$Pr(Hiring\ Propensity_i = 1|PCA_i, \boldsymbol{X}) = \Phi(\beta_0 + \beta_1 PCA_i + \boldsymbol{X\gamma}) \quad (1)$$

Regarding the second and third dependent variables, we focus on the subsample of 345 firms that intend to hire. In the case of the second covariate, we examine the demand for highly educated workers (i.e., with at least an ITS diploma—Lv. 3 of education). Therefore, the covariate $Highlyeducated\ Demand_i$ is equal to 1 when firms intend to hire at least one worker with a high level of competencies, regardless of the demand shown for low-educated individuals. Equation 2 shows the related Probit model.

$$Pr(Highly\ educated\ Demand_i = 1|PCA_i, \boldsymbol{X}) = \Phi(\beta_0 + \beta_1 PCA_i + \boldsymbol{X\gamma}) \quad (2)$$

Lastly, we investigate the effect of digital investments on the demand only for highly educated workers. In this case, the dependent variable $Only\ Highly\ educated\ Demand_i$ is equal to 1 when the companies indicate the intention to hire only workers with educational achievements above Lv. 3—ITS diploma. Equation 3 shows the associated Probit model specification.

$$Pr(Only\ Highly\ educated\ Demand_i = 1|PCA_i, \boldsymbol{X}) = \Phi(\beta_0 + \beta_1 PCA_i + \boldsymbol{X\gamma}) \quad (3)$$

In Eqs. 1, 2, and 3, the variable PCA_i is a continuous variable tracing firms' digital investment paths between 2019 and 2021, while $\boldsymbol{X}$ is a vector of covariates including firm-level information and foreign business control variables. Firm-level information encompasses the number of employees, revenues and EBITDA in 2020, a categorical variable indicating the firms' industry sector, and three dummies. The first dummy denotes whether firms outsource any part of their production. The second one measures whether firms hired highly educated workers (those with tertiary education) between 2018 and 2020. The third dummy indicates if firms hired low-educated workers (those with Lv.1 no qualifications or Lv. 2 secondary education) between 2018 and 2020. Foreign business controls, instead, include two dummies specifying whether the firms have carried out exporting businesses in 2020 and 2021.

The second econometric layer of our analysis is based on a standard Probit approach as well, but it focuses on the digital investment decisions planned for 2021. In this case, we also implement three specifications based on the above dependent variables. However, here, we measure digitalization through a categorical variable that identifies six ranges of firms' digital investment in 2021, as presented in Table 2. The resulting Probit models take the following three forms:

$$Pr(Hiring\ Propensity_i = 1|Dig\ Inv_i, \boldsymbol{X}) = \Phi(\beta_0 + \beta_1 Dig\ Inv_i + \boldsymbol{X\gamma}) \quad (4)$$

$$Pr(Highly\ educated\ Demand_i = 1|Dig\ Inv_i, \boldsymbol{X}) = \Phi(\beta_0 + \beta_1 Dig\ Inv_i + \boldsymbol{X\gamma}) \quad (5)$$

$$Pr(Only\ Highly\ educated\ Demand_i = 1|Dig\ Inv_i, \boldsymbol{X}) = \Phi(\beta_0 + \beta_1 Dig\ Inv_i + \boldsymbol{X\gamma}) \quad (6)$$

In Eqs. 4, 5, and 6, the variable $Dig\ Inv_i$ (abbreviation for $Digital\ Investments_i$) is a scale variable measuring firms' innovation spending in digital technologies in 2021, while $\boldsymbol{X}$ is a vector of covariates including firm-level information, foreign business control variables, and innovation tendency features. Firm-level information and foreign business controls are the same as in Eqs. 1 to 3. Innovation tendency features are, instead, included for the first time in this step of the analysis and encompass intangible assets in 2020 and a dummy indicating whether firms invested a positive amount of money in digital technologies in 2019 or 2020. Since the PCA strategy already considers firms' innovation tendency in the years before 2021, we do not include the latter two variables in Eqs. 1 to 3.

4.2 Tobit I model

The Tobit I model specification represents the third layer of the empirical strategy designed for this research. It resembles the standard Probit model approach, which focuses on companies' demand for highly educated workers regardless of their hiring choice for low-educated individuals. The Tobit I model is based on a continuous dependent variable censoring at zero the demand for low-educated workers (i.e., Lv. 1 no qualification or Lv. 2 high school diploma). Consequently, the variable solely measures the demand for highly educated workers (from Lv. 3 ITS diploma to Lv. 6 post-MSc or PhD qualification in STEM fields). This econometric exercise aims to expand the scope of the Probit specification, allowing us to quantify the effect of digital investment decisions on the probability of hiring highly competent workers. Equation 7 shows the Tobit I model specification.

$$Pr(Highly\ educated\ Demand_i > 0 | Dig\ Inv_i, \boldsymbol{X}) = \Phi(\beta_0 + \beta_1 Dig\ Inv_i + \boldsymbol{X\gamma}) \tag{7}$$

$Highly\ educated\ Demand_i$ takes a positive value ranging from 1 to 100 if the firms plan to recruit individuals with at least Lv. 3 of education (i.e., with an ITS diploma), and 0 otherwise. When, instead, $Highly\ educated\ Demand_i = 0$, firms do not recruit highly educated workers and, therefore, are censored at zero. Then, the variable $Dig\ Inv_i$ (abbreviation for $Digital\ Investments_i$) is a scale variable measuring firms' innovation spending in digital technologies in 2021. In addition, $\boldsymbol{X}$ is a vector of covariates, including firm-level information, foreign business controls, and innovation tendency features, as in the case of Eqs. 4 to 6. In particular, firm-level information includes the number of employees, revenues and EBITDA in 2020, a categorical variable indicating the firms' industry sector, and three dummy variables. The first dummy signifies whether firms outsource any part of their production. The second one measures whether firms hired highly educated workers (those with tertiary education) between 2018 and 2020. The third dummy indicates if firms hired low-educated workers (those with no qualifications or secondary education) between 2018 and 2020. Concerning foreign business variables, we consider two dummy variables specifying whether the firms engaged in exporting businesses in 2020 and 2021. Ultimately, the innovation tendency features include intangible assets in 2020 and a dummy variable indicating whether firms invested a positive amount of money in digital technologies in 2019 or 2020.

4.3 Multivariate Probit model

To further expand the analysis of the relationship between digital investments and firms' demand for highly educated workers, we implement two versions of multivariate Probit models. Following the model developed by Chib and Greenberg (1998), Eq. 8 presents the bivariate Probit specification, while Eq. 9 shows the 6-variate Probit specification.

$$Workers\ Demand_{ij} = \boldsymbol{X\beta} + u_{ij},\ \ i = 1, \ldots, N,\ \ j = 1, 2\ \text{ and }\ u_i \sim NID(0, 1) \tag{8}$$

$$Workers\ Demand_{ij} = \boldsymbol{X\beta} + u_{ij},\ \ i = 1, \ldots, N,\ \ j = 1, \ldots, 6\ \text{ and }\ u_i \sim NID(0, 1) \tag{9}$$

In the two specifications above, $Workers\ Demand_{ij}$ represents firms' latent utility of hiring a new employee with level of education j. In Eq. 8, the bivariate case, we distinguish between low and highly educated workers. Therefore, $j = 1$ refers to the demand for workers with Lv. 1 no qualifications or Lv. 2 high school diploma (i.e., low-educated individuals), and $j = 2$ indicates the demand for workers with tertiary education (from Lv. 3 ITS diploma to Lv. 6 PhD or post-MSc qualification in STEM fields). In Eq. 9, the 6-variate case, we investigate the demand for all the six levels of education we are able to identify. Therefore, $j = 1, \ldots, 6$ according to the specific level of education under analysis, from Lv. 1 no qualification to Lv. 6 PhD or post-MSc qualification in STEM fields.

In Eqs. 8 and 9, $\boldsymbol{X}$ represents a vector of regressors, including $Digital\ Investments_i$ and control variables. In particular, $Digital\ Investments_i$ is the same scale variable measuring firms' innovation spending in digital technologies in 2021 used in previous specifications. Likewise, the control variables are the same as in the previous models, including firm-level information, foreign business controls, and innovation tendency features. Specifically, firm-level data includes the number of employees, revenues and EBITDA in 2020, a categorical variable for the industry sector, and three dummy variables. The first dummy indicates if firms outsource any part of their production. The second reflects whether firms employed highly educated workers (with tertiary education) from 2018 to 2020. The third dummy shows if firms hired low-educated workers (with no qualifications or only secondary education) from 2018 to 2020. Regarding foreign business activities, we consider two dummy variables that indicate if the firms engaged in exporting activities in 2020 and 2021. Lastly, innovation tendencies are represented by intangible assets in 2020 and a dummy variable indicating whether firms invested in digital technologies in 2019 or 2020.

By estimating a multivariate Probit model, we also estimate $\frac{J(J-1)}{2}$ unknown correlation parameters ($\rho_{p,q}$), where J indicates the number of dependent variables and p and q indicates couples of covariates such that $p \neq q$, so as not to compare the same models to each other[2]. Depending on the statistical significance of these parameters, we can understand whether a multivariate Probit model is appropriate and useful instead of a series of standard Probit models. Note that the $\frac{J(J-1)}{2}$ estimated parameters measure the correlation between all the pairs of models. As a consequence, we are able to observe the correlation between models that capture not only adjacent levels of education but also *distant* educational attainment levels (e.g., Lv. 1 non-qualified workers and Lv. 5 Ba's or MSc' degree in STEM fields). This characteristic of the multivariate Probit model allows us to examine potential trends in the hiring choices of the firms that intend to carry out mixed hiring strategies (i.e., firms that want to hire both low and highly educated workers).

In the bivariate case, we estimate one correlation term (i.e., ρ_{12}). In the 6-variate case, instead, since we identify six dependent variables, the model estimates 15 correlation terms. It is worth noting that the potential for overlapping values of the dependent variables in these models (i.e., for them to be simultaneously equal to 1) is not only desired but the main reason for adopting this empirical strategy. Indeed, by estimating the correlation terms, this model allows us to understand the connection of hiring decisions among different educational levels of workers as well as the human capital upscaling that firms try to pursue.

5 Results

Following the methodology presented above, we first show the effect of digitalization through the PCA transformation, providing a first glance at the relationship between digital investment and hiring patterns within a Probit model environment. Secondly, we present the Probit results related to the effect of the firms' digital investments planned in 2021. Thirdly, the estimates related to the Tobit I regression follow. Finally, we show the findings of the multivariate Probit models. All the estimation results refer to weighted regressions calculated according to firms' province of origin, industry sector, and size class. All the results follow a stepwise approach for the addition of control variables. In the notes of each table of results, we list the control variables used in the regressions.

