"Look where you are!"
Firms' eco-innovations and digital technologies in urban vs. rural areas

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PRELIMINARY VERSION

Abstract (100 words)
We investigate the extent to which the adoption of digital technologies by firms correlates with their propensity to eco-innovate by distinguishing their location. We maintain that digitalisation affects firms' eco-innovation more in urban than rural areas, and that their twinning is stronger in large than in small cities/villages. Using the EU-Flash-Eurobarometer-486, we test these hypotheses for about 14,000 firms across 36 European countries in 2020 and confirm them partially. Firms in rural areas display a higher propensity to eco-innovate notwithstanding their poorer digital adoption. However, it is an urban (and small) location that reinforces the eco-innovative impact of digital technologies.

Key-words: digital technologies, eco-innovation, twin transition, geographical areas

JEL Codes: 030, Q55, R12

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1. Introduction

At a time in which the "net-zero transition" is an urgent imperative to avoid catastrophic climate change consequences (Fankhauser et al., 2022), the advancement of digital technologies associated to the so-called Industry 4.0, is posing new environmental threats and opportunities to its achievement. On the one hand, the development and adoption of digital technologies has been having harmful consequences on the depletion of rare input materials, energy and material consumption, electronic waste generation and disposal, and eventually carbon footprint (Schwarzer and Peduzzi, 2021). On the other hand, Industry 4.0 technologies are offering important opportunities to improve the green efficiency and footprint of current production and consumption modes and to facilitate the development of new green technologies for that to happen (Barteková and Börkey, 2022). In brief, as it was earlier recognised with respect to the previous wave of ICT (Faucheux and Nicolaï, 2011), digital technologies can be "green digital" and "digital for green", and their relationship with environmental sustainability is so complex to require reduction for the sake of analytical tractability.

Focusing on the digital-for-green side,[1] an important starting point is that nearly 50% of the reduction in CO2 emissions to reach the net-zero-transition by 2050 is expected to accrue from not-yet-existing cleaner technologies (IEA, 2021), making firms' eco-innovations (EI) a crucial leverage of environmental sustainability. In the light of that, within the context of the so-called twin-transition (EC, 2020; Muench et al., 2022), it becomes important to investigate to which extent the new wave of digital technologies can be harnessed by firms for the sake of EI.[2]

Despite all the hype about the "twin transition", this research pledge has been undertaken only recently and, through some few and (at the time of this writing) still unpublished works, it has started showing that digitalisation makes firms more eco-innovative with interesting nuances (Montresor and Vezzani, 2022; Kesidou and Ri, 2021; Demirel et al., 2022). Given its incipient stage, this literature inevitably still presents some gaps. Among these, an important one is represented by the scant knowledge about the spatial context in which the "twinning firms" are located.[3] The

[1] While of extreme relevance, the green-digital side will be not addressed in this paper and the interested reader is referred to an amounting stream of literature on the topic (see, for example, Patsavellas & Salonitis, 2019).

[2] Following a standard definition, this can be meant as the "production, assimilation or exploitation of a product, production process, service or management or business methods that is novel to the firm [or organization] and which results, through-out its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives" (Kemp and Pontoglio, 2007, p. 10)"

[3] Another crucial issue in these studies concerns the difficulty in distinguishing with available data between the invention/development and the adoption/use of digital technologies by firms.

progress of a spatial analysis of firms' EIs has in fact remained so far "blocked" in-between two different research streams. In a first stream, evolutionary economic geography has extended to green technologies (e.g., Cicerone et al., 2022; Castellani et al., 2022; Montresor and Quatraro, 2020; Santoalha and Boschma, 2021; Santoalha et al., 2021) a "relatedness approach" (Balland, 2016), which maps and investigates regional EI on a systematic basis (i.e., across ample samples of regions) by georeferencing green patent data in aggregate terms: that is, without keeping track of the individual firms and of the other micro-agents that contribute to build up the regional knowledge base. A micro-analysis of firms' EI across regions is instead present in a second stream about "new regional industrial path development" (Hassink et al., 2019); however, this looks at the unfolding of environmentally sustainable paths with a comparative case-study methodology, hampering the generalization of the relative results (Trippl et al., 2020).

The previous gap reverberates in the analysis of our relationship between firms' EI and digitalization, which has remained so far largely aspatial. Given the way in which the green and the digital transition are unfolding across places, this is a quite unfortunate gap. Along both the transitions, regional disparities are in fact emerging that risk to make them "unjust", especially in the contraposition between urban and rural areas (Traversa et al., 2022; Szeles, 2018; Wang et al., 2022; Corban et al., 2020), on which we focus in the present paper.

Taking stock of a new set of location-questions posed to a large sample of firms by the EU-Flash-Eurobarometer-486 survey, we contribute to filling this gap. In particular, we aim to investigate the extent to which the expected correlation between firms' digitalization and EIs varies with the urban nature of their location, that is, in terms of population density, size, and of the socio-economic aspects (e.g., agglomeration and status of natural resources) normally entailed by them (Dijkstra and Poelman, 2014).

The rest of the paper is structured as follows. In the next section, we refer to background studies and develop our main research hypothesis. Section 2 presents the dataset and the econometric strategy of our empirical application. Section 3 discusses its results and Section 4 concludes.

2. Background studies and research hypotheses

Applications of Industry 4.0 technologies that can increase firms' environmental sustainability have already attracted consistent academic attention, also with respect to SMEs (Kumar et al., 2020; de Sousa Jabbour et al., 2018). A large gallery of case studies has shown that the digital technologies at stake can improve the efficiency of SMEs in using energy, water, and natural resources, as well as in generating and disposing waste.[4]

The extent to which these digital applications can increase the firms' capacity to EI on a systematic basis has been instead only limitedly investigated. With respect to a sample of 155k Italian firms, Montresor and Vezzani (2022) have shown that, with some nuances, digital investors have a higher propensity to act for the environment and, in doing that, to "redesign their production process and/or adopt new production models". Working on a sample of over 1,000 SMEs in the UK, Kesidou and Ri (2021) have found evidence of manifold synergies between digitalisation and changes in production/ processes to reduce carbon emissions. In an as much recent work, by focusing on a large sample of SMEs within 39 countries, Demirel et al. (2022) show that a well-defined digitalisation strategy is capable to increase the growth impact of EI. With important specificities, the previous evidence is generally taken to support a theoretical view in which, mainly thanks to their GPT nature, digital technologies provide firms with "interfaces" to combine the complex set of knowledge modules required to eco-innovate (Montresor and Vezzani, 2022).

As we have anticipated, in the few studies above the role of the spatial context in which firms are located is not considered. This is particularly the case of the urban vs. rural nature of the areas in which firms are based, on which we concentrate in the following.

