Leveraging networks to develop citizens' digital competences: a pseudo-panel analysis of outreach initiatives in Italy

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ABSTRACT

Social support plays a fundamental role in digital inclusion; thus, many argue that governments should adopt a multi-stakeholder approach to bridge the digital gap, collaborating with civil society and private sector. This study analyzes the presence and activism on the territory of organizations that, in parallel with pursuing their institutional goal, promote outreach activities to achieve better social outcomes. For these organizations – schools, universities, libraries, and third-sector organizations –, we coined the term outreach-oriented organizations (OOOs).

Taking advantage of a dataset mapping all Code Week initiatives – a European-wide initiative that introduces students and adults to the digital world – between 2013 and 2020, we assess the impact of OOOs' activism on citizens' digital competences, by means of a fixed effect pseudo-panel analysis.

Main results: first, it is essential to consider the degree of simultaneous activism and collaboration among organizations, in particular between civil society and schools; second, we confirm that digital competences are strongly linked to social inclusion: the strength of social networks is fundamental to lower digital inequalities and viceversa.

Such results are robust to multiple model specifications, but they are sensitive to the way digital competences are measured and to the variables chosen to measure school activism.

KEYWORDS:
digital competences; Italy; social networks; digital inequality; policy impact

1. Introduction

Non-engagement with digital technologies has become nearly impossible in modern societies, thanks to the ubiquity of ICT in the life of individuals and households (Mariën et al., 2016). However, digitalization initiatives are often undertaken without addressing the issue of those who are left behind (Mariën & Prodnik, 2014).

Digital competences are a crucial element in this scenario (van Dijk, 2020). According to the EU's vision for the "digital decade", for example, 80% of citizens should possess at least basic digital skills by 2030 (European Commission, 2021). Italy, currently ranked 25th among 27 Member States in the *Human capital* dimension of the *Digital Economy and Society Index* (DESI), has translated this ambition into a 70% goal to be reached by 2026, thanks to projects funded by NextGenEU and public-private partnerships.

To tackle digital skills shortages and inequalities among the population, the Italian Government has adopted a bottom-up approach, leveraging on a wide network of public administrations (PAs) and non-profit organizations (NPOs) to impact on what Park (2014) defined "non-users' social environment, including the local community, workplace, and neighborhood."

Taking steps from the academic literature already focusing on this phenomenon, our research addresses the validity of this policy approach by performing a pseudo-panel data analysis of the dynamics of digital competences in Italy between 2013 and 2020. We investigate whether the proactive approach of organizations such as schools, civil society organizations, libraries, and universities – which we define *outreach-oriented organizations* (OOOs) – is associated to an increase in citizens' digital competences, also linking them with drivers of digital and social inclusion.

1.1. Literature review

1.1.1. Digital competences and digital inequalities

Digital competences (DC), skills, and literacy are not exact synonyms. Skills are just one of the components of competence, which is "the ability to successfully meet complex demands in a particular context through the mobilization of knowledge, (cognitive, metacognitive, socio-emotional and practical) skills, attitudes and values" (Miho & Rychen, 2016). Digital literacy or ICT literacy can be used instead to summarize the basic level of digital competences, those necessary for everyday life rather than for the professional life and for ICT specialists (Lankshear, Colin Knobel, 2008; Martin & Grudziecki, 2006). We adopt a holistic view and thus focus on DC, not only on skills or basic literacy.

As technology gets more sophisticated, just learning how to use connectivity or devices cannot is not an answer to the digital divide (Cisotto & Pupolin, 2018). The digital divide goes deeper, also socially (van Dijk, 2020), it is a metaphor of a divided society and is composed by four complementary phases: a) motivation towards gaining access, b) actually obtaining physical access, c) acquiring digital skills, and d) actual use of digital media. Along these dimensions, however, we should not conceive a binary divide between *haves* and *have-nots*, but rather a continuous spectrum of digital inequalities ranging from people having no access and use at all to all-round daily competent users (Livingstone & Helsper, 2007).