5.1 Probit model results

Table 6 shows the stepwise findings related to the Probit model specifications where the main regressor has been obtained by implementing the PCA strategy. The table is divided into three panels. In the first one, the dependent variable is a dummy indicating whether firms intend to hire in 2021. Therefore, in the first panel, the objective is to understand how the digital investment decisions taken between 2019 and 2021 influence the intention to hire as opposed to not hiring at all, disregarding, at this stage, the workers' educational level. In this case, the sample used is the full one, composed of 845 non-micro firms. Starting from the row model (Column 1) up to the full control specification in Column 3, we can observe that the coefficients related to the effect of digital investments are positive and statistically significant at the 1% level. Therefore, the investment

[2] For a formal description of the multivariate Probit model, see Section 9, in the Appendix.

Table 6 Standard Probit model results—PCA strategy

	Dependent variable: Propensity to hire in 2021			Highly educated workers demand			Only highly educated workers demand		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PCA - digital investments	0.161***	0.103***	0.103***	0.195***	0.122**	0.117**	0.0653*	0.081*	0.078**
	(0.019)	(0.024)	(0.024)	(0.049)	(0.061)	(0.060)	(0.037)	(0.046)	(0.046)
(log) Employees		0.111	0.117*		0.017	−0.026		−0.290*	−0.316**
		(0.069)	(0.070)		(0.167)	(0.165)		(0.158)	(0.153)
Industry sector									
Textile		0.067	0.071		−0.116	−0.199		−0.094	−0.165
		(0.205)	(0.205)		(0.419)	(0.406)		(0.382)	(0.386)
Wood		−0.187	−0.200		0.260	0.166		0.129	0.048
		(0.361)	(0.362)		(0.700)	(0.704)		(0.647)	(0.660)
Chemical		0.196	0.204		−0.721*	−0.774**		−0.460	−0.470
		(0.203)	(0.204)		(0.408)	(0.386)		(0.354)	(0.359)
Metal		0.256	0.258		0.217	0.154		−0.008	−0.058
		(0.179)	(0.179)		(0.395)	(0.377)		(0.327)	(0.333)
Electric		0.316	0.317		1.370**	1.293**		0.759*	0.687*
		(0.238)	(0.239)		(0.579)	(0.551)		(0.394)	(0.392)
Mechanical		0.384**	0.395**		0.253	0.131		0.183	0.094
		(0.189)	(0.189)		(0.421)	(0.405)		(0.329)	(0.332)
Transportation		0.281	0.287		0.379	0.335		0.411	0.406
		(0.261)	(0.261)		(0.452)	(0.451)		(0.461)	(0.455)
Other Industries		0.361*	0.351*		0.033	0.006		0.074	0.058
		(0.204)	(0.204)		(0.417)	(0.404)		(0.362)	(0.366)
Jewelry		0.530*	0.531*		−0.430	−0.484		−0.236	−0.276
		(0.321)	(0.321)		(0.593)	(0.595)		(0.598)	(0.612)

Table 6 continued

(log) Revenues (2020)		−0.009	−0.005		0.130	0.117		0.296**	0.269**
		(0.044)	(0.045)		(0.094)	(0.098)		(0.127)	(0.125)
EBITDA (2020)		0.011	0.010		−0.008	−0.004		−0.017***	−0.015**
		(0.007)	(0.007)		(0.016)	(0.017)		(0.002)	(0.006)
Outsourcing		0.095	0.095		−0.137	−0.100		−0.039	−0.007
		(0.101)	(0.101)		(0.242)	(0.251)		(0.189)	(0.191)
Past highly edu recruitment		0.531***	0.537***		0.201	0.246		0.278	0.346
		(0.104)	(0.104)		(0.395)	(0.387)		(0.354)	(0.348)
Past low-edu recruitment		0.401***	0.397***		0.671**	0.659**		0.058	0.036
		(0.094)	(0.094)		(0.324)	(0.333)		(0.209)	(0.210)
Exports (2021)			0.063			0.098			0.037
			(0.290)			(0.608)			(0.753)
Exports (2020)			−0.143			0.229			0.352
			(0.289)			(0.609)			(0.751)
Constant	−0.186***	−1.343***	−1.344***	1.042***	−0.696	−0.632	0.081	−1.751*	−1.712*
	(0.045)	(0.355)	(0.355)	(0.104)	(0.787)	(0.806)	(0.085)	(0.900)	(0.897)
Observations	845	845	845	345	345	345	345	345	345
Firm-level controls	✗	✓	✓	✗	✓	✓	✗	✓	✓
Foreign business controls	✗	✗	✓	✗	✗	✓	✗	✗	✓
Log likelihood	−539.456	−503.925	−501.653	−72.851	−62.787	−62.270	−117.122	−107.649	−106.603
McFadden Pseudo-R^2	0.066	0.130	0.131	0.081	0.208	0.215	0.011	0.091	0.100

Note: This presents the results of the Probit model *weighted* regressions. In Columns 1 to 3, the covariate is a dummy equal to 1 if the firms plan to hire a positive number of workers in 2021, and 0 otherwise. In Columns 4 to 6, the covariate is a dummy equal to 1 if the firms plan to hire a positive number of workers with tertiary education in 2021, and 0 otherwise. In Columns 7 to 9, the covariate is a dummy equal to 1 if the firms plan to hire *only* workers with tertiary education in 2021, and 0 otherwise. The main regressor is the continuous variable measuring digitalization through PCA transformation. *Firm-level controls* include the log of employees, industry sector, log of revenues in 2020, EBITDA in 2020, a dummy indicating whether the firms outsource (part of) their production, and two dummies for past recruitment of workers with tertiary education and for low-educated workers demand. *Foreign business controls* add two dummies indicating whether the firms engaged in exporting activities in 2020 and 2021. Robust SE are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. In Columns 1 to 3, we use the full sample of *non-micro* firms. In Columns 4 to 9, we use the hiring firms sample, restricted to *non-micro* firms that plan to hire a positive number of workers in 2021. The weights applied in the regressions are calculated according to province, industry sector, and size choices taken by firms from 2019 to 2021 positively influence the firms' propensity to hire in 2021.

Adding firm-level controls (Column 2) reduces the magnitude of the estimate but does not weaken the statistical significance. At the same time, including foreign business controls (Column 3) does not bring relevant changes in the results. Note that the specifications presented within Table 6 do not include innovation control variables, as opposed to all other steps of the empirical strategy, because the main regressor deriving from the application of the PCA strategy already provides information on firms' innovation tendency from 2019 to 2021. In the second and third panels, we concentrate on the hiring firms sample of 345 companies. In Columns 4 to 6, the second panel, the dependent variable is a dummy indicating whether firms intend to hire a positive number of workers with tertiary education (from Lv. 3 to 6), regardless of whether they are willing to hire workers with lower education. In Columns 7 to 9, the third panel, we characterize a third specification of the Probit model that concentrates on the demand of only highly educated workers. In this last case, the outcome variable is a dummy indicating firms' intention to hire only workers with tertiary education and no interest for workers with no qualifications or with secondary education (Lv. 1 and Lv. 2, respectively).

From Column 4 to Column 9 of Table 6, we can observe that the companies' digital investment paths also have a positive and statistically significant effect on the human capital intensity of the firms. Indeed, they play a relevant role in determining the demand for highly educated workers for firms with mixed recruitment strategies and for firms that target only highly educated individuals. In terms of magnitude, the influence of digital investment choices is stronger in the second panel when analyzing the influence on the demand for highly educated workers regardless of recruitment choices about low-educated individuals (i.e., contemplating mixed hiring strategies). Nevertheless, in the full control specifications (i.e., Columns 6 and 9), the results remain statistically significant at the 5% level.

From the second econometric exercise, we focus on the effect of digital investment choices planned for 2021. Table 7 presents the results related to the estimation of the standard Probit models. In this case, we add a further level of control variables related to the companies' innovation tendency, i.e., intangible assets in 2020, and a dummy variable indicating whether firms invested a positive amount of money in digital technologies in 2019 or 2020. Another variable we could have added to the set of controls related to the innovation tendency of firms is a dummy identifying innovative startups. However, given that within the data available to us, innovative startups are all micro firms, and considering that these are excluded from the analysis, the variable was not included in the regressions. Concerning the first panel (Columns 1 to 4), we observe that digital investments have a positive and, in all cases, statistically significant influence on the probability of firms hiring new workers in 2021, at least until Column 3. This is valid for each level of digital investments, with stronger estimates for those firms that plan to invest at least €50k. Once we also consider control variables related to companies' innovation tendency (i.e., Column 4), only two categories of investments in digital technologies remain significant in defining the probability of hiring new workers: between €50k and €100k and between €100k and €200k. Thus, these findings give us evidence that investments in digital technologies are not necessarily related to the expansion of the company staff, except in specific categories of investment, once we also control for the firms' intangible assets and past investments in digital technologies.

The analysis proceeds by focusing on companies' demand for highly educated workers to better understand firms' choices about human capital intensity and the relationship with digital investment decisions.

In Columns 5 to 8, the findings show that, regardless of the progressive addition of control variables, the estimates remain stable concerning their statistical significance for all the investment categories. Consequently, regardless of the level of investment, the decision to spend a certain amount of funds on digital technologies has a positive and statistically significant correlation with the probability of hiring highly educated workers.

Therefore, these results represent preliminary evidence of the relationship between digital investments and the firms' decision-making processes related to their internal human capital intensity. The third panel of Table 7, Columns 9 to 12, shows the findings of the Probit model concentrating on the demand for only highly educated workers. Looking at the correlation between digital investments and this specific recruitment decision-making process, we can observe how three particular ranges of digital investment present consistent estimates regarding the probability of hiring only highly educated workers, i.e., between €15k and €50k, between €100k and €200k, and over €200k

Table 7 Standard Probit model results

	Dependent variable: Propensity to hire in 2021				Highly educated workers demand				Only highly educated workers demand			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Digital investments in 2021												
< €15k	0.603***	0.580***	0.585***	0.176	0.532*	0.700**	0.715**	0.999***	0.359	0.342	0.352	0.615
	(0.161)	(0.172)	(0.173)	(0.214)	(0.322)	(0.322)	(0.327)	(0.387)	(0.295)	(0.307)	(0.314)	(0.378)
€15k–€50k	0.721***	0.500***	0.524***	0.223	1.009***	0.938***	0.895***	1.242***	0.796***	0.825***	0.788**	1.059***
	(0.164)	(0.189)	(0.191)	(0.226)	(0.327)	(0.343)	(0.338)	(0.420)	(0.294)	(0.306)	(0.310)	(0.391)
€50k–€100k	1.145***	0.911***	0.929***	0.628**	0.856***	0.677**	0.651**	0.922**	0.455	0.343	0.324	0.576
	(0.207)	(0.223)	(0.225)	(0.255)	(0.324)	(0.314)	(0.309)	(0.384)	(0.316)	(0.320)	(0.320)	(0.386)
€100k–€200k	0.996***	0.851***	0.865***	0.544*	1.365***	1.180**	1.166**	1.519***	0.731**	0.651*	0.635*	0.900**
	(0.249)	(0.274)	(0.275)	(0.307)	(0.432)	(0.474)	(0.479)	(0.541)	(0.358)	(0.371)	(0.376)	(0.439)
>€200k	1.170***	0.539**	0.552**	0.272	1.547***	1.040**	1.056**	1.391**	0.714**	0.870**	0.873**	1.114**
	(0.236)	(0.255)	(0.255)	(0.283)	(0.403)	(0.424)	(0.419)	(0.587)	(0.356)	(0.404)	(0.405)	(0.457)
Constant	−0.764***	−1.400***	−1.393***	−1.471***	0.220	−1.675**	−1.613**	−1.354	−0.417*	−2.355***	−2.302***	−2.111**
	(0.118)	(0.436)	(0.424)	(0.440)	(0.233)	(0.791)	(0.789)	(0.826)	(0.242)	(0.901)	(0.890)	(0.897)
Observations	845	845	845	845	345	345	345	345	345	345	345	345
Firm-level controls	✗	✓	✓	✓	✗	✓	✓	✓	✗	✓	✓	✓
Foreign business controls	✗	✗	✓	✓	✗	✗	✓	✓	✗	✗	✓	✓
Innovation tendency controls	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	✗	✓
Log likelihood	−239.723	−240.349	−239.262	−237.641	−71.756	−60.720	−60.276	−58.610	−114.816	−105.116	−104.261	−103.817
McFadden Pseudo-R^2	0.074	0.142	0.143	0.149	0.095	0.234	0.240	0.261	0.031	0.113	0.120	0.124