As far as firms' EIs are concerned, to the best of our knowledge, the distinction between urban and rural areas has been only recently considered (Galliano et al., 2022; 2017). At first sight, as the population density at the basis of the identification of urban areas concur to determine the intensity of the agglomeration economies they could potentially host it would appear natural to conclude that firms in urban areas are more eco-innovative than rural ones across the board. Indeed, there is multiple evidence that, especially with respect to firms of a smaller size, specialisation economies entailed by co-located firms within the same sector (i.e., Marshallian agglomeration) facilitate EIs (Antonioli et al. 2016; Cainelli et al. 2011, 2012; Mazzanti and Zoboli 2008; Galliano et al., 2022), through a variety of mechanisms that more probably act in urban areas. An urban praise in firms' EIs can also be expected by considering the other concomitant distinguishing features of urbanisation, in terms of public facilities and infrastructures, pool of consumers and employees, and concentration of services and tertiary activities (Dijkstra and Poelman, 2014): a pool of features that

[4] Just to make an example, novel sensor-based technologies enable firms to monitor in real and continuous time their machine utilization and the relative energy need (Song and Wang, 2017).

facilitate the EI drivers that the literature has recognised since long (Hojnik and Ruzzier, 2016). An urban location can finally be expected to facilitate the EIs of its firms passing through the variety of the knowledge its actors generate and disseminate. Urban areas normally host a variety of industries and non-industrial players (like, for example, research organisations and public administrations), with heterogeneous resources and capabilities, among which there is frequent cross-fertilisation of ideas, which facilitates the process of knowledge recombination at the basis of EIs (Montresor and Quatraro, 2020). All in all, based on the previous set of mechanisms, it would appear naturally to expect the following first research hypothesis:

Hp1: *Firms in urban areas have a higher capacity/propensity to eco-innovate than in rural ones*.

While this is our main expectation, it is important to retain that also rural areas can represent a vital basin of EIs for their hosted firms. In general terms, rurality does not entail the absence of innovativeness at all. Rural areas are rather marked by a more hidden kind of innovation processes, in which SMEs innovate more slowly and less technologically, following a Doing, Using and Interactive (DUI) mode (Jensen et al., 2007) that relies on the production of new synthetic (rather than analytical) knowledge and on its exchange through personal networks and face-to-face interactions. The same mode of innovating extends to the firms' adoption of EIs (Galliano et al., 2019; Marzucchi and Montresor, 2017), for whose occurrence rural areas benefit from the additional advantage of local natural resources: for example, local soya crops could facilitate EI in biodiesel, while coasts and solar exposure could make rural firms more prone to EI in the energy sector. Furthermore, rural areas typically host SMEs, micro and individual firms that, while hampered by many EI barriers (see Marin et al., 2015), have a high capacity to create and mobilise networks of local actors, who can collaborate, share and make a collective use of otherwise negligible individual environmental resources and green assets (Grillitsch and Nilsson 2015; Esparcia 2014). In the light of all these considerations, the expected EI advantage of urban over rural firms is not guaranteed and the test of Hp1 would help us to assess it. A similar argument applies to a second hypothesis, which represents a sort of specification of Hp1 when we look at the (population) size of the urban areas in which potentially eco-innovative firms reside. In this last respect too, one might be induced to expect that larger cities and/or villages are more harbingers of agglomeration economies and induced effects. However, larger urban areas are also potentially more affected by congestion problems and diseconomies of agglomeration also in the EI domain – like in the use of natural resources and in the cost of land - and this remits to empirical validation also the following hypothesis:

Hp2: *Firms in large urban areas have a higher capacity/propensity to eco-innovate than those in small ones*.

The distinction between urban and rural areas, as well as between larger and smaller cities/villages, is also relevant in looking at the firms' adoption of digital technologies and, more importantly for our focal research question, at the enabling role of digital technologies for firms' EIs. As is well known, a wide literature already exists about the so-called "digital urban-rural divide", recognising the higher digitalisation of the former and investigating both its determinants and regional effects (among very recent studies, see Cowie et al., 2020; Guzhavina, 2021; Jamil, 2021; Holl and Rhama, 2022). With few exceptions, this literature is usually based on regional case-studies and on limited comparative analyses of different contexts (i.e., regions hosting urban and rural areas). Still, what emerges from it induces us to expect that, also on a systematic basis, an urban-rural (larger-smaller cities) digital divide exists in our empirical application too. More importantly, we expect that such a digital divide also determines a lower capacity of rural (and small-area based) firms to render digitalisation functional to the green transition through the introduction of EIs. Such an expectation is based on two related arguments. Firstly, as Montresor and Vezzani (2022) have argued and shown, digital technologies do not help firms with EIs across the board, irrespectively from their typology, but only with respect to the most "enabling" of the Industry 4.0 paradigm (like AI, IoT, and additive manufacturing). Unfortunately, empirical evidence seems to reveal that, because of both infrastructural and competence gaps (see above), rural areas are left behind mainly by this "complex" part of the digital transformation (Cowie et al., 20220). Secondly, as suggested and revealed by all the background studies we have mentioned at the beginning of the section, firms' EIs benefit from digitalisation in the presence of digital ecosystems. In turn, these digital eco-systems require a scale and scope of digital activities, and a set of other local stakeholders and networks (usually described with the "triple helix" model), which the literature about digitalisation has shown to require large markets, typically hosted in urban and large areas (Forman et al., 2005). By combining these two arguments, we put forward our last two hypotheses:

Hp3: *Firms* in *urban areas show a higher correlation between eco-innovation and digital technologies than in rural ones.*

Hp4: *Firms in large urban areas show a higher correlation between eco-innovation and digital technologies than those based in small urban ones.*

3. Empirical analysis

Using firm micro-data from the EU Flash Eurobarometer 486 on "SMEs, Start-ups, Scale-ups and Entrepreneurship", we test our hypotheses on a large sample of about 14,000 firms across 36 European countries (the EU28 (pre-Brexit) plus 8 extra-EU countries (Turkey, Croatia, Makedonia, Serbia, Norway, Iceland, Bosnia and Herzegovina and Kosovo) interviewed with respect to the period 2016-2019.[5] Despite its cross-sectional nature, which prevents us from claiming causality, this is the first study that searches for a cross-country, systematic correlation between firms' EI and digital technologies also by retaining the nature of their location.

3.1. Dependent variable

Our main dependent variable is a dummy, EI_i, which takes value 1 if the focal firm, *i*, has declared to have introduced an "innovation with environmental benefits, including energy and resource efficiency" (Q19 in the survey), which we consider as an eco-innovation in general terms. Furthermore, to investigate if digitalisation can make firms more eco-innovative in a stricter technological manner, we also build up another dummy, EI_Tech_i, which takes value 1 if the EI amounts to a product and/or process innovation: i.e., a technological eco-innovation.