This implies adopting a sociopolitical approach (Jaeger et al., 2012), rather than merely focusing on technological gaps, emphasizing the role of digital technology as a means to be engaged in society. Several studies highlight the role of sociodemographic variables on digital inequalities (G. Blank & Groselj, 2014; Helsper, 2010; Mossberger et al., 2003). The literature review by Scheerder et al. (2017) provides a comprehensive overview of the determinants of Internet skills, uses and outcomes, underlining how social and cultural determinants have been relatively less studied. We focus on one social determinant that is particularly overlooked: the impact of initiatives promoted on the territory by a specific set of organizations: schools, non-profit organizations, libraries, and universities.

1.1.2. Social support and Outreach-Oriented Organizations (OOOs)

Traditional approaches to digital inequalities that consider being digitally included exclusively as an individual responsibility cannot cope with the current context (Mariën et al., 2016). Summarizing previous research, Mariën & Van Audenhove (2010) highlight the role of social support for digital inclusion: individuals that belong to ICT-rich social networks, characterized by high levels of access, usage, and skills, are more incited to use ICT; members of the network stimulate one another to start using new ICT or new applications; they also have more ways to obtain support when confronted with technical problems or questions regarding more operational or formal aspects.

van Deursen et al. (2014) and Asmar et al., (2020) show that patterns of support-seeking have a strong influence on the development of DC, the benefits one can attain from the internet, and the quality of the support received – also influenced by the strength of the relationships between individuals. Thus, for policy it is fundamental to understand where digital inclusion can flourish, e.g., in learning communities, in the workplace, within families (Asmar et al., 2020).

Wong et al. (2009) suggest that the strategy to bridge the digital gap should be a multi-stakeholder approach that includes the government's efforts in collaboration with civil society and the private sector. Among other measures, they suggest organizing at the community level to mobilize volunteers, peers, and leaders to match them with those who need IT support. In this way, community-level capacity can also compensate for limited e-leadership at the national level (Graham & Hanna, 2011), especially for fragile groups such as the elderly (Sourbati, 2009).

Hence, we focus on those entities that, in parallel with the pursuit of their institutional goal, are able to promote *outreach* activities to increase DC and achieve better social outcomes. "Outreach" essentially entails services being taken out from their normative and mainstream institutional settings and being provided in local community settings (Dewson et al., 2006). An outreach program can be defined as a program aimed to help, uplift, and support those deprived of certain services and rights (Childhope Philippines, 2021). Such activities can also include needs assessment and information provision, making potential customers aware of the available help (Basler, 2005). Key components of outreach services are that they are provided as close as possible to the underserved community and that they are usually voluntary, meaning that it is not mandatory for customers to participate (Dewson et al., 2006).

We group together the main actors that can offer these services – schools, NPOs, libraries, universities – under the label *outreach-oriented organizations* (OOOs), to be operationalized in our quantitative analysis. The following paragraphs provide a short overview of their role.

Schools

In recent years, the idea of school-community partnerships has regained attention (Valli et al., 2016). Statti & Torres (2020) propose a "Community school-model," a model of school that is highly connected with the whole society, highlighting the importance of an integrated view of community organizations. A community school can be defined as "a place and a set of partnerships connecting a school, the families of students, and the surrounding community" (M. Blank et al., 2012). Following this approach, schools can bridge the digital divide not only for students, but also for parents and low-income neighborhoods as a whole (Epstein et al., 2019).

Libraries

Libraries are ideally positioned to lead the way in developing information literate communities because of their diverse client base and lifelong contact with members (Harding, 2008). They can be seen as a 'third place' alternative to the home-school dichotomy (Elmborg, 2011). Differently from other actors, they can provide both internet connection and devices (Jaeger et al., 2012) and have the employees necessary to provide assistance and training to their audience (Kinney, 2010). There are several possible ways in which libraries can do outreach activities, categorized as: community access, information literacy, cooperation, exchange and partnership, and exhibitions and scholarly events (Harding, 2008).