Note: This presents the results of the Probit model *weighted* regressions. In Columns 1 to 4, the covariate is a dummy equal to 1 if the firms plan to hire a positive number of workers in 2021, and 0 otherwise. In Columns 5 to 8, the covariate is a dummy equal to 1 if the firms plan to hire a positive number of workers with tertiary education in 2021, and 0 otherwise. In Columns 9 to 12, the covariate is a dummy equal to 1 if the firms plan to hire *only* workers with tertiary education in 2021, and 0 otherwise. The main regressor is a categorical variable indicating the *level* of digital investments in 2021. The reference state refers to companies not investing. *Firm level controls* include the log of employees, industry sector, log of revenues in 2020, EBITDA in 2020, a dummy indicating whether the firms outsource (part of) their production, and two dummies for past recruitment of workers with tertiary education and for low-educated workers demand. *Foreign business controls* add two dummies indicating whether the firms engaged in exporting activities in 2020 and 2021. *Innovation tendency controls* refers to firms' intangible assets in 2020, and a dummy indicating whether the firms invested in digital in 2019 or 2020. Robust SE are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. In Columns 1 to 3, we use the full sample of *non-micro* firms. In Columns 4 to 9, we use the hiring firms sample, restricted to *non-micro* firms that plan to hire a positive number of workers in 2021. The weights applied in the regressions are calculated according to province, industry sector, and size per year. These results appear to be quantitatively lower than in the second panel of results but still statistically significant.

In summary, as we narrow the study's focus to the demand only for high competencies, the effect of digital investments shows a well-defined path of variation that points to specific categories of annual investments. Having controlled for companies' key characteristics, their foreign activities, as well as their tendency to innovate, the results presented in Table 7 show evidence of how digital technology investments are linked to the recruitment decision-making processes for new staff with high levels of educational attainments. The concentration of statistical significance in the second, fourth, and last category of investments observed in the last panel of results may indicate, in the case of the category between €15k and €50k annual investment, a dynamic of internalization of strong competencies by companies that have been investing in digital recently (or have just started to do so) and are looking for suitable personnel to leverage these technologies. On the other hand, in the case of investment categories of at least €100k and over €200k annually, it might indicate a dynamic of retention or expansion by companies that are part of a path of technological innovation, already equipped with highly educated personnel, and that need to maintain the in-house performance standard or even expand it.

5.2 Tobit I model results

The econometric analysis continues by implementing a Tobit I model to expand the investigation of the firms' demand for highly educated workers, regardless of whether firms also intend to hire low-educated individuals. It is worth mentioning again that, during the survey, firms that expressed the intention of hiring new workers also indicated the percentage of individuals they intended to hire per level of education. Therefore, focusing the attention on the demand for workers with tertiary education (i.e., from Lv. 3 ITS diploma to Lv. 6 post-MSc qualifications or a PhD in STEM fields), we have created a continuous left-censored dependent variable that gives zero to all positive percentages expressed for workers with Lv. 1 and 2 of education (i.e., non-qualified workers and workers with secondary education, respectively). The resulting continuous variable represents a score naturally bounded between 0 and 100 through which firms signal their intention to strengthen their internal human capital intensity.

Table 8 presents the results of the Tobit I model, where the outcome variable measures the portion of workers that firms intend to hire in 2021 with high educational attainments. The four columns of the table follow the same control stepwise approach as the previous tables. Even if Tobit I also represents a non-linear model, the interpretation of our estimates is essentially the same as that of a standard OLS model. Therefore, the coefficients related to digital investment determine the linear increase in the outcome variable (the demand for highly educated workers) when one of the investment ranges is activated. Moreover, considering that the dependent variable is naturally scaled from 0 to 100, the findings of Table 8 can be seen as percentages.

We can observe that once we control for variables that consider the innovation tendency of the firms (Column 4), the estimates related to all the digital investments categories are statistically significant (even though the third category of investment, between €50k and €100k annually, is significant only at the 10% level). From a magnitude point of view, the estimates show a well-defined pattern aligned with the findings obtained in the third panel of Table 7. Indeed, even though we observe statistically significant results for all the investment categories, the firms that plan to invest between €15k and €50k, between €100k and €200k, and over €200k show a markedly higher probability than in the other categories related to the intention to hire new workers with higher educational attainments. Yet, it is worth noting that also in the Tobit I model case, the findings we observe in the table relate to the probability of hiring highly educated workers as opposed to firms that do not plan to invest any funds in digital technologies in 2021. Quantitatively, these results suggest that firms planning to invest a positive amount of funds to enhance the endowment of the internal digital technology equipment (software, hardware, and services) are between 27.6% and 44.8% more likely to hire new staff with high levels of education in 2021 compared to firms with no intention to invest.

In further detail, those firms that invest below €15k and between €50k and €100k per year show a higher probability to hire highly educated workers, around 29%, with respect to firms that do not plan to invest. On the other hand, companies that plan to invest in the other three categories exhibit a probability between 40% and

Table 8 Tobit I model results—highly educated workers demand

	Dependent variable: % of highly educated workers to be hired in the next 12 months			
	(1)	(2)	(3)	(4)
Digital investments in 2021				
<€15k	16.508	15.920	16.513	32.159**
	(13.649)	(13.155)	(13.072)	(15.186)
€15k–€50k	35.727***	33.395***	31.099***	44.761***
	(12.983)	(12.249)	(11.871)	(15.021)
€50k–€100k	24.405*	15.928	14.757	27.626*
	(13.786)	(12.178)	(11.678)	(14.211)
€100k–€200k	39.162***	29.822**	28.706**	42.201***
	(13.835)	(13.388)	(13.146)	(15.973)
> €200k	43.917***	26.509**	26.222**	39.666***
	(12.987)	(12.554)	(12.437)	(15.186)
Constant	40.380***	3.243	0.938	2.298
	(11.919)	(43.165)	(24.170)	(24.326)
Observations	345	345	345	345
Firm-level controls	✗	✓	✓	✓
Foreign business controls	✗	✗	✓	✓
Innovation tendency controls	✗	✗	✗	✓
Log Likelihood	−778.467	−768.966	−766.750	−765.309
Wald Chi^2	18.408**	32.256**	37.608**	43.832**

Note: This presents the results of the Tobit I model *weighted* regressions. The covariate measures the share of workers firms intend to hire in 2021 with tertiary education. The main regressor is a categorical variable indicating the *level* of digital investments in 2021. The reference state refers to companies not investing. *Firm level controls* include the log of employees, industry sector, log of revenues in 2020, EBITDA in 2020, a dummy indicating whether the firms outsource (part of) their production, and two dummies for past recruitment of workers with tertiary education and for low-educated workers demand. *Foreign business controls* add two dummies indicating whether the firms engaged in exporting activities in 2020 and 2021. *Innovation tendency controls* refers to firms' intangible assets in 2020, and a dummy indicating whether the firms invested in digital in 2019 or 2020. Robust SE are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample used is restricted to *non-micro* firms that plan to hire a positive number of workers in 2021

45% greater than non-investing firms to enhance the internal human capital intensity by employing workers with tertiary educational attainments. Interestingly, this dynamic confirms the one obtained in the case of the Probit model regression shown in the third panel of Table 7, showing stronger effects for the second category of digital investments (between €15k and €50k) (around 45%), the fourth one (between €100k and €200k) (around 42%), and the last one (over €200k) (around 40%). These findings confirm the reasoning according to which, in the case of the category between €15k and €50k of annual investment, there might exist an internalization process of high expertise by hiring highly qualified personnel by companies that have recently started investing in digital and want to reinforce the innovation process they have undertaken. On the other hand, the case of the last two categories of annual investments might indicate a dynamics of maintenance or upscaling by companies already on a path of technological innovation, staffed with highly qualified personnel, to maintain the level of internal skill intensity or increase it.

5.3 Multivariate Probit model results

The last econometric application of this paper refers to the multivariate Probit models. In this step of the analysis, as in the previous two, we focus on the hiring firms sample, considering only companies that intend to hire in 2021. We perform a bivariate and a 6-variate model. As explained in Section 4, estimating a multivariate Probit model, we also obtain estimates for $\frac{J(J-1)}{2}$ correlation terms between every pair of outcome variables, where J represents the number of dependent variables we are simultaneously considering. Therefore, we obtain one correlation term in the bivariate model, while in the 6-variate model, the parameters are 15. These parameters allow us to understand the correlation between the models to trace decision patterns in firms' hiring processes within the manufacturing sector. By highlighting recruitment choices per educational attainment, we are able to distinguish between complementary effects—$\rho_{p,q} > 0$—and substitution effects—$\rho_{p,q} < 0$.

Starting with estimating the bivariate Probit model, we investigate the demand for both low and highly educated workers. For this purpose, we formulate two outcome variables that communicate with each other. The first one indicates when firms plan to hire non-qualified workers (Lv. 1) or workers with secondary education (Lv. 2), regardless of what the company indicates for individuals with higher levels of education. The second one expresses firms' intention to hire workers with a high level of education (from Lv. 3 to Lv. 6), regardless of what the company indicates for individuals with lower qualifications. It is worth noting that by allowing the two dummy variables to take the value 1 even when the firms intend to hire both low and highly educated workers, we are automatically admitting the possibility of any correlation between the two models. As a consequence, we acknowledge the presence of firms with mixed recruiting strategies within the model.

Table 9 shows the bivariate Probit results. Since, in this case, the estimation of each regression produces coefficient estimates for two different models, each column of results contains a set of two columns of estimated coefficients, the first related to low-educated workers' demand and the second linked to highly educated workers' demand. The estimation follows the usual stepwise approach of control variables addition, starting from the row model in Column 1 and concluding with the full control model in Column 4. Under each pair of estimated models are the correlation parameters ρ_{12}, indicating the correlation between the two dependent variables. The results show that, regardless of the level of digital investments, the decision to spend a positive amount of funds on software, hardware, and services related to digital technologies has a positive and statistically significant influence on the probability of hiring workers with high levels of education. When it comes to the demand for low-educated workers, the results show that being positioned in the second and fifth categories of digital investment (i.e., between €15k and €50k and over €200k) has a negative and statistically significant effect on the probability to hire workers with low levels of education. These results remain valid over the four columns of estimates, also sequentially adding control variables to the estimated model. In Columns 2 to 4, even the other investment categories show statistically significant negative estimates, even if only at the 10% level and with lower magnitudes.