3.2. Main regressors

The focal regressor of our analysis is represented by the firms' adoption of digital technologies that fall under the heading of the Industry 4.0, and that the Eurobarometer survey identifies in: Artificial intelligence, Cloud computing, Robotics, Smart devices, Big data analytics, High speed infrastructure, and Blockchain (Q23). Given the high share of SMEs in our sample of European countries, we deem the adoption of at least one of these six brand-new technologies, irrespectively from their typology, an already important identifier of their status of modern digitalisation. Accordingly, we build up a dummy $Digit_i$, taking value 1 in this case, and 0 otherwise.

Figure 1 shows that, as expected, the most widely adopted digital technologies by the firms of the sample are cloud-computing, high-speed connection, and smart devices. These are in fact

[5] The choice of countries has been driven by the opportunity of having more homogeneity across the interviewed firms, especially with respect to the declarative question about the firm's location (urban vs. rural). In a robustness check of our analysis, we repeat our estimates with respect to the entire set of 40 countries of the Eurobarometer, adding Brazil, Canada, Japan, and the US. Results, reported in Tables B.5 in on-line Appendix B, are in general robust.

technologies for collecting, storing, and transmitting data marked by a lower resource and competence needs than the most demanding, costly and enabling ones of the Industry 4.0 (Martinelli et al., 2021), that is: big data, robotics, AI, and blockchain, which our sample firms adopt to a much lower extent.

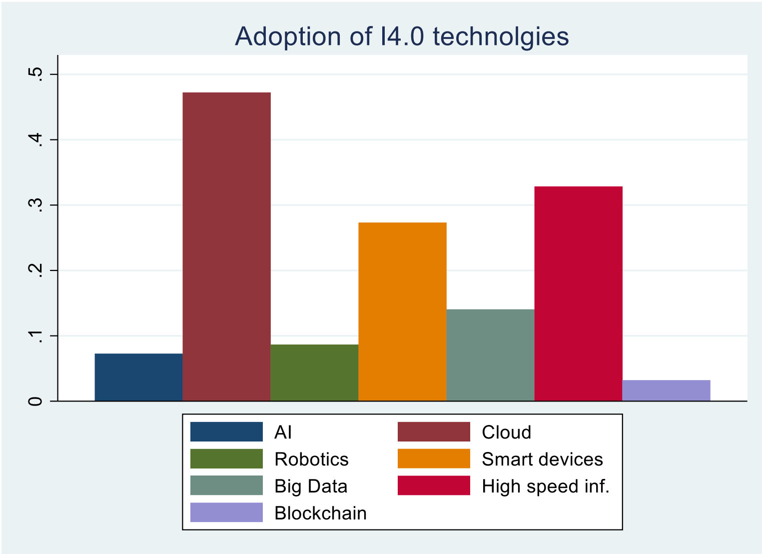

Figure 1: Shares (%) of firms adopting digital technologies by typology

Given the higher enabling potential of these four enabling technologies, it could be interesting to investigate whether their absence from the firms' digital portfolio could compromise the relationship between digitalisation and EI we are investigating. In order to do that, in an alternative specification of our baseline model, instead of $Digit_i$ we use a $Digit\_minus_i$ dummy, which takes value 1 if the focal firm has adopted at least one the indicated digital technologies, with the exception of big data, robotics, AI, and blockchain.

The adoption of digital technologies, signalling the firms' disposal of digital capabilities, is of course only one of the drivers of their EIs, to be searched using the "regulatory, demand-pull, and technology-push" approach (Horbach et al., 2012). Unfortunately, the Eurobarometer survey is lacking in questions to detect these drivers in an accurate way, but it enables us to capture them through some proxies. Firstly, the role of environmental regulations, normally deemed the first EI trigger, can be proxied by a dummy, $PolicyEI\_support_i$, which takes value 1 if firm *i* has declared to have received policy support to become more sustainable (Q16). As for science-push factors, like in other studies, we could retain them proxied (at least partially) by the dummy $Patent\_holder_i$, taking value 1 if firm *i* has at least one patent application. As for demand-pull drivers, the dummy *Export*$_i$, denoting if firm i export goods or services, tells us whether it is present in the international markets.

The list of the relevant regressors also includes structural variables like *Firm_size*$_i$, captured through a series of dummy variables for firms that are micro (2-9), small (10-49), medium (10-49), and large (250+); *Firm_age*$_i$, calculated by subtracting the survey-year to the year of SME establishment and transformed in ln; *Family_owned*$_i$, captured by a dummy for the relative status. Industry dummies – at the NACE 1 digit – and Country dummies - based on the country of SME establishment – conclude the list.

In addition to the previous standard list of variables, the Eurobarometer 486 has the new distinguishing feature of enabling us to detect the kind of location firms are based, and which we exploit to test our research hypotheses. While it keeps on avoiding reporting the geographical coordinates of the surveyed firms – in so doing fulfilling the anonymity requirement of the previous Eurobarometers – the one at stake asks the enterprise *i* whether it is located in a gallery of locations. By referring to them, we have calculated two dummies – *Large_Urban_Area*$_i$, and *Small_Urban_Area*$_i$ – which we plug in our regression by retaining *Rural_Area*$_i$ as the benchmark case. [6]

Table 1 displays descriptive statistics for our sample of 14,332 firms. Table 2 reports their correlation without revealing collinearity problems among the selected covariates.

[6] As not mutually exclusive with respect to the previous ones, the declared locations in an “industrial area” and “near a border with an (a non-) EU country” are simply used as controls.

Table 1 – Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
EI	14,332	0.22	0.42	0	1
DIGIT	14,332	0.67	0.47	0	1
Urban Area	14,332	0.85	0.36	0	1
Large Urban Area	14,332	0.49	0.50	0	1
Small Urban Area	14,332	0.36	0.48	0	1
Rural Area	14,332	0.10	0.30	0	1
EI support	14,332	0.09	0.28	0	1
border	14,332	0.11	0.32	0	1
industrial	14,332	0.12	0.33	0	1
Micro Firm	14,332	0.55	0.50	0	1
Small firm	14,332	0.25	0.43	0	1
Medium Firm	14,332	0.14	0.35	0	1
Large Firm	14,332	0.06	0.23	0	1
Exporter	14,332	0.36	0.48	0	1
Family business	14,332	0.20	0.40	0	1
Patent holder	14,332	0.06	0.24	0	1
Firm age (ln)	14,332	2.93	0.80	0	6.93
No interest in digitalization	14,332	0.04	0.20	0	1