Universities

In the past, the role of university has often been limited to tackling the shortage of digitally competent graduates, to benefit the economic system rather than society as a whole (Davenport et al., 2020; Johnston, 2020). However, in the last decades the concept of outreach for universities was expanded to services and programs that achieve full engagement with their communities (Kellogg Commission, 1999). Nowadays, the terms "global impact," "knowledge transfer," and "partner with society" figure prominently among university mission statements (Leong, 2013). Universities can fulfill this mission for example through university-community partnerships that, thanks to shared expertise and resources, can be beneficial for the local communities surrounding those institutions (Slagter van Tryon, 2013).

Telecentres, Internet cafés, and Makerspaces

There are many examples of facilities that provide access and educational opportunities to those who lack connectivity or skills: ICT centers, telecentres, and public internet access points (Arifoglu et al., 2012; Park, 2014). These actors can be important not only to address basic digital inequalities, but also to support an effective use of ICT for private and public tasks (Wolske et al., 2012).

Similar actors include municipal ICT schools (Hartviksen et al., 2002), vocational colleges (Ngqulu et al., 2019), and senior centers (Lenstra, 2017). Also internet cafés are able to increase the digital and social inclusion of clients, if the support given by public subsidies allows to offer computer support and training provided by the staff (Ferlander & Timms, 2006).

Makerspaces are a new actor that can support creative and critical engagement with digital technologies through hands-on experimentation across multiple tools (Kafai et al., 2014; Ratto, 2011). Makerspaces are ideal spaces for schools to experiment innovation in educational design (Macann & Carvalho, 2021) and have brought an opportunity for libraries to transform their learning environment (Julian & Parrott, 2017), for example in the case of people with disabilities (Brady et al., 2014).

1.2. Knowledge gaps and research questions

So far, studies who have focused on specific organizations to enhance citizens' DC only consist in:

- Overviews of the actives performed by an actor in a specific region and of the difficulties encountered (e.g., Wong et al., 2009);
- Suggestions about the role that an actor can play (e.g., Martinez, 2019);
- Descriptions of specific initiatives – often with a pedagogical perspective (e.g., Kumpulainen et al., 2020);
- Interviews and short surveys to representatives of such organizations (e.g., Unterfrauner et al., 2020; Yilmaz & Cevher, 2015).

Starting from the knowledge gaps illustrated in this section, this research aims at answering the following research question: **How does the activism of outreach-oriented organizations (OOOs) in a specific area impact on the digital competences of citizens?**

This RQ can be further decomposed into sub-RQs:

RQ1.1 Do territories with higher density of OOOs show higher levels of DC among their citizens?

RQ1.2 Which OOOs are the most effective in impacting the whole community? In particular, do civil society and school initiatives have a positive impact?

RQ1.3 How relevant is the interaction among OOOs?

RQ1.4 What role do social networks play in fostering competences, in light of the activities promoted by OOOs?

2. Data

2.1. AVQ survey, unit of analysis, and pseudo-panel approach

Information on the use of internet by Italian citizens can be retrieved from the multi-purpose household survey *Aspetti della Vita Quotidiana* (AVQ), conducted by Istat since 1993. Each year, a stratified random sample of more than 40k individuals and more than 18k households is extracted to fill a questionnaire, accounting for more than 700 variables per wave – including some geographical information. Up to 8 modules are devoted to investigating the use of digital devices and of the internet, which are used by Istat and Eurostat to compute digital skills indexes at the regional and national level, employed within the DESI.

More importantly, the survey sample is built with the purpose of being representative of the population at different levels, i.e., alternatively by: 1) region of residence; 2) municipality type; 3) age group; 4) education level. The estimates produced by Istat are always representative of these dimensions also when coupled with gender, but such dimensions cannot always be coupled together without losing the degree of representativeness required by the institute's quality standards. For example, Istat publishes data detailed at the gender-education-age level but, when each of the above-listed variables is coupled with the region of residence, the sample size is still too little to guarantee solid estimates for all regions.