For what concerns, instead, the correlation parameter ρ_{12}, Table 9 shows that it appears negative and statistically significant in all four model specifications. This result suggests a significant negative relationship between the two outcome variables analyzed in this model, also revealing preliminary evidence of a substitution effect between low and high educational attainments. In other words, investing in digital technologies increases the probability of hiring workers with high educational levels, but it simultaneously weakens the likelihood of hiring low-educated individuals. Yet, while this result might seem obvious, it is not self-evident if one considers the high percentage of companies in the sample (about 32%) that indicated a mixed hiring strategy between tertiary-educated and non-tertiary-educated workers (see Table 5 in Section 3). Indeed, it is important to underline that the estimate obtained for the correlation parameter ρ_{12} is not linked to the relationship between digital investments and human capital intensity. What ρ_{12} shows is the mere correlation between the two dependent variables, indicating that the demand for low and highly educated workers goes in opposite directions. Instead, what the upper part of Table 9 shows is additional evidence that investment in digital technologies is indeed associated with firms' recruiting choices in relation to workers' educational levels.

The results related to the bivariate Probit model pave the way for further analysis to investigate in more detail how investments in digital technologies drive firms' strategic human capital upscaling. Indeed, the data at our disposal allows us to identify six different levels of educational attainment, enabling us to understand

Table 9 Bivariate Probit model results

	Dependent variables: Lv. 1-2 workers demand & Lv. 3-4-5-6 workers demand							
	(1)		(2)		(3)		(4)	
Digital investments in 2021								
<€15k	−0.374	0.538*	−0.513	0.684**	−0.511	0.672**	−0.707*	1.051**
	(0.295)	(0.286)	(0.340)	(0.299)	(0.335)	(0.289)	(0.429)	(0.423)
€15k–€50k	−0.809***	1.065***	−0.974***	1.029***	−0.982***	1.033***	−1.185***	1.414***
	(0.295)	(0.300)	(0.332)	(0.330)	(0.332)	(0.341)	(0.449)	(0.478)
€50k–€100k	−0.456	0.791***	−0.554*	0.627*	−0.557*	0.625*	−0.736*	0.966**
	(0.317)	(0.300)	(0.326)	(0.363)	(0.326)	(0.361)	(0.429)	(0.467)
€100k–€200k	−0.747**	1.365***	−0.631*	1.387***	−0.633*	1.393***	−0.823*	1.726***
	(0.359)	(0.396)	(0.379)	(0.477)	(0.377)	(0.477)	(0.471)	(0.553)
>€200k	−0.722**	1.328***	−0.957***	1.483***	−0.957***	1.478***	−1.130***	1.688***
	(0.357)	(0.357)	(0.369)	(0.419)	(0.368)	(0.422)	(0.454)	(0.502)
Constant	0.425*	−1.359***	1.947**	−1.224***	1.963**	−1.226***	1.771*	−1.225***
	(0.243)	(0.160)	(0.940)	(0.189)	(0.945)	(0.193)	(0.973)	(0.199)
ρ_{12}	−0.876***		−0.841***		−0.841***		−0.841***	
	(0.037)		(0.055)		(0.056)		(0.058)	
Observations	345		345		345		345	
Firm-level controls	✗		✓		✓		✓	
Foreign business controls	✗		✗		✓		✓	
Innovation tendency controls	✗		✗		✗		✓	
Log Pseudo-likelihood	−166.711		−117.764		−117.663		−116.489	
Wald Chi^2	24.34***		174.38***		179.75***		178.93***	
Likelihood ratio test of $\rho_{12} = 0$ (χ^2 df = 1)	417.611***		283.670***		283.107***		277.939***	

Note: This presents the results of the bivariate Probit model *weighted* regressions. The covariates are two dummies. The first one indicates the demand for non-qualified workers (Lv. 1) or with secondary education (Lv. 2), regardless of the demand for individuals with *higher* levels of education. The second one indicates the demand for high educational levels (from Lv. 3 to Lv. 6), regardless of the demand for workers with *lower* levels of education. The main regressor is a categorical variable indicating the *level* of digital investments in 2021. The reference state refers to companies not investing. The model estimates pairs of regressions, each with one of the two dependent variables. *Firm level controls* include the log of employees, industry sector, log of revenues in 2020, EBITDA in 2020, a dummy indicating whether the firms outsource (part of) their production, and two dummies for past recruitment of workers with tertiary education and for low-educated workers demand. *Foreign business controls* add two dummies indicating whether the firms engaged in exporting activities in 2020 and 2021. *Innovation tendency controls* refers to firms' intangible assets in 2020, and a dummy indicating whether the firms invested in digital in 2019 or 2020. Robust SE are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample used is restricted to *non-micro* firms that plan to hire a positive number of workers in 2021 which specific attainment levels are being driven in demand by digital investments. Therefore, in the 6-variate Probit model, we define six different outcome variables, each of which is a dummy indicating firms' demand for a specific level of education, from non-qualified workers (Lv. 1) to workers with a post-MSc qualification or a PhD in STEM fields (Lv. 6). It is worth noting that, as in the bivariate case, it is fundamental for the outcome variables to be allowed to communicate with each other. This means that, depending on firms' hiring choices, the six dummy variables can activate simultaneously for each company. In other words, in every specific firm case, the six outcome variables identify the level of competencies firms are targeting. Estimating six models where each outcome variable identifies a different level of education allows us to connect these recruitment choices and understand how they relate. Yet, as we focus only on hiring firms, while all six dummies can activate simultaneously, there is no conceivable case in which all are equal to 0. Consequently, in every case, at least one of the six covariates must be equal to 1.

Table 10 shows the 6-variate Probit results. The main regressor is the categorical variable, which classifies the digital investment levels planned for 2021, where the baseline does not include investing firms. Moreover, since the model simultaneously estimates six different regressions, for the sake of a direct approach, Table 10 only shows the full control regression results. As a consequence, the six columns we can observe within the table below refer to the same model, each of which implements a different outcome variable related to the demand for a specific level of education.[3]

Starting from non-qualified workers' demand (Column 1), the results demonstrate that digital investments do not incentivize the probability of hiring this category of workers, but neither do they discourage it. Indeed, even if the estimates are almost all negative, none is statistically significant. Column 2 also displays negative estimates regarding the demand for workers with secondary education, with statistical significance only in the second and last investment categories. This means that only investing between €15k and €50k and over €200k has a negative and significant effect on the probability of not hiring workers with secondary education for a firm that does not plan to invest in digital technologies in 2021.

From Column 3 onward, we analyze the demand for workers with tertiary education. The results of Column 3 show a positive correlation between digital investments and the probability of hiring a positive percentage of workers with an ITS diploma, with statistically significant coefficients for all the investment categories, except for firms that plan to invest between €50k and €100k in 2021. Digital investments between €15k and €50k and between €100k and €200k display a higher significance level. These findings are also in line with the information presented within Table 4, in Section 3, where firms that invest in the two categories €15k-€50k and €100k-€200k concentrate their hiring choices on workers with post-secondary technical education (Lv. 3, ITS diploma). For the first and the last categories of investments (below €15k and over €200k per year) in Column 3, the coefficients are consistently lower with respect to the second and fourth categories and are statistically significant only at the 10% level.

In Columns 4 and 5, we find significant results only for the first investment category (below €15k) related to the demand for workers with a Bachelor's or Master's degree in STEM fields (Lv. 5). All the other estimates are not statistically significant, and in some case even with a negative sign (particularly in Column 4). When it comes to Column 6, the results show stronger and more widespread correlations on the probability of exhibiting demand for workers who have obtained a post-MSc qualification or a PhD in STEM fields.

Specifically, the investment categories that drive these substantial results with solid statistical significance are the first (below €15k) and the fourth (between €100k and €200k). The third and last categories of investment (between €50k and €100k and over €200k, respectively) display statistically significant results at the 5% level, although slightly lower in magnitude than the abovementioned categories. It is worth mentioning that even the second investment category (between €15k and €50k) presents a significant estimate, even if at the 10% level.

Considering that the results reported so far relate to the manufacturing sector of the Piedmont region, the heterogeneity of these results can be traced back to the very different operations that are performed daily within this industry. The ranges of investment in digital technologies are defined on a firm-by-firm basis, considering internal production activities and the

[3] In the Appendix, Tables 17, 19, and 18 present the results of the 6-variate Probit models related to the row specification, the model containing only firm-level controls, and the model with firm-level and foreign business control variables, respectively.

Table 10 6-variate Probit model results—full control variables model

	Dependent variables:					
	No qualification	High school diploma	ITS	BA/MA (no STEM)	BA/MSc (STEM)	Post-MSc/PhD (STEM)
	(1)	(2)	(3)	(4)	(5)	(6)
Digital investments in 2021						
<€15k	−0.193	−0.303	0.588*	−0.253	0.650*	1.567***
	(0.348)	(0.361)	(0.349)	(0.428)	(0.392)	(0.499)
€15k–€50k	−0.497	−0.668*	1.003***	−0.252	−0.050	0.865*
	(0.339)	(0.382)	(0.362)	(0.431)	(0.396)	(0.481)
€50k–€100k	0.154	−0.441	0.155	0.332	0.559	1.039**
	(0.336)	(0.390)	(0.370)	(0.475)	(0.395)	(0.474)
€100k–€200k	−0.438	−0.392	0.964**	−0.467	0.061	1.498**
	(0.429)	(0.449)	(0.442)	(0.506)	(0.446)	(0.595)
>€200k	−0.644	−0.903**	0.656*	0.383	0.599	1.096**
	(0.398)	(0.455)	(0.420)	(0.492)	(0.442)	(0.519)
Constant	−0.186	1.299	−0.143	−2.022**	−3.875***	−2.922***
	(0.799)	(0.800)	(0.732)	(0.950)	(0.951)	(1.089)
ρ_{12}	−0.030	ρ_{23}	−0.168	ρ_{35}	−0.084	
	(0.102)		(0.112)		(0.122)	
ρ_{13}	−0.386***	ρ_{24}	0.073	ρ_{36}	−0.067	
	(0.088)		(0.131)		(0.143)	
ρ_{14}	0.227**	ρ_{25}	−0.014	ρ_{45}	0.422***	
	(0.096)		(0.109)		(0.112)	
ρ_{15}	0.040	ρ_{26}	0.015	ρ_{46}	0.278*	
	(0.103)		(0.165)		(0.163)	
ρ_{16}	−0.072	ρ_{34}	0.059	ρ_{56}	0.220*	
	(0.125)		(0.120)		(0.133)	
Observations				345		
Firm-level controls				✓		
Foreign business controls				✓		
Innovation tendency controls				✓		
Log Pseudo-likelihood				−435.221		
Likelihood ratio test of all $\rho_{p,q} = 0$ (χ^2 df = 15)				924.604***		

Note: This presents the results of the 6-variate Probit model *weighted* regression. The covariates are six. Each indicates if the firms plan to hire at least a worker with a specific level of skills among the six degrees of educational attainments identified in this paper, regardless of what they indicate for individuals with *different* levels of education. The main regressor is a categorical variable indicating the *level* of digital investments in 2021. The reference state refers to companies not investing. The model estimates groups of six regressions, one for each dependent variable. This presents the estimates of the model with full control variables. *Firm level controls* include the log of employees, industry sector, log of revenues in 2020, EBITDA in 2020, a dummy indicating whether the firms outsource (part of) their production, and two dummies for past recruitment of workers with tertiary education and for low-educated workers demand. *Foreign business controls* add two dummies indicating whether the firms engaged in exporting activities in 2020 and 2021. *Innovation tendency controls* refers to firms' intangible assets in 2020, and a dummy indicating whether the firms invested in digital in 2019 or 2020. Robust SE are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample used is restricted to *non-micro* firms that plan to hire a positive number of workers in 2021 innovation opportunities presented by emerging digital technologies. Once we control for all the main characteristics of the firms that can influence the hiring decision-making, we observe a direct connection between companies' needs in terms of desired human capital intensity in response to a certain amount of investment in digitalization with the aim to innovate their manufacturing activities.

