Digital technologies and eco-innovation. Evidence of the twin transition from Italian firms

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Abstract

We investigate how the twin transition (digital & green) unfolds within firms by relating investments in digital technologies to the propensity of eco-innovating production processes and models. Extending previous studies on Information Technologies and eco-innovation, and drawing from recent research on Industry 4.0, we posit that digital technologies should enable eco-innovation across the board. However, a greater eco-innovation impact is expected from Artificial Intelligence and from bundling digital investments. Using the new Permanent Census of Firms of the Italian National Statistical Office, we test our hypotheses on a large sample of more than 150,000 firms. Results confirm that the contribution of digital technologies to firm's eco-innovation is mainly driven by investments in AI, while investments in other digital technologies work more selectively. Moreover, new eco-innovative production processes and models benefit from bundling investments in different digital technologies.

Keywords: Twin transition; digital technologies; eco-innovation; artificial intelligence; Industry 4.0.
JEL codes: 030; O32; Q55; Q57.

1. Introduction

The decarbonisation of the economy has become one of the main objectives of the European Union (EU) to guarantee growth without diminishing future progress and prosperity. The new EU action plan for eco-innovation and the circular economy recognises that much of this green transition relies on new and cleaner technologies. In the new EU industrial strategy, the decarbonisation objective is coupled with the recognition that new digital technologies, like Artificial Intelligence (AI) and Internet of the Things (IoT), are making factories smarter and environmentally more efficient. The green and digital transitions are thus linked, and so intrinsically linked to be considered as "twin transitions" (EC, 2020).

The last generation of digital technologies, often referred as "Industry 4.0 technologies", enable firms to radically transform their production processes, value chains and business models in such a way to reach higher efficiency and organisational flexibility (Holmström et al., 2016). Moreover, the new wave of digital technologies has also been envisaged to allow firms to increase the environmental (e.g., resource and energy) efficiency of the entire array of their business processes, from eco-design and new product development to transformative production processes, from the heating and cooling systems of plants to process re-engineering and waste disposal. In other words, the technologies of the so-called "smart factory" are expected to allow firms to achieve higher efficiency and minimize their negative environmental impacts (Jena et al., 2020; Azadi et al., 2021).[1] Industry 4.0 could increase the environmental sustainability of SMEs too (Kumar et al., 2002; Bonilla et al., 2018), though with differences with respect to their large and multinational counterparts (Horváth & Szabó, 2019). Indeed, Industry 4.0 is posing new challenges and threats to SMEs, limiting the exploitation of those technologies that would allow for the most profound transformations in their production and business processes (Moef et al., 2018; Müller et al., 2018).

Despite the analyses of the green opportunities offered by digital technologies at the company level, the extent to which firms take stock of them has been limitedly addressed so far. To the best of our knowledge, no attention has been paid yet to the role that firms' investments in digital technologies can have in stimulating their capacity of designing and introducing new production models and processes with a higher environmental sustainability: in brief, the role of digital investments in enabling firms' eco-innovation (EI) related to production. Given the importance that EIs have in

[1] As we will notice, digital technologies have also severe negative environmental externalities, in terms of rare material depletion, high energy consumption, CO2 emissions and hardly recyclable waste, whose attenuation would make the twin transition "full".

favouring firm environmental sustainability and their possible linkage with firm growth and industrial dynamics (Leoncini et al., 2019), this represents an important gap in the analysis of the twin transition at the firm level, which the present paper aims at filling.

By combining research on different "vintages" of digital technologies, in Section 2 we propose that firms could increase their EI propensity by investing in all the identified Industry 4.0 technologies, but with a heterogeneous and complementary impact across them. The empirical application that we present in Section 3 is based on a large sample (about 155k) of Italian firms drawn from the first wave of the new Permanent Census of the Italian National Statistical Office (ISTAT). The results generally support our research hypotheses. However, this occurs with some interesting nuances, discussed in Section 4, which also descend from the endogenous selection entailed by the structure of the survey. As illustrated in Section 5, important policy implications can be drawn from these results.

2. Background literature and research hypotheses

The role of digital technologies in spurring firms to adopt new environmentally sustainable practices finds its roots in a stream of research that in the last decade has investigated the relationship between Information Technologies (IT) and EIs. With respect to an anterior set of digital technologies than those we focus on,[2] the relationship between IT and EI has been recognised as dual and consisting of *green IT* and *IT for green* (Faucheux and Nicolaï, 2011).

In brief, new *green IT* are constituted by EI in the IT sector, through which IT production (first order effect) and use (second order effect) can exert a lower environmental impact. This encompasses a wide range of product and process innovations that can attenuate the environmental damages caused by IT and recognised since the first IT revolution: the use of non-renewable and toxic materials in their production, the consumption of high levels of energy and water in their production and use, and the generation of dangerous electrical and electronic waste in their dismantling (Erdmann et al., 2004; Hilty, 2008; Hilty et al., 2005).[3]

[2] Before of the advent of the Industry 4.0 concept, IT were broadly meant to cover all the techniques used in information processing and transmission, mainly telecommunications and the Internet (OECD, 2009). As we will say, the new wave of digital technologies, on which we focus, is both wider in terms of scope and more specific in terms of applications.
[3] In the domain of the Industry 4.0 IT, these EI could be represented, for example, by less energy consuming cloud systems or new secondary material-based robotics.

IT for green are instead represented by opportunities to eco-innovate obtained through the adoption and development of IT, also and above all by firms in other sectors than the digital ones. As Faucheux and Nicolaï (2011) pose, a "true" twin-transition would occur by making IT at work for green. Still, rendering IT functional to the discovery and exploitation of new EI opportunities represents an important and demanding side of the twin transition, on which we focus in this paper.

Earlies studies on *IT for green* mainly focused on electronic applications, like digital photography or e-commerce, showed that the virtualisation or dematerialisation of hardware that they entail could more than compensate the environmental rebound effects of their production (Faucheux et al., 2002; Haake and Gueorguievsky, 2010). Then the attention has moved to EIs in the form of more energy and resource efficient production processes entailed by novel applications of IT; in particular, within sectors like transport, building and energy distribution, which are among the greatest contributors to CO2 emissions (Faucheux and Nicolaï, 2011).

The advent of Industry 4.0 is making available to firms a new set of digital technologies with potential green applications. With respect to the previous wave of IT technologies, usually associated to the third industrial revolution (Philbeck and Davis, 2018), new digital technologies associated to the Industry 4.0 penetrate more intensively in company operations and business ecosystems by reshaping their production, supply chain, and organisation (Frank et al., 2019). Accordingly, we posit that the firms' capacity to eco-innovate could be increased by building up and reinforcing the stock of digital technologies related to Industry 4.0: in brief, by investing in digital technologies of the last generation.