Table 2 – Correlation matrix

ID	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	EI	1																	
2	DIGIT	0.18	1																
3	Urban Area	-0.05	0.02	1															
4	Large Urban Area	-0.02	0.06	0.41	1														
5	Small Urban Area	-0.01	-0.05	0.31	-0.74	1													
6	Rural Area	0.04	-0.04	-0.80	-0.33	-0.25	1												
7	EI support	0.06	0.04	-0.01	0.01	-0.02	-0.01	1											
8	border	0.04	0.02	-0.08	-0.11	0.06	0.01	0.00	1										
9	industrial	0.07	0.08	-0.21	-0.09	-0.06	-0.07	0.02	0.07	1									
10	Micro Firm	-0.13	-0.17	0.01	-0.01	0.02	0.03	-0.05	-0.02	-0.09	1								
11	Small firm	0.02	0.05	-0.01	0.00	-0.01	-0.01	0.01	-0.01	0.02	-0.64	1							
12	Medium Firm	0.09	0.12	-0.01	-0.01	0.01	-0.02	0.02	0.02	0.07	-0.45	-0.23	1						
13	Large Firm	0.10	0.09	0.00	0.04	-0.04	-0.02	0.05	0.02	0.04	-0.27	-0.14	-0.10	1					
14	Exporter	0.09	0.15	-0.05	0.00	-0.04	0.01	0.00	0.07	0.11	-0.19	0.05	0.14	0.11	1				
15	Family business	0.10	0.08	-0.05	-0.05	0.02	0.04	0.01	0.03	0.11	-0.02	0.02	0.01	-0.01	0.03	1			
16	Patent holder	0.15	0.11	-0.01	0.02	-0.02	-0.01	0.04	0.04	0.09	-0.12	0.00	0.09	0.11	0.17	0.08	1		
17	Firm age (ln)	0.08	0.05	-0.04	-0.09	0.06	0.02	0.00	0.04	0.08	-0.23	0.06	0.16	0.14	0.05	0.13	0.05	1	
18	No interest in digitalization	-0.06	-0.14	-0.01	0.00	0.00	0.01	-0.03	-0.01	-0.02	0.08	-0.04	-0.04	-0.04	-0.05	-0.03	-0.04	-0.03	1

Before moving to our econometric strategy, it is interesting to note that the incidence of urban vs. rural firms has an interesting variability across the (EU) countries of the sample.

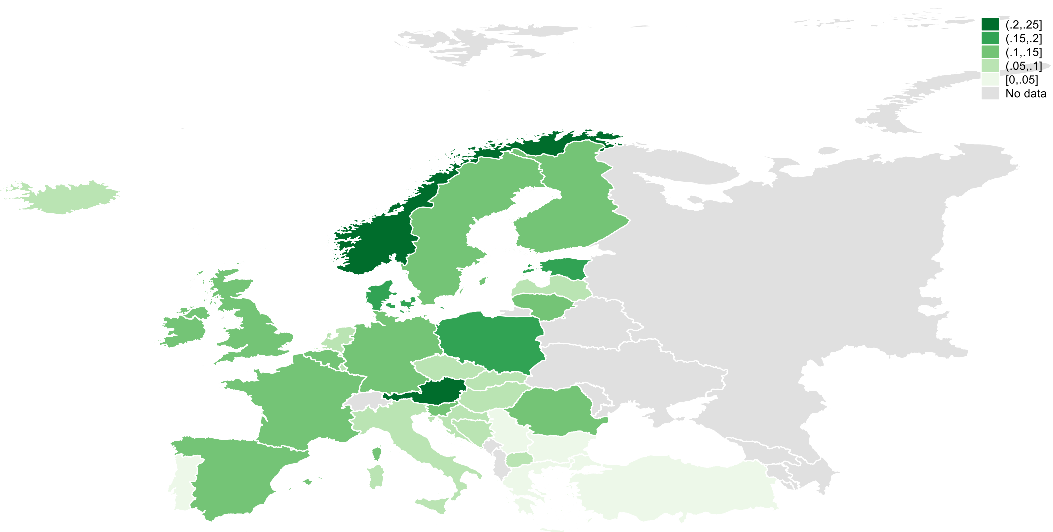

Figure 2 – Share of rural-based firms across European countries

As Figure 2 shows, the incidence of firms based in (declared and perceived) rural areas, which is at the most 23% in the sample countries, is the highest in Norway and Austria, followed by Finland, the Spain, Poland and the UK. Italy, Portugal and Eastern countries lag further behind. While more granular heterogeneity would for sure emerge at a lower level of regional aggregation (unfortunately not available from the Eurobarometer), this suggests that the “firm-location” we are investigating has a geography that deserves attention for the twin-transition too.

3.3. Econometric strategy

To estimate the relationship between EIs and the interplay between digital technologies adoption and firms’ localisation, we first run a battery of seemingly unrelated bivariate probit models of the following form:

$$DIGIT_i = \beta_3 X'_i + u_{1i} \qquad (1)$$

$$EI_i = \beta_1 DIGIT_i + \beta_2 X'_i + u_{2i} \qquad (2)$$

$$\begin{pmatrix} u_{1i} \\ u_{2i} \end{pmatrix} \sim N\left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right\} \qquad (3)$$

where the dependent variable $DIGIT_i$ in equation (1) is the adoption of digital technologies by firm *i* as measured with a dummy variable taking value 1 in case firm *i* has adopted at least one of the 7 Industry 4.0 technologies listed in Q23 of the questionnaire and 0 otherwise; the dependent variable EI_i in equation (2) is a dummy variable that takes value 1 in case firm *i* introduced at least one eco-innovation in the period of interest and 0 otherwise; the horizontal vector *X'* contains both controls and location dummies discussed in the previous section; finally, u_{1i} and u_{2i} are the error terms in equations (1) and (2), respectively. We resort to a seemingly unrelated equation system as we posit in section 2 that eco-innovations and digital innovations may not be mutually independent, due to either complementarities and/or common unobservable factors. The innovation literature, on the other hand, has highlighted only mixed evidence concerning the mutual independence of different types of innovation, as it is in the case of product *vs* process innovation, with contributions both in favour (Reichstein and Salter, 2006; Hall, Lotti, and Mairesse, 2009) and against (Criscuolo, Laursen, Reichstein and Salter, 2017). In this model, if EI_i and $DIGIT_i$ are independent, their error terms (u_{1i} and u_{2i}) can be tested to be uncorrelated as the relative coefficient (ρ) is not statistically different from 0. In this case, the two equations can be estimated with two separate probit models. On the contrary, if EI_i and $DIGIT_i$ are correlated (ρ ≠ 0), the parameters of the two equation must be jointly estimated.