Therefore, the AVQ data qualifies as a rich, repeated cross-section dataset, representative of the Italian population up to a certain granularity. To hypothesize any possible causal impact on our dependent variable, however, cross-sectional information is not sufficient. Thus, we have identified a synthetic UoA in order to build a pseudo-panel, balancing representativeness and statistical power.

Pseudo-panel methods are one way of making up for the lack of panel data, and have been used to model a wide range of topics (Guillerm, 2017). Their use dates back to Deaton (1985), who was the first to suggest using panel methods on repeated cross-sectional data. The advantage of these data is their availability and the fact that they can cover long periods of time, many surveys being carried out at regular intervals over time. They generally include independent repeated cross-sections, i.e., different samples. However, when the same individuals cannot be followed, types of individuals, generally referred to as "cohorts" or "cells" can be followed.

Hence, we shift our UoA to an aggregate level, producing estimates on our stratified sample that use the triplet: region (r) – 21 items; municipality type (m) – 3 categories; age group (a) – 7 groups obtained aggregating the ones identified by Istat. In this way, we can also merge the initial AVQ dataset with further variables proceeding from other sources that provide information for at least 2 variables of the triplet above.

The following paragraphs describe all the variables composing our rich and novel dataset, including the data handling operations we had to perform to make the variables coherent in terms of UoA.

2.2. Dependent variable: measuring Digital Competences

DigComp is the reference framework used in Europe to define digital competences, updated in May 2022 to version 2.2 (Vuorikari et al., 2022). DigComp defines 21 digital competences, grouped in 5 competence areas: 1) Information and data literacy; 2) Communication and collaboration; 3) Digital content creation; 4) Safety; 5) Problem solving.

The framework, however, does not provide indications about the *measurement* of such competences. Hence, Eurostat and the European Commission (DG CNECT) have translated DigComp into a composite DC index that aggregates several indicators of *self-declared internet use* – i.e., proxies of DC – derived from AVQ and the other national surveys (Eurostat, 2021, 2022). Respondents – and thus populations – are assigned a comprehensive level of digital skills (*above basic, basic, low, narrow, limited, no skill*) depending on the number of activities performed for each area.

In addition to all these potential threats to construct validity, the Eurostat methodology has changed over time and not all variables needed to compute the index have been measured each year; as a result, official Eurostat estimates are not available for the years 2013, 2018, and 2020. This also implies, for our regression, that we expect part of the variation in y to be explained by yearly changes in measurement – in other words, we expect significant annual fixed effects.

To support our identification strategy and to obtain a robust dependent variable, we have elaborated different configurations for the DC index (that we label *DigComp* in our models), using alternatively:

1. Only the variables employed in the Eurostat methodology (*perfect match*) that are available for all years under exam, aggregated using the same discrete thresholds used by Eurostat, which are transformed into scores and then composed in a weighted-average index;
2. Only perfect match variables available all years, composed in a weighted-average index directly from the competence area scores;
3. Perfect match variables *plus* a set of year-specific proxies – to substitute the variables of the framework that were not measured every year –, aggregated using Eurostat thresholds and then averaged out;
4. Perfect match variables and proxy variables, using weighted averages in both steps.

Proxy variables have been identified:

- either resorting to variables with a definition that was similar to that of missing variables, i.e., using comparable constructs; for example, in the area *Safety*, we have proxied the activity "Reading privacy statements before providing personal data" with the variable "(s)he believes (s)he is capable of protecting his/her own personal data;"
- or by resorting to variables that behaved similarly in the years were all variables are observed; similarity between variables is computed using Hamming distances (Bookstein et al., 2002).

Figure A1 displays the distributions of the four configurations.