The support to our argument about the eco-innovation relevance of investments in digital technologies comes from two diverse strands of studies. Recent works in the field of engineering and production economics (e.g., Jena et al., 2020; Liao et al., 2021) have maintained that by building up internal digital capabilities firms are able to make the same technologies functional to novel (environmentally) sustainable production processes and models. For example, by investing in AI and big data analytics firms acquire knowledge through which they can design and implement more efficient transformation processes (e.g., involving less energy/resource use and reducing waste) and heating-cooling systems (e.g., by tracking the number of processes per plant). Through robotics investments, firms can introduce new processes that remove unnecessary steps and reduce human-errors across the different stages of their value-chain (processes re-engineering). These are cases of the capacity that digital technologies have in facilitating the process of knowledge recombination on which EIs normally rely (Barbieri et al., 2020). Quite interestingly, this capacity has been so far directly investigated in a second strand of studies at the regional level (Cicerone et al., 2019; Castellacci et al., 2020). In extreme synthesis, these studies claim that digital technologies, like AI, can create interfaces for existing knowledge modules in the region to be originally recombined into new green technologies. Such a meso-argument is usually developed by scaling up at the regional level, the micro-argument that firms can take stock of the general-purpose technology (GPT) properties of digital technologies to better grasp the complex knowledge inputs that lead them to eco-innovate: for example, by combining and hybridising green and non-green knowledge. We test for this argument in our first research hypothesis. In line with the studies in engineering and production economics we have referred above, which mainly (if not exclusively) identify EI opportunities emerging from the application of digital technologies to production processes and models, we put forward the following hypothesis:

Hp1: *Firms investing in digital technologies are more likely to introduce new environmentally sustainable production models and processes, that is, to eco-innovate*.

In addition, we submit to empirical verification other two hypotheses related to the heterogeneity that digital technologies may have in enabling the EI at stake. In spite of being commonly grouped within the Industry 4.0 paradigm, technologies like IoT, big data, cloud computing, robotics, AI and additive manufacturing, are heterogeneous in several respects; spanning from the different stage of their life-cycle, to their specific functions and capacity, like being front-end or base technologies (Frank et al., 2019).

Among these differentiating aspects, a relevant one for our study concerns the heterogeneity that Industry 4.0 technologies reveal with respect to their technological and industrial knowledge base, their enabling, and their GPT properties (Bresnahan, 2010). A useful guideline in this respect is provided by the recent study by Martinelli et al. (2021), based on patent data. A first important difference that emerges from this study concerns the industrial base of the patenting activity of the investigated technologies. Some of these technologies, among which the fundamental duo of AI and big data, appear rooted in industries that are pervasive suppliers to many other industries (like manufacturing of computers, communication equipment, and office machinery). Conversely, other digital technologies like 3D printing and robotics, are rooted in less pervasively supplying industries (like manufacturing of medical equipment and manufacturing of metal forming machinery and machine tools). Thinking of the embodied diffusion of knowledge that occurs through intersectoral exchanges of intermediate and capital goods (Jaffe, 1986; Castellacci, 2008), we expect that among the digital technologies characterizing the Industry 4.0, investments in the AI realm (which in our dataset encompasses big data) could be the source of broader embodied digital-knowledge diffusion and of wider EI opportunities for the firm.

More importantly, Martinelli et al. (2021) find also that big data and AI appear the only digital technologies with distinctive GPT features (i.e., very general in forward- and very original in backward-citations); while the other technologies appear at most enabling, in the light of their longevity and diffusion (Teece, 2018). To the extent at which, as we said, the GPT properties of digital technologies favour recombinant innovation in the green realm, we expect that investing in AI allows firms higher opportunities of innovating their production processes and models in a sustainable way. We thus put forward our second research hypothesis:

Hp2: *Investing in AI increases the firms' capacity to eco-innovate to a greater extent than in other digital technology areas.*

The third hypothesis we propose still relates to the heterogeneity of digital technologies. Differently from Hp2, it focuses on the benefits deriving for the complementarities that can arise when firms decide to invest in different types of digital technologies, by possibly bundling them together. On the one hand, by investing in a wider range of digital technologies firms become better equipped to understand and exploit the fertilisation of ideas across digital domains that mark the evolution of their knowledge base. As the digital technologies at the heart of Industry 4.0 evolve also by drawing knowledge one from the other (Martinelli et al., 2021), getting competencies (by investing) in more of them thus widens the opportunities of knowledge re-combination that can enable firms to eco-innovate. On the other hand, digital technologies do also interoperate functionally, enable and complement each other in their operations by reinforcing their enabling and GPT capacities (Carlaw and Lipsey, 2002). Indeed, the development of Industry 4.0 is arguably linked to the integration of its constitutive enabling technologies (Muscio and Cifollili, 2020). Accordingly, investing in several Industry 4.0 technologies contribute reinforcing the digital knowledge base and the digital business model of the firm. In turn, this digital bundling could be conducive to EIs more than picking and investing in one or few digital technologies (Díaz-Chao et al., 2021). We thus put forward the following final hypothesis:

Hp3: *Investing in bundles of digital technologies increases the firms' capacity to eco-innovate to a greater extent than in single digital technology areas*.

3. Empirical application

We test our three hypotheses on a large sample of firms in Italy: a country where the digital and the green transition are receiving increasing research and policy attention and are at the center of the recovery and resilience plan to relaunch the economy after the Covid19 crisis. Given its well-known industrial structure, marked by a large presence of SMEs and low/mid-tech industrial specialisations, Italy represents an interesting case of twin transition, against which to eventually benchmark other European economies.

The dataset for the analysis refers to the first wave of the "Permanent Census of Italian Firms" run by the Italian National Institute of Statistics (ISTAT) in 2019.[4] This is a brand-new survey of about 200k firms in any industry, and with 3 or more employees, whose questionnaire includes relevant digital and green information. Given the filters of the questionnaire, we are capable to exploit its information for as many as 154,782 firms. The reference year for the collected information is 2018 and, in some cases, questions refer to the previous triennium (2018-2016). See Appendix A.1 for more details on the data.

3.1. Main variables

The dependent variable used to test our hypotheses is a binary and equal to 1 if a firm declares that it has redesigned its production process and/or adopted new production models to promote its environmental sustainability. A positive reply to this question indicates that the firm has introduced an eco-innovation in the realm of its production processes, hereafter *Eco-innovation*. However, the question has been posed only to firms that have declared to have put in place some (generic) action to reduce the environmental impact of their activities, hereafter *Eco-action*. Therefore, firms replying to *Eco-innovation* are filtered by the questionnaire design on the basis of their reply to the question on *Eco-action*, causing potential endogenous selection issues (see Appendix A.1 for more details on the two variables).

[4] https://www.istat.it/it/censimenti-permanenti/imprese.

Our main regressor is a set of dichotomic variables that capture whether firms have invested (in the period 2016-2018) in an array of digital technologies. Unfortunately, we do not have information on the firm domain (e.g., R&D rather than production) in which investments have occurred. Still, this is a relevant piece of information to proxy firms' resources and capabilities in the field of digital technologies.

Following the structure of the questionnaire, we first consider the original classification proposed and test our hypotheses by distinguishing digital investments along three *areas* (see Table 1, first column):

1) Internet based technologies (*Internet*), encompassing specific digital domains (second and third columns of Table 1) that refer to the application of internet to connectivity between devices and between devices and objects;

2) Areas of application of *Artificial Intelligence*, including big data analytics, augmented and virtual reality, automatization, robotics and smart-systems;

3) Other technological areas (*Other digital*), grouping digital domains that do not fall in the previous two, like 3D printing, simulation of interconnected machines, and cyber-security.

Despite their heterogeneity and possible alternatives for grouping the specific items, we use this categorization for the sake of consistency with the survey design.

In the second part of the analysis, to get more accurate tests of our hypotheses, we repeat our estimates unpacking digital investments along the two domains illustrated in Table 1. For each technological area, we single out the digital domain that is generally associated with Industry 4.0 and recognized as more enabling, and we keep the other (relatively less enabling) digital technologies together. This approach allows us to pinpoint the following three Industry 4.0 technologies: *Internet of Things*, *Big data* analytics, and *3D printing.* [5]

[5] The identification of Industry 4.0 technologies is not univocal, and heterogeneous is also the ranking of their degree of importance for the paradigm. Drawing on the extant literature (see, for example, Dalenogare et al., 2018) we are confident to retain IoT as one of the most typical Industry 4.0 domains, due to the internet-object interoperability it adds to the other internet-based technologies covered by our survey (Gilchrist, 2016). Similarly, 3D printing is directly related to the fundamental dimension of additive manufacturing (Weller et al., 2015), which affects Industry 4.0 production process of firms more directly than security and simulation digital applications. Big data elaboration and analysis are possibly as enabling for Industry 4.0 as the other interactive technologies that our survey encompasses. However, we follow the literature and consider the former separately from the latter because of its potential in bringing the greatest "jump" for the unfolding of Industry 4.0 (Wamba et al., 2015).