In order to test our Hp1 and Hp2, within vector **X** we fix a rural location as benchmark and plug in the estimates for EI_i the two dummies *urban_small*$_i$ and *urban_large*$_i$. In order to test our Hp3 and Hp4, we interact the previous dummies with $Digit_i$ and see whether they moderate its positive expected impact on *EI*. However, the vector X' is not perfectly identical in these two equations. On the one hand, the dummy accounting for EI policy support (*PolicyEI_support*$_i$) is omitted in equation (1) as it is only capable to affect eco-innovations[7]. On the other hand, equation (2) includes an additional variable, *No_digitalisation_interest*$_i$, which we omit in equation (1) as an excluded instrument to exploit the features of the bivariate probit model to implement an instrumental variable approach to address the potential endogeneity deriving from the binary covariate $DIGIT_i$.

In fact, the class of models we use is particularly desirable in our research design as they enable us to address the potential endogeneity of our main regressor. Indeed, one could easily claim that a

[7] In order to check the absence of correlation between DIGIT and *PolicyEI_support*$_i$ we estimated an alternative version of the seemingly unrelated bivariate probit model by adding this last variable to equation (1). Results obtained in this way are in line with those presented in section 4 thus endorsing their robustness while the coefficient associated with *PolicyEI_support*$_i$ in equation (1) is not significant, as expected. Results form this further check are available upon request.

reverse causality (EI stimulating digitalisation) and a problem of unobserved heterogeneity (factors accounting for both EI and Digit) affect the adoption of digital technologies. In order to account for this problem and given that the potentially endogenous regressor (*DIGIT*$_i$) is binary, we follow Wooldridge's (2010, Section 15.7.2) approach and use as instrumental variable a dummy, *No_digitalisation_interest*$_i$, which takes value 1 if the focal SME has declared "to have no interest at all in digitalisation" in responding about the barriers to the relative adoption (Q21); indeed, the effect of this variable on EI can only pass through its impact on *Digit*.

In the same kind of model, we can also take into account the fact that SMEs' decisions concerning the introduction of EIs and the adoption of digital technologies are arguably interrelated among them. Interestingly, the correlation coefficient (ρ) among the errors terms of the two equations reported in Table 3 in the Results section is statistically significant across all specifications thus confirming that unobserved factors determining digital adoptions also determine EIs adoption. This particular evidence is also confirmed when reference is made to all of the robustness checks we implemented (see Appendix B) and constitutes a further endorsement to our econometric strategy which is based on seemingly unrelated probit models.

Finally, as a robustness check, we also estimate our model with a Conditional Recursive Mixed Process (CRMP) (Roodman, 2011). This is also a bivariate seemingly unrelated probit, in which the endogenous regressor is instrumented recursively still on the basis of the variable *Digitalisation_interest*$_i$.[8]

4. Results

4.1 Baseline estimates

As an introduction to the results of our estimates, Appendix A (available on-line) reports some descriptive statistics for the dependent variable (*EI*), the focal regressor (*Digit*) and their relationship. As expected, the share of digital adopters is the lowest (highest) in rural areas (large urban areas), while, somehow unexpectedly, the opposite is true for eco-innovative firms. Eco-

[8] The models at stake are estimated simultaneously using the Stata routine *cmp*, developed by Roodman (2011). This program fundamentally fits a seemingly unrelated regression system (SUR) and estimates parameters that are consistent in case the system itself is "recursive, with clearly defined stages, and that are fully observed, meaning that endogenous variables appear on the right-hand side only as observed". In this case, the first stage of the seemingly unrelated probit includes an instrument (*Digitalisation_interest*$_i$) intended to address the endogeneity of DIGIT. As a consequence, only the final stage displays 'full observability' and the estimation can be described as 'limited-information maximum likelihood'.

innovative digital adopters are more numerous than non-digital ones, and the gap is relatively lower in rural areas, pointing to the relevance of our investigation.

Coming to the econometric results, Table 3 reports the estimates of the Seemingly Unrelated Bivariate probit model – with respect to *EI* and *DIGIT* in the first and second columns, respectively – by progressively incorporating in the baseline for EI (panel (a)), our focal regressor *Digit* (panel (b)), and its interaction with the location dummies, *Urban_small* and *Urban_large* (panel (c)). To start with, let us notice that the controls we have identified generally work as expected (see Table B.1 in Appendix B on-line). In particular, across all the panels, having received a policy support for the sake of environmental sustainability makes eco-innovating more probable (*PolicyEI_support* significantly positive), while the propensity to get digital expectedly decreases in the absence of an interest in digitalisation (*No_ digital_interest* significantly negative).

Table 3 – EI and digital technologies by firms in different areas

	(a)		(b)		(c)	
	EI	DIGIT	Eco-innovator	DIGIT	Eco-innovator	DIGIT
Urban_large	-0.0995^{***} (0.0369)	0.1882^{***} (0.0355)	-0.1516^{***} (0.0380)	0.1835^{***} (0.0356)	-0.2609^{***} (0.0684)	0.1848^{***} (0.0355)
Urban_small	-0.1317^{***} (0.0378)	0.0666^{*} (0.0360)	-0.1480^{***} (0.0380)	0.0610^{*} (0.0361)	-0.2588^{***} (0.0688)	0.0623^{*} (0.0360)
DIGIT			0.9181^{***} (0.1687)		0.8007^{***} (0.1785)	
DIGIT * Urban large					0.1507^{*} (0.0782)	
DIGIT * Urban small					0.1555^{*} (0.0801)	
EIpolicy support	0.2459^{***} (0.0418)		0.2261^{***} (0.0419)		0.2263^{***} (0.0419)	
No digital interest		-0.6042^{***} (0.0575)		-0.6504^{***} (0.0573)		-0.6505^{***} (0.0572)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	14332		14332		14332	
Chi2	3086		3807		3816	
Rho	0.2542^{***}		-0.3059^{***}		-0.3121^{***}	

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Coming to our research hypotheses, urban firms (used instead of urban based firms, hereafter) display a lower propensity to eco-innovate than rural ones across the board. In all the specifications (a – c), the coefficients of *Urban_small* and *Urban_large* for *EI* (first columns) are significantly negative with respect to the benchmark (rural firms). Conversely, the size of the two urban coefficients is not significantly different (in the saturated model, c), suggesting that a larger urban dimension does not provide firms with an advantage in eco-innovating, and a disadvantage either. These are two first important results, which do not support our Hp1 and Hp2. Quite interestingly, the EI enabling conditions that the literature has identified in rural areas seem to more than compensate the disadvantages these areas arguably suffer in terms of arguably lower agglomeration and infrastructural economies. What is more, with respect to urban areas, the size of the city and/or village where SMEs reside does not appear to make a difference in eco-innovating. In absence of richer data about the location area of the sample firms, we can only hint that, across our wide set of countries, urbanisation diseconomies (e.g., from congestion) and economies (of specialisation and/or variety) somehow mutually counterbalance and cancel out their effects on EIs by the resident firms.