Since it is the most complete but also the one less distorted by arbitrary decisions about the thresholds that identify DC levels, we always employ DigComp4. The alternatives are tested in section 4.2.

2.3. Independent variables: measuring OOOs' activism

We have constructed several variables to measure the degree of activism of OOOs in the field of DC. Whenever a measure of activism is not available, we proxy it by looking at an organization's presence on the territory. Inspired by Åslund & Fredriksson (2009), Dustmann et al. (2013), and Siciliano et al. (2020), we interpret these densities as measures of individuals' exposure to a network.

A pivotal variable for our analysis relates to the number of Code Week initiatives. Code Week is an international initiative born in 2012 that promotes collaboration, problem solving, and coding skills, targeting mainly school students but also adults and senior citizens. Each year workshops and group activities are organized by schools and civil society organizations over the course of two weeks. In 2021, a total of 4 million people from more than 80 countries took part in Code Week initiatives, ranging from learning basic programming concepts and practicing computational thinking to manipulating data. The average age of participants was 11 years old, and 49% of them were women; 88% of the 78k activities were held in schools, promoted by a network of about 30k teachers.

We use the number of Code Week events per 1000 inhabitants for each region and municipality type in Italy between 2013 and 2020 as a measure of joint schools-civil society activism to foster DC.

The following paragraphs illustrate the independent variables used for the other OOO-related constructs.

Schools

Data about Italian schools come from *ScuolaInChiaro*, a public database managed by the Italian Ministry of Education that contains information about the 35,700 Italian primary and secondary schools of 18 out of 21 regions.[1] More than 100 indicators are available on the platform, including KPIs about school projects and schools' relationships with the local community. Four variables measuring the activism of schools in each UoA were extracted and then included in our dataset:

- Share of schools with ICT-related school projects dedicated to students;
- Share of schools with ICT-related training courses for teachers;
- Share of schools that have signed formal agreements to organize events, educational initiatives, sport initiatives, or cultural initiatives of territorial interest;
- Share of schools that have signed agreements with Third Sector associations.

Unfortunately, the platform does not provide time series but only values for the latest year, which were imputed to the whole period as time-invariant measure.

Civil society

Three variables measure the activism of NPOs by looking at their geographical distribution:

- Number of community centers[2] per 1000 inhabitants;
- Number of social facilities[3] per 1000 inhabitants;
- Share of population that takes part into volunteering activities.

The first two variables have been computed extracting data through OpenStreetMap (OSM), a collaborative project whose objective is to create an openly editable geographic database of the world, that includes also tagged objects ("amenities"). Also in these cases no time series is available and we employ the latest observed values for all years under exam.

The third variable is provided by Istat in the AVQ, and it is the only case of time-varying independent variable in addition to the Code Week variable.

Libraries

Anagrafe delle Biblioteche Italiane is the most reliable census of Italian libraries, with geolocated data updated in real time. Hence, we included in our dataset the number of libraries per 1000 inhabitants, for each region and municipality type. Also in this case the platform does not provide historical data.

Universities

Data about the geographical distribution of university facilities come from *ETER* (European Tertiary Education Register), an EU-funded public database of European higher education institutions. We used data for the year 2019 to compute the number of university facility per 1000 inhabitants, for each region and municipality type.

2.4. Control variables

To minimize omitted variable bias, we used the categorization proposed by Scheerder et al. (2017) to include a wide set of control variables that measure the determinants of internet skills, use and outcomes. These variables are provided by Istat – either through AVQ, or through the platform *Atlante Statistico dei Comuni* (ASC), or through the main public dashboard of the institute – or have been extracted from the Eurostat database.

[1] Provincia Autonoma di Trento, Provincia Autonoma di Bolzano, and Valle d'Aosta are outside the national education system, so data about schools in these regions is not available.

[2] Spaces used for local events, gatherings and group activities, including special interest and special age groups.

[3] Facilities providing social services such as group and nursing homes, workshops for the disabled, ambulatories, youth centers.