Table 1 – Digital technology areas and domains

Areas	Main Industry 4.0 domain	Other domains
1) Internet based technologies	Internet of Things	Internet connection *(optic-fiber ultra-broadband connection + mobility connection (4G and 5G))*
2) Areas of application of AI	Elaboration and analysis of big data	Interactive technologies *(immersive technologies + advanced automatization, collaborative robots and smart systems)*
3) Other technological areas	3D printing	Security and simulation (simulation of interconnected machines + cyber-security)

Note: authors elaboration on the possible answers to the question: has the company invested in the 2016-2018 period in the following digital technologies? In the last column the specific items are those reported within parentheses.

In the final part of the analysis, we refer to all the nine digital items from the questionnaire and sum them to construct a measure of digital bundling, which results in an ordinal variable spanning from 0 (none) to 9 (all).

3.2 Control variables

In our estimates we include a series of variables to control for observable characteristics that may influence a firm propensity toward *eco-action* and *eco-innovation*. The inclusion of these variables is meant to better identify the relationship between digital technologies and eco-innovation.

First of all, to control for knowledge inputs of the firm we include two binary variables, *R&D high* and *HC high*, that are equal to 1 when a firm has declared a high investment intensity in Research & Development, and in human capital and training during the 2016-2018 period.[6] The crucial role of R&D and human capital in fostering (eco-)innovation is an established result in the literature, in which R&D has been also proven to moderate the relationship between the development of green technologies and softer types of intangible assets (Ghisetti et al., 2021). We also account for the fact that a firm might have invested intensively (high), still during the 2016-2018 period, in machines and equipment with a binary variable: *capital*. As we are considering eco-innovations in the domain of firm production processes, generic physical investments are a relevant factor to control for.

Given the increasing importance of an open eco-innovation mode (Ghisetti et al., 2015), we also control for the presence of collaborations with other firms or public organizations in the form of *formal agreements* (e.g., join ventures or consortia) and *informal agreements*. Similarly, we control for the role that internationalisation has for eco-innovating, as emerged from previous studies (e.g.,

[6] The other alternatives were medium, low, and no investment.

Cainelli et al., 2012), by including the variable *international markets* that is equal to 1 if a firm has exported goods and services outside Italy.

Finally, in the estimates we include variables that control for the structural features of the focal firms: *size* (micro, small, medium and large), and whether they are controlled by a physical person or family (*Family firm*), rather than being a public company (e.g., limited liability companies). Regional (20) and industry (70) fixed effects are included to control for the spatial and industry location of the focal firms.

Table A.1 in Appendix 2 reports the descriptive statistics of the variables used in the analysis.

3.3 Econometric strategy

Given the selection introduced by the questionnaire design, a standard probit model to estimate *Eco_innovation* may lead to biased results. Accordingly, we account for endogenous sample selection (Heckman, 1979) fitting a probit model for *Eco_innovation* with selection on *Eco_action*:

$$Eco\_innovation_i = 1\ (digital_i\beta + controls_i\gamma + u_i > 0)$$
$$Eco\_action_i = 1\ (digital_i\beta_s + controls_i\gamma_s + Z_i\alpha_s\ +\ u_{si} > 0)$$

where $Eco\_innovation_i$ (= 0,1) is observed only if Eco_action_i = 1. $Digital_i$ is the vector of digital technology investments, and $controls_i$ are the other variables included in the regression analysis. The subscripts s are used to differentiate the parameters estimated in the selection equation and the relative error term.

The selection process induced by *Eco_action* is relevant, as it filters out about 40% of firms in the sample. To model this selection process, we include in the *Eco_action* equation a vector Z_i of two variables. The first, *Outsourcing*, is equal to 1 if the focal firm has declared to have resorted to external providers for undertaking its "non-core" business activities (i.e., ancillary activities like distribution, storage, marketing, and the like). Outsourcing can in fact entail a reduction of a firm environmental impact as it could be a channel through which externalizing some polluting activities. Of course, by outsourcing knowledge and core business functions (e.g., R&D), a firm could also increase its capacity to eco-innovate (Leoncini et al., 2016). To rule out this direct link from outsourcing to *Eco_innovation* we thus consider outsourcing only of non-core business activities. By doing so, we expect that outsourcing firms tend to have higher propensity to put in place activities to reduce their environmental impact, which are not necessarily linked to eco-innovation.

The second variable in Z is intended to capture what we call the *environmental numbness* of a firm. By this we mean the incapacity and/or unwillingness of a firm to put in place environmental actions – like reducing the consumption of natural resources or managing waste and emissions in a sustainable way – that go beyond legal requirements. To build up this variable we have relied on a question in which firms are asked to indicate whether they have implemented a detailed list of 11 eco- and circular-economy actions (see Appendix A.1). *Environmental numbness* is a binary variable equal to 1 if the firm has declared to have just sticked to environmental regulations for all the 11 activities. We include this variable to capture "false positives": firms that do not have an environmental sensibility, and that might thus have interpreted the question about *eco-action* differently from the others.[7] In particular, these firms should not have replied "yes" to the question about *eco-action* (that entail the setting of environmental objectives within the firm) and when they did, one can expect that the numbness is reflected into a lower propensity to invest in the development or adoption of eco-innovations. Table A.2 in Appendix 2 reports two-way tabulations of *environmental numbness* against *eco-action* and *eco-innovation*. Among the environmental numbed firms, 32% have declared to have taken eco-action (against the 76% for the other firms) and eco-innovation is rather infrequent (5% vs. 18% of other firms). These marked differences suggest that *environmental numbness* is capable to discriminate against false positives and therefore relevant to model the endogenous selection process.

4. Results

4.1 Eco-innovations and digital technologies in the Italian production system

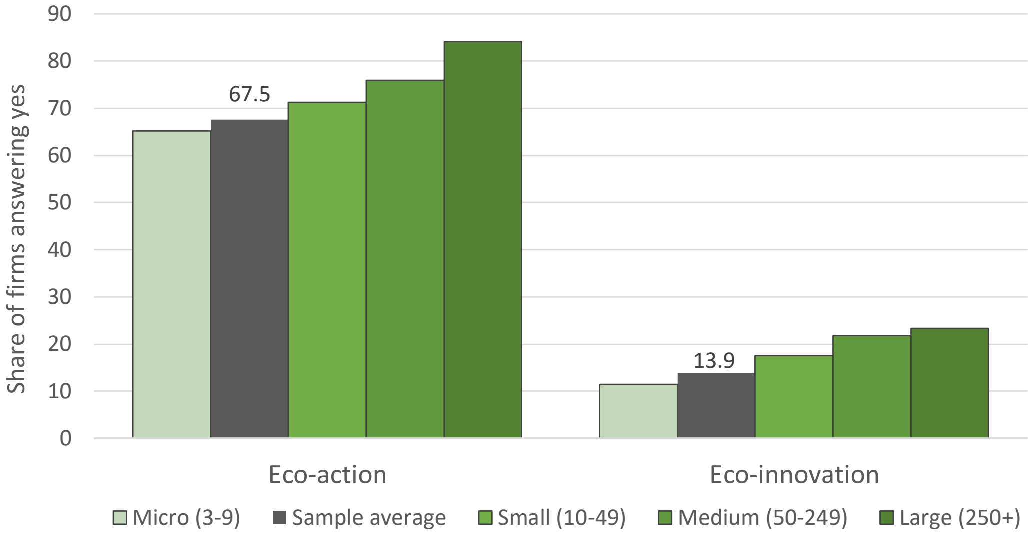
Before moving to the results of the econometric estimates, we present some descriptive evidence on eco-innovation and digital investment in the Italian production system.