As far as digitalisation is concerned, Table 3 provides two important confirmations of previous studies. Firstly, in line with the urban-rural digital divide literature, rural firms are less prone to adopt digital technologies than urban ones, and those in larger urban areas have a more significant probability to do so. Across all the specifications (a – c), the coefficients of *Urban_small* and *Urban_large* in the second columns are in fact positive and significant with respect to the benchmark (rural firms), and the latter at a greater significant level. Secondly, confirming recent evidence about the twin-transition at the firm level (e.g., Montresor and Vezzani, 2022), panels (b) and (c) reveal that *Digit* is significantly and positively correlate with *EI* (first columns). Given the paucity of evidence about the functional use of digital technologies for the sake of EI, limited to appreciable samples of firms only in some specific countries (see Section 2), this is another important result. Indeed, it conveys to us signs of the existence of a twin-transition passing through EIs also across a wide set of countries.

The last set of results concern our Hp3 and Hp4. Quite interestingly, panel (c) in Table 3 reveals that also these Hps are confirmed only partially. On the one hand, as we did expect in Hp3, the twin transition at stake (i.e., digit for EI) seems to work more for firms in urban than in rural areas: though at an only 10% significance level, the interactive terms of *Digit* with *Urban_large* and *Urban_small* are both positive. As we had envisaged, urban areas apparently seem to facilitate the constitution of eco-systems in which digital technologies can interoperate among them on a larger scale and can thus be more effectively exploited by digital firms to eco-innovate. On the other hand, contrary to our expected Hp4, there is no apparently significant difference between the coefficients of the digit interaction term with *Urban_large* and *Urban_small*. In other words, while an urban eco-system is possibly more enabling of the effect of digital technologies on EIs, for the firms at stake, this does not occur to a greater extent when such an eco-system is larges in size. Once more, this is an unexpected result, which points to the possible existence of urbanisation economies vs. diseconomies also in the twin-transition, on which future research should concentrate.

4.2 Robustness checks and additional results

The tables reported in the on-line Appendix reveal that the previous baseline results are generally confirmed in a set of alternative specifications, from which interesting nuances emerge.

Firstly, it is reassuring to notice that the results we have obtained are robust when we run our Seemingly Unrelated Bivariate probit model by using a Conditional Recursive Mixed Process (C(R)MP) (Table B.2). As we said, this enables us to strengthen our results against the potential endogeneity of our focal regressors.

Secondly, baseline results are robust when we focus on EI that firms introduce in the technological domain (*EI_tech*), that is, by developing new sustainable products and/or processes. Quite interestingly, as Table B.3 (Appendix B) reveals, the interaction term between *Digit* and *Urban_Small* increases in significance (to 5%) with respect to the rural benchmark. This suggests that firms in urban areas are possibly better positioned than rural ones in a twin-transition that involves the development of green technologies rather than the adoption of green (organisational) behaviours or practices. Once more and unexpectedly, the significance is larger only for firms in small urban areas, pointing to the fact that diseconomies of agglomeration might affect technological EI more than non-technological ones.

Thirdly, results are in general robust when we replace *Digit* with our alternative digital regressor, *Digit_minus*, which excludes (through a 0 in the dummy) the “fewer” firms that have adopted the most enabling of the Industry 4.0 technologies (big data, AI and the like). To be sure, Table B.4 reveals an interesting difference with respect to our focal interaction terms. Unlike for *Digit*, the interaction terms between *Digit_minus* and the urban areas dummies are not significant. But this somehow reinforces our main results and our Hp3 in particular. It is *only* in the twin transition that includes also the most powerful digital technologies (i.e., *Digit*) that firms in urban areas have a twinning advantage. If we just retain digital technologies for collecting and exchanging data (i.e., *Digit_minus*), the urban prise disappears and rural areas do not lag behind in the twin-transition.

Fourthly, results are robust when we repeat our estimates with respect to the full sample of 40 countries of the Eurobarometer, including Brazil, Canada, Japan, and the US. Furthermore, as showed by Table B.5, the significance of the coefficients, and especially of the interaction terms, is higher. Quite interestingly, the presumable difference with which firms in these extra-European countries perceive and declare the nature of their location area does not affect and, on the contrary, reinforces our results.

5. Conclusions

Responding to the pressing policy request to "twin" the digital and the green transition, academic research has recently started investigating the extent to which firms can make their digitalisation functional to their environmental performances, also and above all in terms of eco-innovations. The few analyses that have been realised so far have provided evidence that indeed the new wave of digital technologies (of the so-called Industry 4.0) can provide firms with capabilities that can serve them to develop new green technologies and render their production and business processes more environmentally sustainable. However, this micro-data-based evidence is still limited to few countries and, above all, has so far neglected the role of the spatial context in which eco-innovative firms are based. Given the disparities than both the green and the digital transitions are generating across places, possibly accentuating the peripherality of the "places that do not matter" (Rodríguez-Pose, 2018), this is a quite unfortunate gap.

In trying to fill this gap, by taking stock of a new location-question contained in the EU Flash-Eurobarometer-486, in this paper we have for the first time investigated on a large scale whether an urban rather a rural context, and the size of it, can affect the capacity of the residing firms to eco-innovate and to render their digitalisation functional to it. The estimation of Seemingly Unrelated Bivariate probit models for a sample of about 14,000 firms in 36 EU and extra EU countries with respect to the year 2020, has provided interesting results, from which important policy implications can be drawn. Firstly, in partial violation of theoretical expectations and in contrast with previous single-country-based studies, rural firms reveal a higher propensity to eco-innovate than urban ones. The implications of this first result are ambivalent. Given their pervasiveness across EU and extra-EU countries, rural areas could provide an important basin of new eco-innovative solutions by firms, which policy makers should exploit to face the technological and non-technological needs of the net-zero-transition. Furthermore, given the notable "win-win" (environmental and economic) impact they have been recognised to have, EIs could serve to reduce the gap that rural areas display with respect to urban ones in different domains, thus attributing to rural green policies a cohesive flavour. On the other hand, firms appear less eco-innovative where they should be most, given the worse environmental performances (e.g., in terms of pollution and CO_2 emissions) of urban areas; this renders the implementation of urban green policies possibly more important than rural ones.