The variables employed for our analysis are the following, divided by category.

Sociodemographics

- Population density: number of inhabitants per squared-km;
- Fertility rate: average number of children per woman.

Economic wellbeing

- Average taxable personal income;
- Employment rate;
- Regional Gini index;
- Number of firms with more than 50 employees, per 1000 inhabitants.

Human capital

- Tertiary graduates: share of individuals having at least a tertiary degree;
- Lower secondary graduates: share of individuals without a high school diploma;

Social capital

- Participation in society: degree of participation to social life, computed aggregating information about the participation to political parties, unions, associations;
- Share of individuals who declare having no friends;
- One-person households: share of households composed by a single individual;
- Trust: share of individuals who claim to trust others;
- Separate waste collection: average share of waste correctly separated, as a proxy of care for the community and respect for the environment;
- Childcare density: number of places available in childcare centres for children below the age of 2, as a proxy for social policies and generalized trust.

Cultural capital

- Museum density: number of museums per 1000 inhabitants;
- Religious practice: share of individuals who have attended a place of worship at least weekly.

Social (subjective) wellbeing

- Health status: share of individuals who claim they are in good health;
- Life satisfaction: share of individuals who are highly satisfied with their personal life, in terms of leisure time, economics, health, environment and relationships with friends and family.

Material and motivational access

- Broadband take-up: Share of individuals with broadband connection available at home;
- Firms' digital maturity, proxied by the share of medium and large companies having a website.

3. Model

3.1. Panel data analysis

We start from this initial model:

$$y_{it} = \alpha + \beta_1 \tilde{x}_{it} + \beta_C x_i^C + \beta_S x_i^S + \beta_L x_i^L + \beta_U x_i^U + \boldsymbol{\gamma} Z_{it} + \varepsilon_{it} \tag{1}$$

Where:

- $i = 1, \dots, N$ is the number of units of analysis available each year;
- $y_i \in (0,1)$ is the level of citizens' digital competences observed for each UoA;

- $t = \{2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020\}$ is the time index;
- $\tilde{x}_{it}$ is a time-varying independent variable (we have only two in our dataset);
- x_{it}s represent the other independent variables, which distinguish between civil society (C), schools (S), libraries (L), and universities (U);
- Z_{it} is a set of control variables;
- α is the intercept and ε_{it} is the random error term, following the usual convention.

3.1.1. *Testing the pseudo-panel approach: Pooled OLS vs Fixed Effects*

Given our data generating process, we should verify whether these observations are just a "time series of cross sections" (Parker, 2011). To verify this assumption, we test whether the correct model specification is that of pooled data or instead we should resort to fixed effects (FE) models. We hypothesize the presence of FE given the structure of our data, but each of the following tests has been cross-checked also with reference to random effects (RE) models.

The pooled OLS estimator is obtained by estimating:

$$y_{it} = \alpha + \boldsymbol{x}'_{it}\beta + \boldsymbol{\gamma} Z_{it} + \varepsilon_{it} \tag{2}$$

Pooled OLS is appropriate if the constant-coefficients are appropriate; it is inconsistent if the fixed effects model is appropriate, i.e., explanatory variables leave individual effects unexplained, so this supports the idea of some individual effect to be relevant. To see which model is most appropriate, we test the eventuality of a fixed effect (LSDV) model *vis-à-vis* pooled OLS, performing a Wald test.

The results of the test for poolability are illustrated in Table A1.

3.1.2. *Diagnostics: heteroskedasticity and serial correlation*

We also need to assess whether the data is characterized by heteroskedasticity and serial correlation (Wooldridge, 2019) because, depending on their presence, we need to:

- use heteroskedasticity-robust standard errors (if only heteroskedasticity is present) or clustered errors (if both are present) in our models;
- implement the Mundlak approach instead of a simple Wald test to choose between FE and RE.