With that in mind, estimating a 6-variate Probit model also gives as results 15 correlation parameters ($\rho_{p,q}$) that allow us to understand which models are linked in terms of demand for workers with different levels of education. In this context, Table 10 shows 5 statistically significant correlation terms out of the 15 (i.e., ρ_{13}, ρ_{14}, ρ_{45}, ρ_{46}, and ρ_{56}). In the first place, ρ_{13} shows a significant negative correlation between demand for non-qualified workers (Lv. 1) and workers with an ITS diploma (Lv. 3). This means that firms that show a preference for hiring individuals that have obtained an ITS diploma tend to lower the demand for non-qualified workers, and vice versa, showing a substitution effect between these two categories of workers. This finding aligns with the expectation that firms might prefer more qualified workers over non-qualified ones, especially in this case, where their roles tend, to some extent, to overlap. As a result, the demand for non-qualified workers decreases when firms have the option to hire more qualified individuals.

This is not the case when comparing the demand for non-qualified workers (Lv. 1) with the demand for workers holding a Bachelor's or Master's degree in non-STEM fields (Lv. 4), where a complementary effect is observed instead. Indeed, ρ_{14} shows a statistically significant positive coefficient, indicating that firms that tend to hire Lv. 4 workers also target non-qualified individuals. This result is somewhat unexpected and suggests that firms may value a diverse mix of qualifications, where the demand for highly qualified individuals does not reduce the need for non-qualified workers. This complementary relationship likely arises because non-qualified workers and individuals with tertiary non-technical qualifications are often needed for different organizational roles. Non-qualified workers may be employed in positions that do not require specialized training, while Lv. 4 workers may be sought for tasks involving strategic planning or administrative functions. The demand for a broad range of expertise within the organization thus leads to a positive correlation between these two groups.

This dynamic is also valid in all the interactions concerning workers with tertiary University-based education from Lv. 4 (workers with a Bachelor's or Master's degree in non-STEM fields) to Lv. 6 (workers with post-MSc qualifications or a PhD in STEM fields). Indeed, we observe that ρ_{45}, ρ_{46}, and ρ_{56} are positive and statistically significant. Specifically, ρ_{45} shows a higher magnitude (i.e., 0.453) with respect to ρ_{46} and ρ_{56} (i.e., 0.299 and 0.216, respectively). Therefore, in these cases, firms that demonstrate an interest in recruiting workers with a University degree (undergraduate, graduate, or even at the PhD level) tend to show a positive demand for other individuals equipped with the same level of education. This pattern is consistent with the literature, which often suggests that firms engaged in more complex, knowledge-intensive activities require a critical mass of highly educated workers to maximize productivity and innovation.

It is worth mentioning again that the correlation terms $\rho_{p,q}$ do not refer whatsoever to firms' digital investment choices. In fact, in the tables shown above, there is no peculiar pattern between regression coefficients related to the digital investment classes and the correlation terms between models. The statistical significance of these parameters highlights the importance of deploying a multivariate model in addition to univariate analysis, which, as highlighted by the Probit and Tobit I model results, does not capture intriguing and relevant aspects of the dynamics of new staff recruitment decision-making, indicating hiring preferences through complementary and substitution effects between different level of skills.

5.4 Summary of empirical results

In this section, we present a summary of the empirical results. Table 11 shows the different perspectives of workers' demand analyzed and the main empirical findings. First, we analyze firms' propensity to hire (as opposed to not hiring). Digital investments positively influence firms' tendency to hire new workers.

Focusing on investment categories, this dynamic is valid only in two cases: when the companies plan to spend between €50k and €100k or between €100k and €200k. Second, we concentrate only on firms that intend to hire a positive number of workers in 2021. In this context, we analyze the relationship between digital investments and the demand for highly educated

Table 11 Summary empirical results

<table>
<tr><th colspan="2" rowspan="2">Econometric model
Workers demand</th><th colspan="2">Probit</th><th>Tobit</th><th colspan="2">Multivariate Probit</th></tr>
<tr><th>PCA</th><th>Dig Inv categories</th><th>Dig Inv categories</th><th>Bivariate</th><th>6-variate</th></tr>
<tr><td colspan="2">Propensity to hire in 2021</td><td>(+)</td><td>(+)</td><td>//</td><td>//</td><td>//</td></tr>
<tr><td rowspan="2">Low educated workers demand</td><td>Lv. 1 -
No qualification</td><td rowspan="2">//</td><td rowspan="2">//</td><td rowspan="2">//</td><td rowspan="2">(−)</td><td>Not significant</td></tr>
<tr><td>Lv. 2 -
Secondary school diploma</td><td>(−)</td></tr>
<tr><td rowspan="4">Highly educated workers demand</td><td>Lv. 3 -
Technical Institute diploma</td><td rowspan="4">(+)</td><td rowspan="4">(+)</td><td rowspan="4">(+)</td><td rowspan="4">(+)</td><td>(+)</td></tr>
<tr><td>Lv. 4 -
BA/MA no-STEM fields</td><td>Not significant</td></tr>
<tr><td>Lv. 5 -
BA/MSc STEM fields</td><td>(+)</td></tr>
<tr><td>Lv. 6 -
post-MSc/PhD STEM fields</td><td>(+)</td></tr>
<tr><td colspan="2">Only highly educated workers demand
Note: mixed hiring strategies not allowed</td><td>(+)</td><td>(+)</td><td>//</td><td>//</td><td>//</td></tr>
</table>

workers. We allow for mixed hiring strategies, implying that we consider firms showing positive demand for highly educated workers even if they report positive demand for low-educated individuals as well. In this case, Probit's results show a rather sharp pattern: the relationship between digital investments and highly educated workers' demand is always positive and significant for all the investment categories. Furthermore, Tobit I's findings suggest that digital investments are correlated to the probability of showing a positive demand for highly educated individuals that can vary between 27.6 and 44.8%, depending on the investment range.

Third, we focus on the demand *only* for highly educated workers, not allowing mixed hiring strategies. We find a positive relationship between digital investments and demand for highly educated individuals. However, looking at the investment categories, we observe that three specific categories of investment drive this dynamic: when the companies plan to spend between €15k and €50k, between €100k and €200k or above €200k.

Fourth, we implement two multivariate Probit models to investigate the relationship between digital investments and the demand for low and highly educated workers simultaneously. Performing the bivariate Probit, we observe positive and significant correlations for every digital investment category that align with previous findings. In addition, bivariate estimates show a negative influence of digital investments on low-educated workers' demand. This is also confirmed by the correlation term—ρ_{12}—found to be statistically significant and negative in each model specification. Regarding, instead, the 6-variate model results, we can notice that the negative effect of investments in digital technologies on the demand for low-educated workers is mainly conveyed by a negative correlation with the demand for individuals with a secondary school diploma (Lv. 2). At the same time, the positive correlation between digital investments and highly educated workers' demand is mainly driven by the demand for individuals with an ITS diploma (Lv. 3) and for individuals with post-MSc qualifications or a PhD in STEM fields (Lv. 6). In addition, the correlation terms estimated within the 6-variate model show complementary effects in the demand for workers with University-based education, spanning from education levels 4 to 6. Additionally, the demand for non-qualified workers (Lv. 1) and individuals with Bachelor's or Master's degrees in non-STEM fields (Lv. 4) exhibits complementary effects. We find, instead, a substitution effect between the demand for workers with an ITS diploma (Lv. 3) and non-qualified workers (Lv. 1). These results are summarized within Table 12, reporting the 6-variate model correlation terms found to be statistically significant.

6 Discussion

The empirical results presented in this study offer a nuanced perspective on the relationship between digital investments and labor demand across varying education levels, viewed through the lens of both innovation and labor market dynamics. This critical discussion integrates our findings with the existing literature and highlights our contributions.

Firstly, the positive influence of digital investments on firms' propensity to hire new workers aligns with the theoretical underpinnings of technological adoption in firms. The observed positive hiring tendencies suggest that digital investments are perceived by firms as enablers of growth, fostering new roles and expanding existing ones, which is consistent with the concept of *reinstating labor* through new tasks enabled by technology (see Acemoglu and Restrepo, 2019). Moreover, by incorporating a comprehensive set of advanced technologies and examining their effects across different investment categories, our study provides a more granular view of how digital investments impact hiring decisions across different financial thresholds.

Secondly, by analyzing the demand for highly educated workers, the study finds a robust positive relationship between digital investments and the need for highly qualified employees across all investment categories. The observed correlation of digital investments with highly educated worker demand ranging from 27.6% to 44.8% reflects the necessity of advanced qualifications to leverage new technologies effectively. More recent works conducted in the same field, such as Falk and Biagi (2017) for the manufacturing sector of seven EU countries and Cirillo et al. (2021) for the Italian labor market as a whole, display comparable results. Moreover, the restriction of the analysis to firms seeking highly educated workers alone—not allowing mixed hiring strategies—underscores a nuanced perspective. The demand remains positively correlated with digital investments, particularly in mid to high-investment categories (€15k to above €200k). This corroborates Balsmeier and Woerter (2019)'s assertion that digitalization drives job creation, predominantly for highly educated workers who can navigate and utilize new digital tools.