Figure 1 shows that the share of firms declaring an *Eco-action* is much larger than that of firms introducing *Eco-innovation* (67.5% versus 13.9%). Both these shares steadily increase with firm size, with the relative increase of *Eco-innovation* being more marked than that of *Eco-action.* The probability that a large firm introduces new environmentally sustainable production models and processes is more than double than that for the average micro-firm (23.4% vs. 11.5%). This suggests

[7] The interpretation of questions and answers is a key element in the design of questionnaires (Krosnick and Presser, 2010).

that economies of scale are more crucial in enabling firms' eco-innovation than eco-action, and that SMEs are more at disadvantage in the former than in the latter.

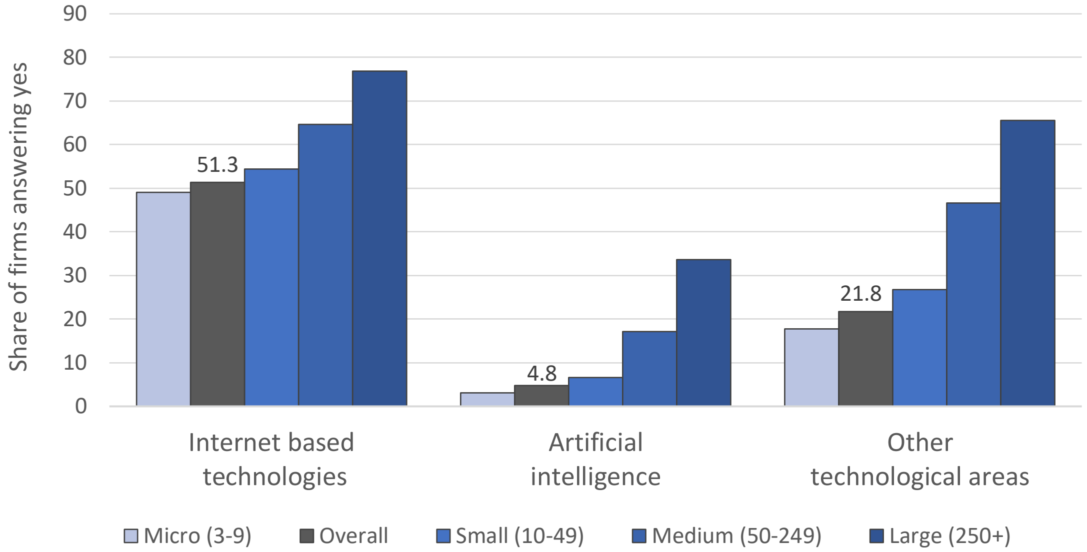
Figure 1. *Eco-action* and *eco-innovation* across firm of different size (%)



Note: weighted figures, representative of the Italian economic system.

When considering digital technologies, firms' investments differ substantially both across the areas identified by the questionnaire and across firm size (Fig. 2). On average, investments in internet-based technologies are present in more than half of the sampled firms (51%) with an incidence among micro-firms slightly lower than 50%, suggesting this is an area where the required investments appears generally affordable. With less than 5% of italian firms investing in technologies in the areas of application of AI, these technologies appears instead quite exclusive with small and micro-firms showing a rather lower incidence. Investments in other digital technology areas – including those in additive manufacturing – lay in-between and concern about 22% of italian firms. The differences across firms size in the propensity to invest in digital technologies are relevant, with large companies systematically outperforming small ones. The gap is particularly maked in the AI area, where the probability that a large firm declares an investment is 11 larger than that of a micro firm and 5 times that of a small firm. As SMEs represent the substrate of the Italian production system, this result requires great attention in the policy efforts to promote the new wave of digitalisation.

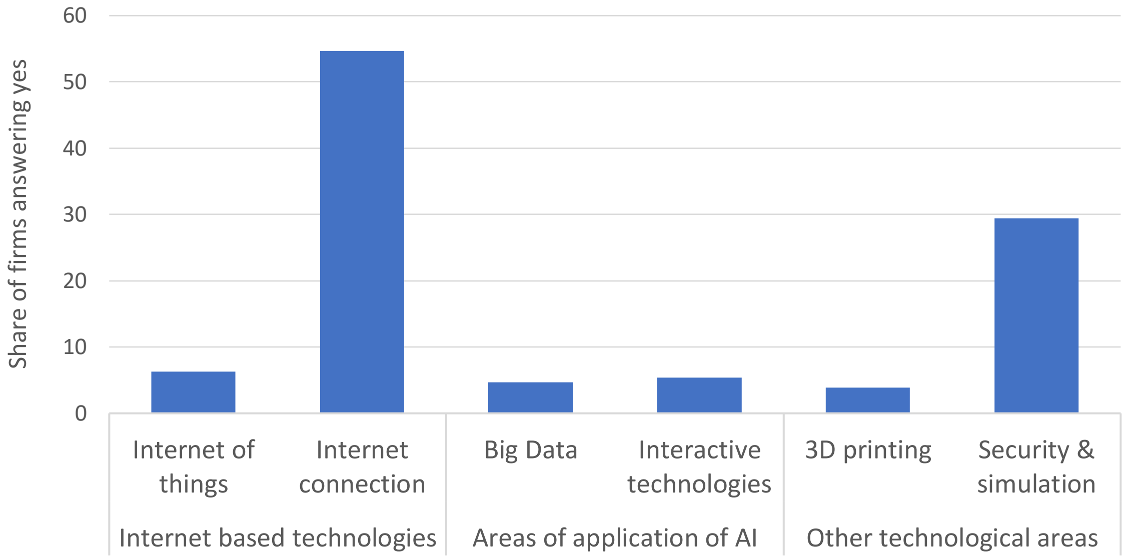
Figure 2. Investment in digital technology areas (Table 1) across firms of different size (%)



Note: weighted figures, representative of the Italian economic system.

Even more remarkable is what emerges from Figure 3. The domains that we have identified as the most Industry 4.0 enabling of the two areas – IoT and 3D printing – reveal the same low shares of investing firms of the AI domains. Conversely, higher shares of investing firms emerge for the other digital domains: security and simulation technology (30% of firms), and other internet connection applications than IoT (55%).

Figure 3. Investments in different digital domains (%)



Note: weighted figures, representative of the Italian economic system.

Overall, this picture suggests that the involvement of Italian firms in the digital technologies characterizing industry 4.0 is still limited and that the Italian system appears still anchored to technologies usually associated to the industrial paradigm of the internet (Third) revolution.

For the sake of our econometric analysis, this evidence suggests that regrouping the digital technologies investments according to the "Industry 4.0" and the "Other" domains may provide more accurate in assessing the impact of digital technologies on firms' eco-innovation than the areas identified by the survey.