Our second set of results confirm that indeed, even across a large set of countries marked by heterogeneous features, digitalisation can help firms with their eco-innovation across the board. In so doing, our study reinforces the message that policy makers should retain and possibly rely on this side-green-effect in implementing digital policies (Montresor and Vezzani, 2022). However, results also suggest that digitalisation apparently help EI by firms more in urban than in rural areas – that is, in areas that are systematically more digitalised – though seemingly more in small than in large ones – that arguably suffer less from urbanisation diseconomies. Quite interestingly, while rural firms appear to have a superior EI propensity than urban ones, this propensity is less sensitive to digital technologies and possibly relies more on other non-technological EI determinants that characterise the same areas. This suggests that digital policies could result less green-twinning in rural areas, where firms are both less propense to digitalise and less capable/willing to render their digital technologies functional to more sustainable practices. In other words, while rural areas could represent an important basin of new eco-innovative solutions, especially by SMEs, their exploitation is comparatively less possible (with respect to urban areas) by relying on digital policies.

As usual, our study is not free from limitations that future research should try to address by relying on additional data. First, knowing the kind of location (urban vs. rural) in which firms are based is only a superficial bit of information about the socio-economic and agglomerative forces that it hosts. Their explicit consideration would definitively provide more accurate insights, but it would also require territorially granular data, not yet available so far unless for single countries (see Galliano et al., 2022). Second, despite the econometric techniques that we have adopted, the relationship we have identified between digital and EI through our cross-sectional application can't be deemed causal. Longitudinal micro-data would be necessary that, once more, are hard to get for large samples of territorial contexts.

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Appendix

A. Descriptive statistics

Table A.1 shows some descriptive statistics for the dependent variable (*EI*) and the focal regressor (*Digit*) broken down by our three types of location: large urban area, small urban area and rural area (Columns 1-4). Column 5 of the same table displays significance levels of the t-test for differences in means across these localisations.

Table A.1 – Cross-location variance of main variables of interest

	(1) Large Urban	(2) Small Urban	(3) Rural	(4) Total	(5) T-test
Digital adopters	70.02	63.49	61.02	66.95	***
Eco-innovators	21.56	21.66	27.35	22.39	***

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The majority (about 67%) of firms included in the sample reportedly adopted at least one of the above-mentioned digital technologies. As expected, and consistently with previous evidence (Holl and Rama, 2021), the share of digital adopters is the lowest (highest) in rural areas (large urban areas), where it remains remarkable (about 61%) but at an appreciable distance from large urban ones (about 71%). Conversely, the share of eco-innovative firms is quite contained overall (about 22%) and shows an opposite distribution across areas: it is the highest (lowest) in rural (small urban) ones, where it reaches a value of about 27%. This is an interesting bit of evidence, which supports the relevance of rural areas for the sustainability outcomes of their firms, which we have recalled in Section 2.

A first insight about the relationship we are investigating is provided by Figure A.1, which shows the share of eco-innovating firms in rural vs. urban (large and small) areas, by discriminating between digital adopters and non-adopters.

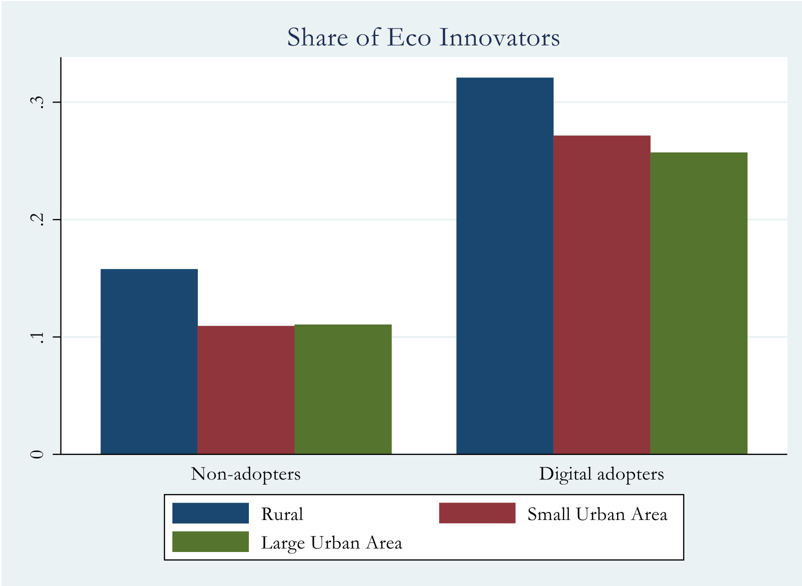

Figure A.1 - Share of eco-innovative SMEs in rural and urban areas

In large urban areas, the share of eco-innovative firms among digital adopters is more than double compared to the same share among non-adopters (25.77% vs 11.04%). In small urban areas, the same share is almost three times higher in the former than in the latter (27.05% vs 10.81%). Conversely, the same gap is relatively lower in rural areas (33.17% vs 17.17%), thus providing preliminary evidence of how localization in urban areas could positively moderate the eco-innovative potential brought about by digital technologies.

B. Robustness checks and additional results

i) Baseline estimates displaying controls

Table B.1 – EI and digital technologies by firms in different areas (with controls)

	(1) EI	(2) EI	(3) EI
Urban large	-0.0995***	-0.1516***	-0.2609***
	(0.0369)	(0.0380)	(0.0684)
Urban small	-0.1317***	-0.1480***	-0.2588***
	(0.0378)	(0.0380)	(0.0688)
DIGIT		0.9181***	0.8007***
		(0.1687)	(0.1785)
DIGIT * Urban large			0.1507*
			(0.0782)

DIGIT * Urban small			0.1555*
			(0.0801)
EI policy support	0.2459***	0.2261***	0.2263***
	(0.0418)	(0.0419)	(0.0419)
Boarder area	0.0650*	0.0564	0.0551
	(0.0388)	(0.0387)	(0.0386)
Industrial	0.0213	-0.0150	-0.0134
	(0.0373)	(0.0379)	(0.0378)
Small firm	0.1588***	0.0717**	0.0712**
	(0.0301)	(0.0360)	(0.0360)
Medium firm	0.3620***	0.1981***	0.1962***
	(0.0370)	(0.0532)	(0.0530)
Large firm	0.5555***	0.3744***	0.3733***
	(0.0526)	(0.0681)	(0.0680)
Exporter	0.1670***	0.0716**	0.0704**
	(0.0278)	(0.0350)	(0.0349)
Family businesses	0.1698***	0.1406***	0.1413***
	(0.0305)	(0.0314)	(0.0314)
Patent holder/applicant	0.4329***	0.3532***	0.3532***
	(0.0470)	(0.0511)	(0.0511)
Firm age (ln)	0.0201	0.0312*	0.0311*
	(0.0167)	(0.0168)	(0.0168)
Constant	-1.0202***	-1.5753***	-1.4913***
	(0.1554)	(0.1788)	(0.1836)
Digital Technology Adopter			
Urban large	0.1882***	0.1835***	0.1848***
	(0.0355)	(0.0356)	(0.0355)
Urban small	0.0666*	0.0610*	0.0623*
	(0.0360)	(0.0361)	(0.0360)
EI policy support	0.0694	0.0586	0.0585
	(0.0440)	(0.0440)	(0.0440)
Boarder area	0.0361	0.0374	0.0374
	(0.0387)	(0.0388)	(0.0388)
Industrial	0.1519***	0.1415***	0.1414***
	(0.0396)	(0.0397)	(0.0397)
Small firm	0.2785***	0.2765***	0.2764***
	(0.0285)	(0.0285)	(0.0285)
Medium firm	0.5776***	0.5777***	0.5777***
	(0.0392)	(0.0392)	(0.0392)