Table 12 6-variate Probit correlation terms—statistically significant estimates

Correlation term	Pair	Coefficient	SE
ρ_{13}	Lv. 1 - No qualification \Lv. 3 - Technical Institute Diploma	−0.386***	0.088
ρ_{14}	Lv. 1 - No qualification \Lv. 4 - BA/MA no-STEM fields	0.227**	0.096
ρ_{45}	Lv. 4 - BA/MA no-STEM fields \Lv. 5 - BA/MSc STEM fields	0.422***	0.112
ρ_{46}	Lv. 4 - BA/MA no-STEM fields \Lv. 6 - post-MSc/PhD STEM fields	0.278*	0.163
ρ_{56}	Lv. 5 - BA/MSc STEM fields \Lv. 6 - post-MSc/PhD STEM fields	0.220*	0.133

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively

Thirdly, differently from previous literature, we are able to distinguish between six educational levels, including the relatively unexplored category of technical diplomas at the tertiary educational level, such as ITS, thus providing deeper insights into the specific educational needs driven by digital investments. Our major research contribution is that the positive correlation between digital investments and highly educated workers is driven by the demand for workers with an ITS diploma (Lv. 3) and post-MSc or PhD qualifications in STEM fields (Lv. 6). This aligns with Autor et al. (2003)'s findings on SBTC and is further supported by recent research by Nogueira and Madaleno (2023), who emphasize the growing demand for specialized qualifications due to SBTC.

Moreover, interestingly, our 6-variate model also shows that the demand for some low and high educational categories, in particular, non-qualified workers (Lv. 1), and individuals with Bachelor's or Master's degrees in non-STEM (Lv. 4) or STEM fields (Lv. 5), remains unaffected by digital investments. This neutrality suggests these roles adapt well to new technologies without significant additional training or occupy positions where human interaction and non-automatable tasks are crucial. Despite technological advancements, this highlights the continued importance of diverse educational backgrounds in the labor market.

Fourthly, the negative impact of digital investments on the demand for low-educated workers, as highlighted in the bivariate and 6-variate Probit models, raises important considerations. Our results suggest that this dynamic is mainly conveyed by a negative correlation with the demand for individuals with secondary education (Lv. 2). This finding offers a more precise mechanism of the job polarization thesis articulated by Goos et al. (2014), where middle-skill jobs diminish, and low-skill jobs may also reduce due to automation, although to a lesser extent.

In addition, multivariate results reveal complementary effects in the demand for University-educated workers, complementary effects between (non-technical) University-educated workers and non-qualified individuals, and substitution effects between workers with an ITS diploma and non-qualified individuals, reflecting the complexity of labor market dynamics in the digital era. The latter finding is supported by Backes-Gellner et al. (2019), who emphasize the innovation contributions of vocational education in Switzerland, suggesting that specific educational pathways, such as ITS (or, more in general, Universities of Applied Sciences (UAS)), can uniquely position workers within the evolving technological landscape. Our study extends this analysis to the Italian context, showing how regional differences in educational attainment and industry specialization influence labor market outcomes. This extension is important as it highlights the specific educational and vocational pathways fostering innovation and adapting to technological changes in Italy.

The complementary effect between non-qualified workers (Lv. 1) and workers with Bachelor's or Master's degrees in non-STEM fields (Lv. 4) indicates that firms value diverse competencies, where different educational backgrounds are required for distinct roles within the organization. This finding aligns with the literature (Autor, 2015), where it is suggested that less-qualified workers and highly educated individuals often fulfill different functions within firms, leading to positive demand for both groups. Our work extends these findings by empirically identifying specific levels of education—namely, non-STEM tertiary education and non-qualified labor—that drive complementary effects in the Italian labor market. This highlights how these educational pathways uniquely contribute to the diverse competency needs of firms in the digital economy, reflecting region- and industry-specific dynamics.

Furthermore, the lack of statistical significance in the correlation coefficient related to the demand for workers with an ITS diploma (Lv. 3) and post-MSc or PhD qualifications in STEM fields (Lv. 6) implies their independence. This observation is consistent with studies such as Battisti et al. (2022), which suggest that technological advancements create distinct demands for various highly qualified workers based on specific technological needs. The lack of significant interaction between these demands suggests that firms recruit based on specific qualification needs without overlap, emphasizing the tailored nature of digital workforce requirements.

Placing our findings within the Italian context reveals significant regional implications. Italy, with diversified regional economies, presents a uniquelandscape for examining the effects of digital investments on labor demand. Northern regions, such as Lombardy and Veneto, are characterized by a higher concentration of advanced manufacturing and technology-intensive industries, which likely drives the positive correlation between digital investments and the demand for highly educated workers. This regional variation underscores the importance of tailored policy interventions considering the specific economic structures and labor market needs of different areas (Bugamelli & Pagano, 2004; Cedefop, 2018). Furthermore, the inclusion of workers with an ITS diploma, a group of technically specialized individuals, in our analysis is particularly relevant for Italy, where vocational education plays a crucial role in bridging the skill gap in the labor market (Ballarino & Cantalini, 2019, 2020). This regional focus contextualizes our findings and provides insights for regional policymakers aiming to enhance the synergy between education and industry needs.

Our empirical findings reveal that digital investments drive demand for highly educated workers, particularly in firms willing to make substantial financial commitments to technology. This dynamic supports the SBTC narrative and highlights the complementary and substitution effects across different education levels. These results resonate with existing literature, reinforcing the view that digitalization creates new job opportunities and reshapes the labor market by altering the demand for various educational levels. The alignment with Autor (2015)'s perspective on the enduring presence of jobs, albeit transformed by technology, underscores the complex interplay between innovation and labor market adjustments. Our study's detailed categorization of educational levels and consideration of mixed hiring strategies significantly advances the understanding of these dynamics, particularly within the context of the Italian regional economy, providing a comprehensive framework for future research and policy development in the era of digital transformation.

7 Conclusion

The digitalization of the economy is significantly impacting job dynamics and workforce qualifications. As businesses adopt digital strategies to enhance efficiency and competitiveness, there is an increasing demand for technically educated individuals, reshaping the job market and economic landscape. Digitalization involves transforming traditional processes into digital formats, enabling organizations to reach broader audiences, make data-driven decisions, and quickly respond to changing market conditions. Consequently, companies require a workforce equipped to manage and innovate within digital environments (Colombari et al., 2023).

This study examines the relationship between digital technology investments and human capital in Piedmont's manufacturing sector, a key industrial region in Italy. Our findings indicate that digital investments favor highly educated workers, particularly those with advanced technical qualifications, while reducing demand for less-educated workers. This trend highlights the importance of SBTC in driving the demand for a more educated workforce, underscoring the need for educational institutions and training programs to adapt to these demands.

The implications are multifaceted: digital investments are not just about technology adoption but also about reshaping the workforce. This has significant implications for workforce development policies, especially in regions where manufacturing plays a critical economic role. Policymakers must prioritize initiatives that support both firms' human capital needs and workers' continuous education to align with the evolving demands of the digital economy.

Moreover, the study highlights potential challenges for mid-sized companies, which may not show the same correlation between digital investments and demand for highly educated workers as larger firms. This could indicate that mid-sized firms face specific barriers in fully realizing the benefits of digitalization, potentially due to resource constraints or a lack of access to the necessary human capital. This potential weakness of mid-size investing companies deserves to be further investigated as they form the technological backbone of Piedmont's manufacturing sector.

The negative impact of digital investments on the demand for less-educated workers, particularly those with secondary education, raises important concerns about job polarization and the potential widening of socioeconomic disparities. As automation and digital technologies reduce the need for less-educated workers, there is an urgent need for policies that facilitate transitions for displaced workers. This might involve continuing education initiatives, enabling these workers to move into more secure and in-demand roles.

Additionally, the study's findings on complementary and substitution effects across different educational levels provide a nuanced understanding of labor market dynamics in the digital era. The complementary demand for university-educated workers alongside non-STEM degree holders suggests that while technology drives demand for highly educated workers, diverse educational backgrounds remain crucial, especially in roles that require human interaction or non-automatable qualifications. This highlights the importance of maintaining a balanced workforce that can adapt to technological changes while preserving essential human elements in various industries.

Regionally, the findings have significant implications for Italy's diverse economic landscape. In regions like Piedmont, where manufacturing is closely linked with technology-intensive industries, the positive correlation between digital investments and the demand for highly educated workers underscores the need for tailored policy interventions. These interventions should focus on aligning educational systems with industry needs, particularly in vocational education, which is vital in bridging skill gaps in the labor market.

This paper presents some limitations and inspiration for future research. First, the analysis is based on regional data over a limited period, and using panel data could help assess if the findings are broadly applicable. Second, a key contribution is identifying various worker education levels, suggesting future research could expand beyond the essential distinction between low and highly educated workers. Third, while we establish a link between digitalization investments and employment across education levels, we lack detailed data on specific technology investments and their adoption timelines. Variations in employment outcomes might stem from different uses of technologies at various stages of production. Thus, further investigation into specific technologies and their applications is needed. Lastly, our study focuses on a highly developed Italian region where manufacturing is economically significant. Extending these findings globally requires considering differences in socioeconomic contexts, political landscapes, and institutional settings, which may influence digital investment strategies and hiring practices.

Appendix 1: Data construction

Table 13 Sample comparison with the universe of Piedmont manufacturing firms

	Unioncamere sample		Manufacturing firms in Piedmont	
	N	%	*N*	%
Industry sector				
Food	222	12.37	4.317	12.56
Textile, clothing and footwear	208	11.59	3.425	9.96
Wood and furniture	111	6.18	3.313	9.64
Chemical, petroleum, and plastics	157	8.75	1.623	4.72
Metal	416	23.18	10.053	29.25
Electrical and electronic	101	5.63	1.695	4.93
Mechanical	211	11.75	2.695	7.84
Transportation equipment	56	3.12	933	2.71
Other industries	255	14.21	5.136	14.94
Jewelry	58	3.23	1.184	3.44
Total	*1795*	*100*	*34.374*	*100*
Province				
Alessandria	232	12.92	3.569	10.38
Asti	181	10.08	1.701	4.95
Biella	189	10.53	1.690	4.92
Cuneo	244	13.59	4.882	14.20
Novara	225	12.53	2.951	8.58
Torino	407	22.67	17.041	49.58
Verbano-Cusio-Ossola	150	8.36	1.214	3.53
Vercelli	167	9.30	1.326	3.86
Total	*1795*	*100*	*34.374*	*100*

Source: Business Dashboard - Analysis of enterprises in the economic and productive activities registry (in Italian *Anagrafe Attivitá Economiche e Produttive* - AAEP) of Piedmont