4.2 Regression analysis

Table 2 reports the results of the regression analysis using the three digital technology areas proposed by the survey (Table 1). Results are organised along two columns: the left column refers to the introduction of new sustainable production models and processes (*Eco-innovation*), while the right column reports the results of the selection equation (*Eco-action*) confirming our expectations about the relevance and sign of outsourcing and environmental numbness. O*utsourcing* is positively related to eco-action (firms that externalise non-core business activities tend to be selected), while *environmental numbness* is strongly negative. This support our arguments about the fact that environmentally numbed firms do not pro-actively pursue *eco-action* and might contribute biasing the results when selection is not accounted for. The correlation among the errors terms of the two columns is statistically significant which, along with results of the likelihood test (at the bottom of the table), supports our econometric strategy. Indeed, the use of a simple probit would have entailed a bias that, as Table A.3 in Appendix 2 reveals, would have led to different results.

Investments in all the three digital areas are positively associated to the firms' *eco-action* (selection equation), with the coefficients attached to *internet* and *other digital* significantly larger than that attached to *AI*. Conversely, *AI* is the only digital area positively and statistically significantly associated with the introduction of *eco-innovation*. This first set of results confutes our HP1 about a generalized positive relationship between investments in digital technologies and the introduction of new environmentally sustainable production models and processes at the firm level. Results also show a prominent (if not exclusive) role played by *AI* for *eco-innovation*, thus supporting the arguments about the special role that this technology could have in the green domain and that led to put forward our HP2.

Table 2 – Digital technologies and Eco-innovation (new environmentally sustainable production processes)

(probit model with endogenous selection on eco-action)

	Eco-innovation	*Eco-action* (selection)
Internet	-0.005	0.157***
	(0.010)	*(0.008)*
Artificial Intelligence	0.229***	0.072***
	(0.016)	*(0.015)*
Other digital	0.005	0.178***
	(0.010)	*(0.009)*
R&D high	0.306***	0.048***
	(0.016)	*(0.017)*
HR high	0.165***	0.200***
	(0.016)	*(0.015)*
Capital	0.110***	0.291***
	(0.011)	*(0.010)*
Small firm (10-49)	0.042***	-0.033***
	(0.012)	*(0.009)*
Medium firm (50-249)	0.028*	0.020
	(0.016)	*(0.013)*
Large firm (250+)	0.006	0.266***
	(0.028)	*(0.029)*
Family firm	0.023**	0.043***
	(0.009)	*(0.008)*
Collaboration agreements	0.055***	0.128***
	(0.010)	*(0.009)*
Informal collaborations	0.027**	0.077***
	(0.011)	*(0.010)*
International markets	0.001	0.035***
	(0.011)	*(0.009)*
Outsourcing		0.095***
		(0.013)
Environmental numbness		-1.029***
		(0.013)
Constant	-0.645	0.811
	(0.556)	*(0.588)*
Industry fixed effects	*Yes*	*Yes*
Regional fixed effects	*Yes*	*Yes*
Correlation among errors	-0.648***	
	(0.018)	
Observations (selected)	154,782 (109,018)	
Chi-2 (p-val)	0.000	
LR test	527	

Note: robust standard errors in parentheses. p<0.01***, p<0.05**, p<0.1*. The regressions include 20 regional and 70 industrial binary variables. The correlation among errors and the LR-test suggest that a selection model should be preferred to a standard probit regression.

The coefficients attached to the control variables show in general the expected signs. Firms with a high R&D intensity have a higher probability both to introduce an *eco-innovation* and to pursue an *eco-action*; and the same holds true for firms showing a high investment intensity in human capital

and training. Quite interestingly, while large firms have a higher probability to pursue an *eco-action* compared to micro firms (the baseline), they do not display a higher propensity to *eco-innovate*. The differences in *eco-innovation* showed in Figure 1 are thus not significant when retaining the endogenous selection and the heterogeneity entailed by the other control variables (as the positive relationship between firm size and both *eco-innovation* and digital investments).
An interesting finding emerges also with respect to the firm exposition to *international markets* as this is positively and significantly associated to *eco-action* but not with *eco-innovation*. In brief, the positive environmental effects that the literature has recognised to firm's internationalisation, appears to stop at the doors of its eco-action and do not enter the implementation of eco-innovations. The positive coefficients attached to family firms in both columns of Table 2 suggest a better performance of this type of firms with respect to the environmental outcomes at stake, a positive result for a production system that is characterized by a high share of family firms. This result is in line with recent literature highlighting that family firms, while eventually investing less in innovation, have a higher conversion rate of innovation input into output, which results in a higher innovation output than non-family firms (Duran et al., 2015). Finally, firms with external collaboration agreements, both formal and informal, tend to perform better with respect to the environmental variables considered, supporting previous results about the importance of an open eco-innovation mode (Ghisetti et al., 2015).

To quantify the strength of the relationship between digital technology investments and our environmental variables, Table 3 reports the average marginal effects of the digital variables, both for the selection and the main equation. On average, firms investing in *AI* have a probability of eco-innovating 7.6 percentage points (p.p.) higher than that of firms not investing in AI: the relationship between AI and *eco-innovation* is remarkable in magnitude. Conversely, firms investing in internet-based technologies and in other digital areas have a higher probability to declare an *eco-action* (+4.8 and +5.3 p.p.) compared to those investing in AI (+2.2 p.p.). This suggests that firms investing in digital areas other than AI may pursue softer types of eco-innovations than those we are referring to by looking at the firm production process.

To evaluate the biases that might derive from a simple probit specification, the average marginal effects commented above can be compared with those resulting from a probit regression of *eco-innovation* (which results are reported in Appendix 2, table A.3). The average marginal effects from a probit estimation are positive also for internet based and other digital technologies (1.5 and 1.9 p.p.), while that for AI is much in line with our main results (7.1 p.p). In other words, a probit estimation would provide upward biased results for internet based and other digital technologies but not for AI, which in any case maintains a much higher average marginal effect.

Table 3 – Average Marginal Effects of digital technologies on eco-innovation

	Eco-innovation		*Eco-action*	
	AME	95% confidence interval	AME	95% confidence interval
Internet	-0.2	[-0.75 || 0.44]	4.8***	[4.36 || 5.26]
Artificial intelligence	7.6***	[6.61 || 8.59]	2.2***	[1.33 || 3.04]
Other digital	0.1	[-0.50 || 0.78]	5.3***	[4.82 || 5.84]

Note: Average marginal effect (AME) are computed averaging the marginal effects for each observation – or having eco-redesigned the production process and/or introduced new eco-models of production (left), and of declaring an environmental action (right).

To obtain a more accurate test of our first two hypotheses, the left-hand panel of Table 4 reports the results of the estimates that distinguish between the most Industry 4.0 enabling technology and the other technologies for each of the three digital areas. The right panel of Table 4 reports instead the results relative to HP3, assessing the impact of the digital bundling on *eco-innovation.* Due to space constraints, our testing approach does not single out the specific combinations of digital investments. By remaining agnostic about the different complementarities among digital technologies (e.g., IoT with big data analytics, rather than 3D printing with robots, in the combination of two domains) and their possibly specific environmental impact, we limit our investigation to testing whether combining a higher number of digital domains – what we called "bundling" – is associated with a higher propensity to eco-act and eco-innovate.

To start with, the regression results using the six digital domains, on the left panel, confirm and further qualify the evidence discussed above. Both domains in the AI area – big data and interactive technologies – show positive and statistically significant coefficients. On the one hand, this result supports our HP2 at the extensive margin, suggesting that the relationship between AI and EI extends to the different domains of the former. On the other hand, these results also suggest that big data and interactive applications might go hand in hand in firms understanding of AI. Considering the other digital areas, the unpacking of technological domains does instead provide additional and interesting evidence. For both the internet and the residual areas, the only digital technologies that are positively associated with EI are in fact the arguably most enabling of the Industry 4.0, that is, IoT and 3D printing. Quite interestingly, while not supported in terms of the broad digital areas of Table 2, HP1 gets confirmed with respect to specific the digital domains within each area. In other words, it is not the digital transition across the board that appears amenable to be exploited for green, but only the specific digital technologies from which the advent of the smart factory is deemed to depend to the greatest extent.