Large firm	0.6620***	0.6558***	0.6559***
	(0.0616)	(0.0612)	(0.0612)
Exporter	0.3377***	0.3355***	0.3355***
	(0.0271)	(0.0271)	(0.0271)
Family businesses	0.0994***	0.0966***	0.0966***
	(0.0316)	(0.0316)	(0.0315)
Patent holder/applicant	0.3781***	0.3897***	0.3900***
	(0.0598)	(0.0604)	(0.0604)
Firm age (ln)	-0.0334**	-0.0342**	-0.0342**
	(0.0162)	(0.0161)	(0.0161)
No interest in digitalization	-0.6042***	-0.6504***	-0.6505***
	(0.0575)	(0.0573)	(0.0572)
Constant	0.2451*	0.2626*	0.2615*
	(0.1446)	(0.1462)	(0.1462)
Rho	0.2542***	-0.3059***	-0.3121***
	(0.0178)	(0.1181)	(0.1173)
Country dummies	*Yes*	*Yes*	*Yes*
Industry dummies	*Yes*	*Yes*	*Yes*
Observations	14332	14332	14332

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ii) Alternative econometric strategies

Table B.2 Conditional Recursive Mixed Process (C(R)MP)

	(a)		(b)		(c)	
	Eco-innovator	DIGIT	Eco-innovator	DIGIT	Eco-innovator	DIGIT
Urban_large	-0.0995***	0.1882***	-0.1516***	0.1835***	-0.2616***	0.1845***
	(0.0369)	(0.0355)	(0.0380)	(0.0356)	(0.0682)	(0.0363)
Urban_small	-0.1317***	0.0666*	-0.1480***	0.0610*	-0.2587***	0.0574
	(0.0378)	(0.0360)	(0.0380)	(0.0361)	(0.0687)	(0.0368)
DIGIT			0.9181***		0.8164***	
			(0.1687)		(0.1779)	
DIGIT * Urban large					0.1506*	
					(0.0780)	
DIGIT * Urban small					0.1555*	
					(0.0799)	
EI policy support	0.2459***		0.2261***		0.2256***	
	(0.0418)		(0.0419)		(0.0419)	
No interest in digitalization		-0.6042***		-0.6504***		-0.5734***
		(0.0575)		(0.0573)		(0.1862)
Country dummies	*Yes*		*Yes*		*Yes*	
Controls	*Yes*		*Yes*		*Yes*	
Industry dummies	*Yes*		*Yes*		*Yes*	
Rho	0.2542***		-0.3058***		-0.3234***	
Chi2	2426		3807		3853	
Observations	14332		14332		14332	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

iii) Baseline estimates with respect to technological EI

Table B.3 –Technological EI and digital technologies by firms in different areas

	(a)		(b)		(c)	
	EI Tech	DIGIT	EI Tech	DIGIT	EI Tech	DIGIT
Urban_large	-0.0277	0.1877***	-0.0797*	0.1846***	-0.2051**	0.1856***
	(0.0422)	(0.0355)	(0.0440)	(0.0356)	(0.0864)	(0.0356)
Urban_small	-0.0982**	0.0672*	-0.1144***	0.0610*	-0.2728***	0.0621*
	(0.0435)	(0.0360)	(0.0438)	(0.0361)	(0.0884)	(0.0360)
DIGIT			0.9488***		0.8084***	
			(0.2108)		(0.2241)	
DIGIT * Urban large					0.1636*	
					(0.0957)	
DIGIT * Urban small					0.2076**	
					(0.0994)	
EI support	0.2582***		0.2380***		0.2385***	
	(0.0469)		(0.0472)		(0.0473)	
No interest in digitalization		-0.6086***		-0.6525***		-0.6527***
		(0.0576)		(0.0578)		(0.0578)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	14332		14332		14332	
Chi2	3035		3628		3628	
Rho	0.2671***		-0.3080**		-0.3145**	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

iv) Baseline estimates with respect to Digit_minus

Table B.4 EI and digital technologies by firms in different areas (Digit_minus)

	(1) Eco-innovator	(2) DIGIT
Urban_large	-0.2315***	0.1631***
	(0.0640)	(0.0358)
Urban_small	-0.2161***	0.0469
	(0.0645)	(0.0363)
DIGIT_minus	0.8588***	
	(0.1820)	
DIGIT * Urban large	0.1186	
	(0.0746)	
DIGIT * Urban small	0.1067	
	(0.0765)	
EI policy support	0.2249***	
	(0.0419)	
No interest in digitalization		-0.5179***
		(0.1849)
Country dummies	*Yes*	
Controls	*Yes*	
Industry dummies	*Yes*	
Rho	-0.3676***	
Chi2	3983	
Observations	14332	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

v) Results for the full sample of 40 countries, including Brasil, Canada, Japan and the US

Table B.5 – EI and digital technologies by firms in different areas (full sample of 40 countries)

	(a)		(b)		(c)	
	EI	DIGIT	EI	DIGIT	EI	DIGIT
Urban_small	-0.119***	0.073**	-0.138***	0.069**	-0.249***	0.070**
	(0.036)	(0.034)	(0.036)	(0.034)	(0.066)	(0.034)
Urban_large	-0.094***	0.197***	-0.147***	0.195***	-0.248***	0.196***
	(0.035)	(0.034)	(0.036)	(0.034)	(0.066)	(0.034)
DIGIT			0.884***		0.774***	
			(0.164)		(0.172)	
DIGIT * Urban_small					0.156**	
					(0.077)	
DIGIT * Urban_large					0.139*	
					(0.075)	
PolicyEI_support	0.243***		0.241***		0.241***	
	(0.038)		(0.038)		(0.038)	
No_digital_interest		-0.613***		-0.656***		-0.656***
		(0.055)		(0.055)		(0.055)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	15,924		15,924		15,924	
Chi2	3398		4108		4122	
Rho	0.250***		-0.274**		-0.280**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1