Table 14 Data construction—Unioncamere Piemonte survey and AIDA dataset

	Unioncamere Piemonte survey				
	Question	Answer	Type of variable	Time interval	Resulting metrics
Dependent variables	In the next 12 months, does the company plan to hire new workers (in any form)?	Yes/no	Dummy	2021	• Propensity to hire in 2021
	If yes: Can you indicate the distribution of expected new hires in the next 12 months with respect to educational qualifications?	Lv. 1 - No qualifications (%) Lv. 2 - High school diploma (%) Lv. 3 - ITS diploma Lv. 4 - BA's or MA's degrees no-STEM (%) Lv. 5 - BA's or MSc's degrees STEM (%) Lv. 6 - PhD or post-MSc qualification STEM (%)	Six continuous variables - interval [0-100]	2021	• Highly educated workers demand • Only highly educated workers demand • % of highly educated workers demand
Independent variables	Out of the total number of new hires in the last 3 years, what percentage held the following educational qualifications as their highest qualification?	Lv. 1 - No qualifications (%) Lv. 2 - High school diploma (%) Lv. 3 - ITS diploma Lv. 4 - BA's or MA's degrees no-STEM (%) Lv. 5 - BA's or MSc's degrees STEM (%) Lv. 6 - PhD or post-MSc qualification STEM (%)	Six continuous variables - interval [0-100]	2018–2020	• Past highly educated recruitment • Past low-educated recruitment
	Can you provide an estimate of the expected costs in 2021 for digital technologies/ services in your company?	€0 <€15k €15k-€50k €50k-€100k €100k-€200k >€200k	Categorical	2021	
	Can you provide an estimate of the expected costs in 2021 for digital technologies/ services in your company?	€0 <€€15k €15k–€50k €50k–€100k €100k–€200k >€200k	Categorical	2020	• Digital investments in 2021 • PCA - digital investments • Past digital investments
	Can you provide an estimate of the expected costs in 2021 for digital technologies/ services in your company?	€0 <€15k €15k–€50k €50k–€100k €100k–€200k >€200k	Categorical	2019	
	Please indicate the total number of employees in the company	*N*	Continous	2021	• Employees

Table 14 continued

Independent variables	Please indicate your production sector	Food Textile, Clothing and Footwear Wood and Furniture Chemical, Petroleum and Plastics Metal Electrical and Electronic Mechanical Transportation Equipment Other Industries Jewelry	Categorical	2021	• Industry sector
	Does the company's production involve other local units, subcontractors, or external subcontractors beyond those in the surveyed unit?	Yes/no	Dummy	2021	• Outsourcing
	Does the company export its products to foreign countries?	Yes/no	Dummy	2021	• Exports (2021)
	Did the company export its product last year to foreign countries?	Yes/no	Dummy	2020	• Exports (2020)
		AIDA dataset			
	Metric	Description	Type of variable	Time interval	Resulting metrics
Independent variables	Revenues	Annual company revenue	Continuous	2020	• Revenues (2020)
	EBITDA	Annual earnings before interest, taxes, depreciation, and amortization	Continuous	2020	• EBITDA (2020)
	Intangible fixed assets	Assets that do not have physical form including patents, copyrights, trademarks, software, etc.	Continuous	2020	• Intangible assets (2020)

Table 15 Unioncamere main variables t-tests—pre- and post-matching with AIDA

Variable	Welch's t-statistic	p value
Propensity to hire in 2021	−0.5671	0.5707
Workers demand in the next 12 months		
Lv. 1 - No qualifications (%)	0.4366	0.6625
Lv. 2 - High school diploma (%)	−0.3267	0.7439
Lv. 3 - ITS diploma	−0.2486	0.8037
Lv. 4 - BA's or MA's degrees no-STEM (%)	−0.0798	0.9364
Lv. 5 - BA's or MSc's degrees STEM (%)	−0.9598	0.3373
Lv. 6 - PhD or post-MSc qualification STEM (%)	−0.4953	0.6205
Workers demand in the past 3 years		
Lv. 1 - No qualifications (%)	0.4830	0.6292
Lv. 2 - High school diploma (%)	0.5084	0.6113
Lv. 3 - ITS diploma	−0.1436	0.8858
Lv. 4 - BA's or MA's degrees no-STEM (%)	−0.2261	0.8211
Lv. 5 - BA's or MSc's degrees STEM (%)	−1.0100	0.3126
Lv. 6 - PhD or post-MSc qualification STEM (%)	−0.5803	0.5618
Digital investments in 2021		
€0	1.1130	0.2659
<€15k	0.5350	0.5927
€15k–€50k	−0.5100	0.6101
€50k–€100k	−0.5965	0.5509
€100k–€200k	−0.7250	0.4685
> €200k	−0.6444	0.5194
Digital investments in 2020		
€0	1.4816	0.1386
<€15k	0.1062	0.9154
€15k–€50k	−0.5575	0.5772
€50k–€100k	−0.7469	0.4552
€100k–€200k	−0.6256	0.5317
>€200k	−0.6369	0.5243
Digital investments in 2019		
€0	1.5157	0.1298

Table 15 continued

<€15k	−0.0290	0.9769
€15k–€50k	−0.5503	0.5822
€50k–€100k	−0.5623	0.5740
€100k–€200k	−0.4365	0.6626
>€200k	−0.7938	0.4274
Industry sector		
Food	0.1986	0.8426
Textile, Clothing and Footwear	0.3944	0.6933
Wood and Furniture	0.5424	0.5876
Chemical, Petroleum and Plastics	−0.1514	0.8796
Metal	0.2083	0.8351
Electrical and Electronic	−0.4520	0.6513
Mechanical	−0.6037	0.5462
Transportation Equipment	−0.0158	0.9874
Other Industries	−0.0215	0.9829
Jewelry	0.1070	0.9148
Employees	−0.7218	0.4705
Outsourcing	−0.9992	0.3178
Exports (2021)	−1.8916*	0.0587
Exports (2020)	−1.9608*	0.0501

Appendix 2: Correlation matrix

Table 16 Cross-correlation table

Variables	Digital investments	PCA - Dig Inv	(log) Employees	Sector	(log) Revenues (2020)	EBITDA 2020	Out-sourcing	Past highly edu recruitment	Past low-edu recruitment	Exports 2021	Exports 2020	Intangible Assets (2020)	Past digital invest-ments
Digital invest-ments	1.000												
PCA - Dig Inv	0.6477	1.000											
log (Employees)	0.4809	0.4104	1.000										
Sector	−0.043	−0.043	−0.004	1.000									
(log) Revenues (2020)	0.442	0.383	0.836	−0.058	1.000								
EBITDA (2020)	0.062	0.042	0.108	−0.013	0.107	1.000							
Outsourcing	0.205	0.163	0.270	0.017	0.234	−0.012	1.000						
Past highly edu recruitment	0.316	0.257	0.235	0.020	0.209	0.013	0.159	1.000					
Past low-edu recruitment	0.114	0.084	0.041	−0.005	0.032	0.002	0.006	0.112	1.000				
Exports (2021)	0.261	0.222	0.329	−0.024	0.358	0.028	0.143	0.192	−0.030	1.000			
Exports (2020)	0.252	0.215	0.325	−0.041	0.350	0.028	0.128	0.179	−0.025	0.929	1.000		
Intangible assets (2020)	0.145	0.097	0.298	0.008	0.241	0.515	0.029	0.048	0.055	0.041	0.040	1.000	
Past digital investments	0.516	0.496	0.166	−0.032	0.172	0.006	0.114	0.342	0.134	0.179	0.143	0.033	1.000

Appendix 3: Multivariate Probit model—formal description

Following the model developed by Chib and Greenberg (1998), the general specification of a multivariate Probit model with J dependent variables in the context of our analysis is as follows:

$$y_{ij}^{*} = \boldsymbol{X\beta} + u_{ij}, \quad i = 1, \ldots, N, \quad j = 1, \ldots, J \text{ and } u_i \sim NID(0, 1)$$

where y_{ij}^{*} represents the latent utility of firm i of hiring a new employee with skills j (identified by the level of education), while $\boldsymbol{X}$ is a vector of covariates (including $Digital\ Investments_i$ and control variables). Then, $\boldsymbol{Y} = (y_{i1}, \ldots, y_{iJ})'$ denote the vector of observable responses on all J variables (one per each level of education) of firm i. The probability that $\boldsymbol{Y} = y_{ij}$, conditioned on $\boldsymbol{\beta}$, covariance matrix $\boldsymbol{\Sigma}$ and $\boldsymbol{X}$, is given by

$$Pr(y_{ij}|\boldsymbol{\beta}, \boldsymbol{\Sigma}) = \int_{A_{iJ}} \cdots \int_{A_{i1}} \phi_J(\boldsymbol{Z}|\boldsymbol{X\beta}, \boldsymbol{\Sigma})\, d\boldsymbol{Z}$$

where $\phi_J(\boldsymbol{Z}|\boldsymbol{X\beta}, \boldsymbol{\Sigma})$ is the density of a J-variate normal distribution with mean vector $\boldsymbol{X\beta}$ and covariance matrix $\boldsymbol{\Sigma}$, while $\boldsymbol{Z} = (z_{i1}, \ldots, z_{iJ})'$ denotes a J-variate normal vector with distribution $\boldsymbol{Z} \sim N_J(\boldsymbol{X\beta}, \boldsymbol{\Sigma})$ and A_{ij} is the interval $(0, \infty)$ if $y_{ij} = 1$ and the interval $(-\infty, 0]$ if $y_{ij} = 0$, according to the sign of z_{ij} since $y_{ij} = \mathbb{1}(z_{ij} > 0)$ with $j = 1, \ldots, J$.

Focusing on the variance-covariance matrix $\boldsymbol{\Sigma}$ of the error terms, it assumes the following generic form:

$$\underset{J\text{x}J}{\boldsymbol{\Sigma}} = \begin{bmatrix} 1 & \rho_{1,2} & \cdots & \rho_{1,j} & \cdots & \rho_{1,J} \\ & \ddots & & \vdots & & \vdots \\ & & \ddots & \rho_{j,j+1} & \cdots & \rho_{j,J} \\ & & & \ddots & & \vdots \\ & & & & \ddots & \rho_{J-1,J} \\ & & & & & 1 \end{bmatrix}$$

Specifically, $\boldsymbol{\Sigma}$ is a correlation matrix with off-diagonal elements $\rho_{p,q}$, s.t. $\{p, q\} \in \{1, \ldots, J\}$ and $p \neq q$. By estimating a multivariate Probit model, we also estimate the $\frac{J(J-1)}{2}$ unknown correlation parameters $(\rho_{p,q})$ from the covariance matrix $\boldsymbol{\Sigma}$ of the error terms. Depending on the statistical significance of these parameters, we can understand whether a multivariate Probit model is appropriate and useful instead of a series of standard Probit models. Note that the $\frac{J(J-1)}{2}$ estimated parameters measure the correlation between all the pairs of models. As a consequence, we are able to observe the correlation between models that capture not only adjacent levels of education but also *distant* educational attainment levels (e.g., Lv. 1 non-qualified workers and Lv. 6 post-MSc or PhD qualification in technical fields). This characteristic of the multivariate Probit model allows us to examine potential trends in the hiring choices of the firms that intend to carry out mixed hiring strategies (i.e., firms that want to hire both low and highly educated workers in the 12 months following the sampling period).