Table 4 – Digital domains and bundling for eco-innovation

Digital domains	Eco-innovation	Eco-action (selection)	Digital bundling	Eco-innovation	Eco-action (selection)
Internet of Things	0.073***	0.137***	One digital technology	-0.017	0.166***
	(0.017)	*(0.017)*		*(0.012)*	*(0.009)*
Internet connection	-0.011	0.149***	Two digital technologies	-0.019	0.253***
	(0.010)	*(0.008)*		*(0.013)*	*(0.010)*
Big Data	0.109***	-0.008	Three digital technologies	0.051***	0.340***
	(0.020)	*(0.020)*		*(0.016)*	*(0.013)*
Interactive technologies	0.218***	0.103***	Four digital technologies	0.160***	0.428***
	(0.018)	*(0.019)*		*(0.022)*	*(0.021)*
3D printing	0.115***	-0.032	Five digital technologies	0.186***	0.426***
	(0.020)	*(0.021)*		*(0.031)*	*(0.033)*
Security & simulation	-0.013	0.181***	Six digital technologies	0.277***	0.519***
	(0.011)	*(0.009)*		*(0.044)*	*(0.051)*
			Seven digital technologies	0.377***	0.621***
				(0.062)	*(0.079)*
			Eight digital technologies	0.587***	0.149
				(0.089)	*(0.094)*
			Nine digital technologies	0.657***	0.582***
				(0.088)	*(0.103)*

Note: full results are reported in the Appendix 2, table A.4.

Moving to our HP3, the right panel of Table 4 provides its confirmation with some interesting nuances. As expected, the probability of introducing new sustainable production processes and models steadily increases with the number of digital technology domains in which a firm invests, that is, with the size of its digital bundle. The result suggests that bundling digital investments enables the firm to exploit cross-fertilisation of ideas and functional complementarities in implementing new eco-sustainable production solutions. However, a minimum size seems required for the digital bundle to exert its positive influence on *eco-innovation*. In our estimates, a firm needs to invest in at least three (out of nine) of the digital items presented by the survey for a positive relationship to emerge as significant. This introduces an interesting specification in testing HP3: not only bundling digital investments increase the firm's propensity to eco-innovate, but a minimum extent of bundling appears necessary for the positive effect to unfold.

5. Conclusions

Combining the green and the digital transition is a target that policy makers, especially in Europe, are trying to pursue in the attempt of making economies recover along sustainable and inclusive growth patterns. An important part of the green & digital transition resides in making digital technologies functional to the diffusion of sustainable production and consumption patterns and to the advancement of new green technologies. At the business level, this entails that firms should be capable to exploit the new wave of digital technologies for introducing new environmentally sustainable production processes and models.

Drawing from recent literature about Industry 4.0 and eco-innovation, we have posited that by investing resources in digital technologies, firms can acquire competencies and capabilities to deal with the complex process of knowledge recombination from which eco-innovations have recognised to descend (Barbieri et al., 2020). On the same line, we have also maintained that investments in the area of AI should have a greater enabling role of the firm's capacity to eco-innovate and that investing in bundles of digital technologies may spur complementarities that can be leveraged for eco-innovating.

We have tested these arguments with respect to a large sample of Italian firms, representing a system whose industrial structure is characterized by the pervasiveness of small and medium enterprises (SMEs). Indeed, descriptive evidence has shown that the share of firms taking eco-actions and adopting eco-innovations increases with their size. Moreover, the firms' involvement in digital investments appears nearly exclusive to large ones, especially when referring to the most enabling Industry 4.0 technologies. In Italy, and arguably in structurally similar countries, the twin-transition proceed following a two-speed pattern and policy makers should be particularly concerned by the slowest (smallest) one.

The results of the econometric analysis generally confirm our hypotheses about the role that firms' digital investments can play in spurring their capability to eco-innovate. However, the results also suggest that the positive relationship between digital technologies and EI works selectively. The AI area is the one from which the firms' propensity to eco-innovate benefit the most, and the only one at an extensive margin. When unpacking the digital areas, AI is in fact the only one with which eco-innovation is significantly associated with respect to both its constitutive domains: big data and interactive technologies like immersive ones, advanced automatization, collaborative robots and smart systems. As expected, AI applications are the digital technologies with the most cogent opportunities to be harnessed for environmental sustainability and the policy support to the twin transition should accordingly focus on their potential applications (World Economic Forum, 2018). However, the unpacking of digital areas also allows us to single out the relevant role played by the other digital technologies typically associated to the Industry 4.0 paradigm, like IoT and 3D printing (as an element of additive manufacturing), pointing to the possible role of bundling effects across different technologies.

Considering the increasing returns that may arise from the bundling of digital investments to eco-innovate, our results also provide nuanced results. The probability that a firm eco-innovate steadily increases with the extent of the digital bundling and, interestingly, a minimum degree of bundling is required before the positive returns arise. This result suggests that to unfold the potential of the twin-transition, firms should diversify their investments over a minimum array of different digital technologies. In this last respect, the issue for policy makers becomes how to support complementary investments in digital technologies, which can be prohibitive for micro and small firms.

Our work, of course is not free from limitations, largely due to the data at our disposal. First, we can hardly claim for causality of our detected relationships; we have dealt with the endogenous sample selection entailed by the questionnaire, but other simultaneity issues in our relationship may be still at play. Second, we cannot isolate the specific firm's domains to which digital investments have been dedicated, and this forced us to remain agnostic about the development or the adoption of digital technologies. Finally, due to space limits, we have neither investigated whether sector specificities arise in the twin-transition, nor assessed explicitly whether specific typologies of bundling matters more than others. These are areas that are worthwhile investigating and that we hope to be able to pursue with further access to the micro-datalab at ISTAT and with the upgrade of the Census we have used at which ISTAT is working.

That said, our analysis has provided empirical evidence supporting the positive relationship between investments in digital technologies and eco-innovation, allowing to single out the role of specific digital domains (AI and Industry 4.0 in particular) on a large sample of firms. We deem the marked differences emerged among firms of different size and the possible complementarities among digital technologies for the twin-transition as interesting avenues for future research.

References

Azadi, M., Moghaddas, Z., Cheng, T.C.E., & Farzipoor Saen, R. (2021). Assessing the sustainability of cloud computing service providers for Industry 4.0: a state-of-the-art analytical approach. International Journal of Production Research, 1-18.

Barbieri, N., Marzucchi, A., & Rizzo, U. (2020). Knowledge sources and impacts on subsequent inventions: Do green technologies differ from non-green ones?. Research Policy, 49(2), 103901.

Bonilla, S. H., Silva, H. R., Terra da Silva, M., Franco Gonçalves, R., & Sacomano, J. B. (2018). Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges. Sustainability, 10(10), 3740.

Bresnahan, T. (2010). General purpose technologies. In Handbook of the economics of innovation, Vol. 2, ed. B. H. Hall, and N. Rosenberg, 761–91. Amsterdam, the Netherlands: Elsevier.

Cainelli, G., Mazzanti, M., & Montresor, S. (2012). Environmental innovations, local networks and internationalization. Industry and Innovation, 19(8), 697-734.

Carlaw, K.I., & Lipsey, R.G. (2002). Externalities, technological complementarities and sustained economic growth. Research Policy, 31(8–9), 1305-1315.

Castellacci, F., Consoli, D., & Santoalha, A. (2020). The role of e-skills in technological diversification in European regions. Regional Studies, 54(8), 1123-1135.

Castellacci, F. (2008), Technological paradigms, regimes and trajectories: manufacturing and service industries in a new taxonomy of sectoral patterns of innovation. Research Policy, 37(6–7), 978–994.

Cicerone, G., Faggian, A., Montresor, S., Rentocchini, F. (2019). Harnessing artificial intelligence for regional eco-innovation: a patent-based analysis of European regions' green-tech diversification. Paper prepared for the 2019 AISRE Conference, GSSI (L'Aquila).

Dalenogare, L.S., Benitez, G.B., Ayala, N.F., & Frank, A.G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. International Journal of Production Economics, 204, 383-394.

Díaz-Chao, Á., Ficapal-Cusí, P., & Torrent-Sellens, J. (2021). Environmental assets, industry 4.0 technologies and firm performance in Spain: A dynamic capabilities path to reward sustainability. Journal of Cleaner Production, 281, 125264.

Duran, P., Kammerlander, N., Van Essen, M., & Zellweger, T. (2016). Doing more with less: Innovation input and output in family firms. Academy of Management Journal, 59(4), 1224-1264.

EC (2020). A New Industrial Strategy for a green and digital Europe. https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age/european-industrial-strategy_en#accelerating-twin-transitions

Erdmann, L., Hilty, L., Goodman, J., Arnfalk, P. (2004). The Future Impact of IT on Environmental Sustainability. Technical Report EUR 21384 EN, EC-JRC. Institute for Prospective Technological Studies.

Faucheux, S., Hue, Ch., Petit, O., (2002). NTIC et environnement : enjeux, risques et opportunités. Futuribles 273, 3–26.

Faucheux, S., & Nicolaï, I. (2011). IT for green and green IT: A proposed typology of eco-innovation. Ecological Economics, 70(11), 2020-2027.

Frank, A.G., Dalenogare, L.S., & Ayala, N.F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. International Journal of Production Economics, 210, 15-26.

Ghisetti, C., Marzucchi, A., & Montresor, S. (2015). The open eco-innovation mode. An empirical investigation of eleven European countries. Research Policy, 44(5), 1080-1093.

Ghisetti, C., Montresor, S., & Vezzani, A. (2021). Design and environmental technologies: Does 'green-matching'actually help?. Research Policy, 50(5), 104208.

Gilchrist, A. (2016). Industry 4.0: the industrial internet of things. Apress.

Jaffe, A.B. (1986). Technological Opportunity and Spillovers of R&D, American Economic Review, 76, 984-1001.

Jena, M.C., Mishra, S.K., & Moharana, H.S. (2020). Application of Industry 4.0 to enhance sustainable manufacturing. Environmental Progress & Sustainable Energy, 39(1), 13360.

Haake, J., Gueorguievsky, B. (2010). L'entreprise légère, Delachaux et Niestlé editions. Collection Changer d'ère.

Heckman, J. (1979). Sample selection bias as a specification error. Econometrica 47: 153–161.

Hilty, L.M. (2008). Information Technology and Sustainability. Verlag Book on Demand, Norderstedt.

Hilty, L.M., et al. (2005). The Precautionary Principle in the Information Society – Effects of Pervasive Computing on Health and Environment. TA-Swiss, Bern.

Holmström, J., Holweg, M., Khajavi, S. H., & Partanen, J. (2016). The direct digital manufacturing (r)evolution: definition of a research agenda. Operations Management Research, 1–10. http://doi.org/10.1007/s12063-016-0106-z.

Horváth, D., & Szabó, R.Z. (2019). Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?. Technological forecasting and social change, 146, 119-132.

ISTAT (2020). Censimento permanente delle imprese 2019: i primi risultati. Istituto Nazionale di Statistica, https://www.istat.it/it/files//2020/02/Report-primi-risultati-censimento-imprese.pdf.

Jena, M.C., Mishra, S.K., & Moharana, H.S. (2020). Application of Industry 4.0 to enhance sustainable manufacturing. Environmental Progress & Sustainable Energy, 39(1), 13360.

Krosnick, J.A. & Presser, S. (2010). Question and Questionnaire Design. In Marsden, P.V. & Wright J.D. (eds.), Handbook of Survey Research, Emerald Group Publishing Limited, 263-313.

Kumar, R., Singh, R.K., & Dwivedi, Y.K. (2020). Application of industry 4.0 technologies in SMEs for ethical and sustainable operations: Analysis of challenges. Journal of cleaner production, 275, 124063.

Liao, M., Lan, K., & Yao, Y. (2021). Sustainability implications of artificial intelligence in the chemical industry: A conceptual framework. Journal of Industrial Ecology.

Leoncini, R., Marzucchi, A., Montresor, S., Rentocchini, F., & Rizzo, U. (2019). 'Better late than never': the interplay between green technology and age for firm growth. Small Business Economics, 52(4), 891-904.

Martinelli, A., Mina, A., Moggi, M. (2021). The enabling technologies of industry 4.0: examining the seeds of the fourth industrial revolution. Industrial and Corporate Change, 2021, Vol. 30 No. 1, 161–188.

Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S., & Barbaray, R. (2018). The industrial management of SMEs in the era of Industry 4.0. International Journal of Production Research, 56(3), 1118-1136.

Müller, J. M., Buliga, O., & Voigt, K. I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. Technological Forecasting and Social Change, 132, 2-17.

Muscio, A., & Ciffolilli, A. (2020). What drives the capacity to integrate Industry 4.0 technologies? Evidence from European R&D projects. Economics of Innovation and New Technology, 29(2), 169-183.

OECD, 2009. Guide to Measuring the Information Society .www.oecd.org/sti/measuringinfoeconomy/guide.

Philbeck, T., & Davis, N. (2018). The fourth industrial revolution. Journal of International Affairs, 72(1), 17-22.

Teece, D. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. Research Policy, 47(8), 1367-1387.

Wamba, F.S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How "big data" can make big impact: findings from a systematic review and a longitudinal case study. Int. J. Prod. Econ. 165, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031.

Weller, C., Kleer, R., & Piller, F.T. (2015). Economic implications of 3D printing: market structure models in light of additive manufacturing revisited. Int. J. Prod. Econ. 164, 43–56. https://doi.org/10.1016/j.ijpe.2015.02.020.

World Economic Forum (2018). Harnessing Artificial Intelligence for the Earth, Fourth Industrial Revolution for the Earth Series, In Collaboration with PwC and Stanford Woods Institute for the Environment.

Appendix 1 – Dataset and environmental variables

The ISTAT Permanent Census of Italian firms

The census is a brand-new survey carried out by ISTAT that provides information combining a stratified sample approach for firms with employees between 3 and 19 with census information for firms with 20+ employees (see ISTAT, 2020). Data are made available to researchers only through the Laboratory for Elementary Data Analysis (ADELE) at ISTAT premises, the sample is made of about 200K firms operating in all types of sectors. This sample corresponds to about 24.0% of Italian firms with 3 or more employees, 84.4% of the national added value, and employing 76.7% of Italian workers (12.7 million). However, the questionnaire is divided into core and optional questions (with the latter submitted to a smaller number of firms), which include our focal ones about eco-innovations and investments in digital technologies. Because of that, the sample used in our empirical application is made up of 154,782 firms. The reference year for the collected information is 2018 and, in some cases, questions refer to the previous triennium (2018-2016).