Therefore, based on this theoretical ground, we can define the following model specifications:

$$Workers\ Demand_{ij} = \boldsymbol{X\beta} + u_{ij}, \quad i = 1, \ldots, N, \quad j = 1, 2 \text{ and } u_i \sim NID(0, 1)$$

$$Workers\ Demand_{ij} = \boldsymbol{X\beta} + u_{ij}, \quad i = 1, \ldots, N, \quad j = 1, \ldots, 6 \text{ and } u_i \sim NID(0, 1)$$

where the first relates to the *bivariate* case, while second one refers to the *6-variate* case. In the bivariate case, $y_{i1} = 1$ if the firm i indicates the intention to hire a positive percentage of workers with education between Lv. 1 non-qualification and Lv. 2 high school diploma, and $y_{i1} = 0$ otherwise, even if the firm i also indicates positive percentages for profiles with higher levels of education, in order to allow for correlation with the dependent variable of the second model. On the other hand, $y_{i2} = 1$ if the firm i recruits between Lv. 3 ITS diploma and Lv. 6 post-MSc or PhD qualifications in technical fields, and $y_{i2} = 0$ otherwise, even if the firm i also indicates positive percentages for profiles between Lv. 1 and Lv. 2 of education, so to allow for correlation with the outcome variable of the first model. In addition, in this bivariate case, the model also estimates one correlation term (i.e., ρ_{12}).

In the 6-variate case, the model is quite similar with respect to the bivariate except for the fact that in this specification we identify six dependent variables, one for each educational level, and $y_{ij} = 1$ if the firm i indicates a positive percentage at least for a worker with level of skills j with $j = 1, 2, \ldots, 6$, regardless of what the company indicates for individuals with a different level of education, thus enabling for correlation among the dependent variables of all model pairs. As a result, the 6-variate model estimates 15 correlation terms.

Appendix 4: 6-variate Probit model results—non-full model specifications

Table 17 6-variate Probit model results—row model

	Dependent variables:					
	Non-qualified	High school diploma	ITS	BA/MA (no STEM)	BA/MSc (STEM)	Post-MSc/PhD (STEM)
	(1)	(2)	(3)	(4)	(5)	(6)
Digital investments in 2021						
<€15k	−0.111	−0.284	0.451	−0.173	0.431	0.314
	(0.294)	(0.302)	(0.289)	(0.414)	(0.336)	(0.398)
€15k–€50k	−0.439	−0.526*	0.739**	0.014	0.455	0.229
	(0.287)	(0.302)	(0.297)	(0.384)	(0.324)	(0.384)
€50k–€100k	0.099	−0.476	−0.0880	0.814**	1.032***	0.827**
	(0.301)	(0.309)	(0.305)	(0.410)	(0.346)	(0.404)
€100k–€200k	−0.361	−0.436	0.891**	0.101	0.775**	0.855*
	(0.361)	(0.367)	(0.366)	(0.427)	(0.381)	(0.450)
>€200k	−0.529	−0.402	0.426	1.616***	1.610***	1.514***
	(0.346)	(0.367)	(0.365)	(0.411)	(0.378)	(0.428)
Constant	−0.536**	−0.186	0.00914	−1.368***	−0.903***	−1.602***
	(0.230)	(0.242)	(0.231)	(0.338)	(0.281)	(0.333)
ρ_{12}	0.045	ρ_{23}	−0.140	ρ_{35}	−0.103	
	(0.101)		(0.111)		(0.102)	
ρ_{13}	−0.391***	ρ_{24}	0.114	ρ_{36}	−0.152	
	(0.088)		(0.130)		(0.105)	
ρ_{14}	0.235**	ρ_{25}	−0.006	ρ_{45}	0.481***	
	(0.097)		(0.115)		(0.102)	
ρ_{15}	−0.012	ρ_{26}	0.010	ρ_{46}	0.397***	
	(0.093)		(0.128)		(0.115)	
ρ_{16}	−0.036	ρ_{34}	−0.016	ρ_{56}	0.531***	
	(0.127)		(0.105)		(0.092)	
Observations				345		
Firm-level controls				✗		
Foreign business controls				✗		
Innovation tendency controls				✗		
Log Pseudo-likelihood				−515.400		
Likelihood ratio test of all $\rho_{p,q} = 0$ (χ^2 df = 15)				1132.36***		

Note: This presents the results of the 6-variate Probit model *weighted* regressions. The covariates are two dummies. The first one indicates the demand for non-qualified workers (Lv. 1) or with secondary education (Lv. 2), regardless of the demand for individuals with *higher* levels of education. The second one indicates the demand for high educational levels (from Lv. 3 to Lv. 6), regardless of the demand for workers with *lower* levels of education. The main regressor is a categorical variable indicating the *level* of digital investments in 2021. The reference state refers to companies not investing. The model estimates pairs of regressions, each with one of the two dependent variables. This presents the estimates of the row model—without any control variable. Robust SE are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample used is restricted to *non-micro* firms that plan to hire a positive number of workers in 2021

Table 18 6-variate Probit model results—firm-level control variables model

	Dependent variables:					
	Non-qualified	High school diploma	ITS	BA/MA (no STEM)	BA/MSc (STEM)	Post-MSc/PhD (STEM)
	(1)	(2)	(3)	(4)	(5)	(6)
Digital investments in 2021						
<€15k	−0.034	−0.252	0.263	−0.023	0.894**	0.946*
	(0.320)	(0.301)	(0.310)	(0.377)	(0.374)	(0.519)
€15k–€50k	−0.453	−0.564*	0.701**	−0.058	0.338	0.204
	(0.304)	(0.303)	(0.316)	(0.370)	(0.376)	(0.489)
€50k–€100k	0.215	−0.399	−0.135	0.505	0.860**	0.825**
	(0.311)	(0.323)	(0.325)	(0.420)	(0.376)	(0.370)
€100k–€200k	−0.329	−0.349	0.656*	−0.310	0.394	0.690
	(0.385)	(0.383)	(0.398)	(0.458)	(0.432)	(0.578)
>€200k	−0.475	−0.829**	0.321	0.684	0.885**	0.836**
	(0.370)	(0.397)	(0.370)	(0.446)	(0.439)	(0.421)
Constant	−0.350	1.317*	0.028	−1.703*	−3.388***	−3.562***
	(0.699)	(0.777)	(0.711)	(0.983)	(0.902)	(1.097)
ρ_{12}	−0.006	ρ_{23}	−0.167	ρ_{35}	−0.083	
	(0.103)		(0.114)		(0.120)	
ρ_{13}	−0.399***	ρ_{24}	0.077	ρ_{36}	−0.068	
	(0.088)		(0.126)		(0.147)	
ρ_{14}	0.252**	ρ_{25}	−0.004	ρ_{45}	0.403***	
	(0.108)		(0.108)		(0.110)	
ρ_{15}	0.018	ρ_{26}	−0.020	ρ_{46}	0.306*	
ρ_{16}	0.003	ρ_{34}	0.044	ρ_{56}	0.179	
	(0.137)		(0.117)		(0.133)	
	(0.093)		(0.161)		(0.158)	
Observations				345		
Firm level controls				✓		
Foreign business controls				✗		
Innovation tendency controls				✗		
Log Pseudo-likelihood				−446.531		
Likelihood ratio test of all $\rho_{p,q} = 0$ (χ^2 df = 15)				950.032***		

Note: This presents the results of the 6-variate Probit model *weighted* regressions. The covariates are two dummies. The first one indicates the demand for non-qualified workers (Lv. 1) or with secondary education (Lv. 2), regardless of the demand for individuals with *higher* levels of education. The second one indicates the demand for high educational levels (from Lv. 3 to Lv. 6), regardless of the demand for workers with *lower* levels of education. The main regressor is a categorical variable indicating the *level* of digital investments in 2021. The reference state refers to companies not investing. The model estimates pairs of regressions, each with one of the two dependent variables. This presents the estimates of the model including only firm-level control variables. *Firm level controls* encompass the log of employees, industry sector, log of revenues in 2020, EBITDA in 2020, a dummy indicating whether the firms outsource (part of) their production, and two dummies for past recruitment of workers with tertiary education and for low-educated workers demand. Robust SE are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample used is restricted to *non-micro* firms that plan to hire a positive number of workers in 2021

Table 19 6-variate Probit model results—firm-level and foreign business control variables model

	Dependent variables:					
	Non-qualified (1)	High school diploma (2)	ITS (3)	BA/MA (no STEM) (4)	BA/MSc (STEM) (5)	Post-MSc/PhD (STEM) (6)
Digital investments in 2021						
<€15k	-0.065	-0.251	0.269	-0.055	0.949**	0.902*
	(0.323)	(0.301)	(0.311)	(0.374)	(0.380)	(0.512)
€15k - €50k	-0.377	-0.563*	0.705**	-0.056	0.326	0.130
	(0.308)	(0.304)	(0.315)	(0.374)	(0.378)	(0.478)
€50k - €100k	0.280	-0.396	-0.139	0.509	0.857**	0.841**
	(0.311)	(0.324)	(0.323)	(0.425)	(0.378)	(0.373)
€100k - €200k	-0.292	-0.347	0.659*	-0.302	0.400	0.689
	(0.399)	(0.382)	(0.399)	(0.459)	(0.434)	(0.573)
>€200k	-0.453	-0.824**	0.322	0.920**	0.368	0.801**
	(0.371)	(0.396)	(0.371)	(0.446)	(0.441)	(0.398)
Constant	-0.379	1.309*	-1.435	-1.629*	-3.522***	-3.362***
	(0.742)	(0.777)	(0.703)	(0.946)	(0.892)	(1.062)
ρ_{12}	-0.017	ρ_{23}	-0.170	ρ_{35}	-0.100	
	(0.101)		(0.114)		(0.120)	
ρ_{13}	-0.400***	ρ_{24}	0.083	ρ_{36}	-0.054	
	(0.088)		(0.128)		(0.153)	
ρ_{14}	0.226**	ρ_{25}	-0.010	ρ_{45}	0.420***	
	(0.096)		(0.106)		(0.107)	
ρ_{15}	0.059	ρ_{26}	-0.043	ρ_{46}	0.292*	
	(0.100)		(0.161)		(0.166)	
ρ_{16}	-0.116	ρ_{34}	0.051	ρ_{56}	0.205	
	(0.125)		(0.118)		(0.132)	
Observations				345		
Firm level controls				✓		
Foreign business controls				✓		
Innovation tendency controls				✗		
Log Pseudo-likelihood				-440.700		
Likelihood ratio test of all $\rho_{p,q} = 0$ (χ^2 df = 15)				937.712***		

Note: This presents the results of the 6-variate Probit model *weighted* regressions. The covariates are two dummies. The first one indicates the demand for non-qualified workers (Lv. 1) or with secondary education (Lv. 2), regardless of the demand for individuals with *higher* levels of education. The second one indicates the demand for high educational levels (from Lv. 3 to Lv. 6), regardless of the demand for workers with *lower* levels of education. The main regressor is a categorical variable indicating the *level* of digital investments in 2021. The reference state refers to companies not investing. The model estimates pairs of regressions, each with one of the two dependent variables. This presents the estimates of the model including firm-level and foreign business control variables. *Firm level controls* include the log of employees, industry sector, log of revenues in 2020, EBITDA in 2020, a dummy indicating whether the firms outsource (part of) their production, and two dummies for past recruitment of workers with tertiary education and for low-educated workers demand. *Foreign business controls* add two dummies indicating whether the firms engaged in exporting activities in 2020 and 2021. Robust SE are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample used is restricted to *non-micro* firms that plan to hire a positive number of workers in 2021

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