The environmental variables used in the analysis refers to the following survey questions and answers:

- For the variable *Eco-Innovation*, we have exploited answer "Redesign the production process and/or adopt new production models" to the question "In the 2016-2018 period, what solutions were adopted by the company to promote environmental sustainability?

- For the variable *Eco-Action*, we have exploited the answer "Reduce the environmental impact of its activities", to the question "Beside achieving satisfactory economic and financial results, what other actions have been taken by the company?"

- For the variable *Environmental numbness*, we have exploited the question "In the three-year period 2016-2018, in addition to what is required by law, did the firm take the following actions to reduce the consumption of natural resources and manage waste and emissions in a sustainable way?"

Firms answering "No" to each of the items proposed have *Environmental numbness* equal to 1:
A. Containment of water withdrawals and consumption
B. Treatment of wastewater aimed at containing and controlling pollutants
C. Reuse and recycling of wastewater
D. Saving of the material used in the production processes
E. Use of secondary raw materials (waste from the production process recovered and returned to production)
F. Waste sorting and recycling of waste
G. Waste management aimed at containing and controlling pollutants
H. Containment of atmospheric emissions
I. Containment of noise and / or light pollution
J. Recourse to suppliers who already adopted processes aimed at reducing the environmental impact of their activities
K. Other actions

Appendix 2 – Descriptive statistics and additional regression results

Table A.1 – Descriptive statistics

Environmental variables	Share	Digital investment	share
Eco-objective	0.704	Internet	0.556
New production models & processes	0.172	Artificial Intelligence	0.084
Firm size	Share	Other digital	0.306
Micro firm (2-9)	0.298	Technological domains	share
Small firm (10-49)	0.543	Internet of things	0.062
Medium firm (10-49)	0.136	Internet connection	0.547
Large firm (250+)	0.023	Big Data	0.047
Other variables	Share	Interactive technologies	0.054
R&D high	0.238	3D printing	0.039
HR high	0.327	Security & simulation	0.294
Capital	0.233	Digital bundling	# firms
Family firm	0.623	No digital technologies	57,728
Collaboration agreements	0.261	One digital technology	39,559
Informal collaborations	0.163	Two digital technologies	30,567
International markets	0.306	Three digital technologies	16,306
Outsourcing	0.080	Four digital technologies	6,149
Regulation fulfillment	0.043	Five digital technologies	2,445
		Six digital technologies	1,044
		Seven digital technologies	490
		Eight digital technologies	249
		Nine digital technologies	245

Table A.2 – Environmental numbness and environmental variables

Environmental numbness	Eco-action *(selection)*		Eco-innovation	
	No	Yes	No	Yes
No	23.8%	76.2%	82.0%	18.0%
Yes	67.6%	32.4%	94.9%	5.1%
Observations	154,782		109,018	

Note: shares should be read by row and separately for eco-action and eco-innovation

Table A.3 – Digital technologies and Eco-innovation, probit estimation

	Eco-innovation
Internet	0.065***
	(0.010)
Artificial Intelligence	0.274***
	(0.016)
Other digital	0.080***
	(0.011)
High R&D intensity	0.352***
	(0.018)
High human capital	0.258***
	(0.016)
Capital	0.237***
	(0.011)
Small firm (10-49)	0.041***
	(0.013)
Medium firm (10-49)	0.038***
	(0.013)
Large firm (250+)	0.081***
	(0.030)
Family firm	0.045**
	(0.010)
Collaboration agreements	0.115***
	(0.011)
Informal collaborations	0.062**
	(0.012)
International markets	0.018
	(0.012)
Constant	-1.177***
	(0.490)
Industry fixed effects	*Yes*
Regional fixed effects	*Yes*
Observations	109,018
Pseudo R2	0.077
Chi-2 (p-val)	0.000

Note: robust standard errors in parentheses. p<0.01***, p<0.05**, p<0.1*. The regressions include 20 regional and 70 industrial binary variables.

Table A.4 – Digital domains and bundling for eco-innovation, full results

Technological domains	Eco-innovation	Eco-action (selection)	Digital bundling	Eco-innovation	Eco-action (selection)
Internet of things	0.073***	0.137***	One digital technology	-0.017	0.166***
	(0.017)	*(0.017)*		*(0.012)*	*(0.009)*
Internet connection	-0.011	0.149***	Two digital technologies	-0.019	0.253***
	(0.010)	*(0.008)*		*(0.013)*	*(0.010)*
Big Data	0.109***	-0.008	Three digital technologies	0.051***	0.340***
	(0.020)	*(0.020)*		*(0.016)*	*(0.013)*
Interactive technologies	0.218***	0.103***	Four digital technologies	0.160***	0.428***
	(0.018)	*(0.019)*		*(0.022)*	*(0.021)*
3D printing	0.115***	-0.032	Five digital technologies	0.186***	0.426***
	(0.020)	*(0.021)*		*(0.031)*	*(0.033)*
Security & simulation	-0.013	0.181***	Six digital technologies	0.277***	0.519***
	(0.011)	*(0.009)*		*(0.044)*	*(0.051)*
			Seven digital technologies	0.377***	0.621***
				(0.062)	*(0.079)*
			Eight digital technologies	0.587***	0.149
				(0.089)	*(0.094)*
			Nine digital technologies	0.657***	0.582***
				(0.088)	*(0.103)*
R&D high	0.291***	0.046***		0.296***	0.039***
	(0.017)	*(0.017)*		*(0.017)*	*(0.017)*
HR high	0.160***	0.198***		0.156***	0.197***
	(0.016)	*(0.015)*		*(0.016)*	*(0.015)*
Capital	0.105***	0.288***		0.112***	0.288***
	(0.011)	*(0.010)*		*(0.011)*	*(0.010)*
Small firm (10-49)	0.044***	-0.033***		0.043***	-0.034***
	(0.012)	*(0.009)*		*(0.012)*	*(0.009)*
Medium firm (10-49)	0.029*	0.021		0.028*	0.019
	(0.016)	*(0.013)*		*(0.016)*	*(0.013)*
Large firm (250+)	-0.006	0.264***		-0.010	0.263***
	(0.028)	*(0.029)*		*(0.028)*	*(0.029)*
Family firm	0.022**	0.042***		0.024***	0.042***
	(0.009)	*(0.008)*		*(0.009)*	*(0.008)*
Collaboration agreements	0.052***	0.127***		0.054***	0.126***
	(0.010)	*(0.009)*		*(0.010)*	*(0.009)*
Informal collaborations	0.025**	0.077***		0.026**	0.076***
	(0.011)	*(0.010)*		*(0.011)*	*(0.010)*
International markets	-0.001	0.036***		0.002	0.035***
	(0.011)	*(0.009)*		*(0.011)*	*(0.009)*
Outsourcing		0.094***			0.094***
		(0.013)			*(0.013)*
Environmental numbness		-1.029***			-1.029***
		(0.010)			*(0.010)*
Constant	-0.657	0.820		-0.717	0.782
	(0.563)	*(0.589)*		*(0.571)*	*(0.590)*
Industry fixed effects	*Yes*	*Yes*		*Yes*	*Yes*

Regional fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Correlation among errors	-0.656***		-0.651***	
	(0.017)		*(0.018)*	
Observations	154,782		154,782	
Not selected	45,764		45,764	
Chi-2 (p-val)	0.000		0.000	
LR test	543		533	

Note: robust standard errors in parentheses. p<0.01***, p<0.05**, p<0.1*. The regressions include 20 regional and 70 industrial binary variables. The correlation among errors and the LR-test suggest that a selection model should be preferred to a standard probit regression.