Heteroskedasticity in FE regression models is tested through a modified Wald test for groupwise heteroskedasticity (Greene, 2003); to test for serial correlation we perform a Wooldridge test (Wooldridge, 2010). The results of these tests are illustrated in Table A2.

The results of the test using the Mundlak (1978) approach are illustrated in Table A3.

3.1.3. *FE model: Within estimators and inclusion of interactions*

Fixed effects models enable to account for time-invariant unobserved individual effects, but do not enable to estimate them. Thus, since we are going to use FE, we can include time fixed effects (λ_t) in our specification but we cannot include, in a standard configuration, time-invariant variables:

$$y_{it} = \alpha + \beta_1 \tilde{x}_{it} + \boldsymbol{\gamma} Z_{it} + \lambda_t + \varepsilon_{it} \tag{3}$$

The basic FE model with year FE is implemented in Table 4.3.

However, we can resort to the properties of Within estimators to include time-invariant variables by means of interactions – as illustrated in Wooldridge (2010, p. 308). In such configuration, we can at least estimate the impact of schools, libraries, and universities as potential moderators of the impact of joint schools-NPOs initiatives. The final specification is then:

$$y_{it} = \alpha + \beta_1 \tilde{x}_{it} + \beta_2 (\tilde{x}_{it} * x_i^o) + \boldsymbol{\gamma} Z_{it} + \lambda_t + \varepsilon_{it} \tag{4}$$

Where:

- $o = \{C, S, L, U\}$ is the index for the different OOOs, interacted with a time-varying regressor;

- β_2 is the vector of coefficients capturing the interactions, i.e., the one that describes the moderation role of each OOO.

The main results of the full model are illustrated in Table 4.3.

3.2. Robustness checks

Once we estimate the full model, we also perform several robustness checks to see whether our results depend on the choice of a specific set of variables and on the preferred specifications. In addition to varying the choice of dependent and control variables, we also implement two different time-series specifications, based on the hypotheses that:

HP1. The effect of our variables on citizens' digital skills could be visible not immediately but in the short term; thus, we set up a predictive model and conceive independent and control variables as Leading Indicators for the outcome variable at $(t + 1)$;

HP2. DigComp, in the presence of serial correlation, is highly path-dependent; hence we also use a simple dynamic linear model, the autoregressive distributed lags model (ARDL).

The Leading Indicator model is based on the assumption that a regressor x anticipates the dynamics of y, and that at time t it is more readily available than y itself (Ghysels & Marcellino, 2018). HP1 translates into the following model:

$$y_{i,t+1} = \alpha + \beta_1\tilde{x}_{it} + \beta_2(\tilde{x}_{it} * x_i^o) + \boldsymbol{\gamma}Z_{it} + \lambda_t + \varepsilon_{i,t+1} \quad (5)$$

In the ARDL(p, q) model the dependent variable is allowed to depend on p lags of itself, and q lags of the regressors, the distributed lag component. HP2 implies a simple specification, an ARDL(1,1) model:

$$y_{it} = \alpha + y_{i,t-1} + \beta_1\tilde{x}_{it} + \beta_2(\tilde{x}_{it} * x_i^o) + \boldsymbol{\gamma}Z_{it} + \lambda_t + \varepsilon_{it} \quad (6)$$

The results of both specifications are illustrated in section 4.2.

Table 4.1: Basic OLS regressions on DigComp level

VARIABLES	(1) DigComp	(2) DigComp	(3) DigComp	(4) DigComp	(5) DigComp	(6) DigComp	(7) DigComp	(8) DigComp	(9) DigComp
C - Density of community centers	0.987***				0.738***	1.050***	0.765***	0.982***	1.018***
	(0.192)				(0.155)	(0.190)	(0.192)	(0.192)	(0.196)
S - School projects, ICT - students	-0.358***	-0.395***	-0.300***	-0.332***					
	(0.0589)	(0.0599)	(0.0604)	(0.0599)					
L - Density of libraries (log)	0.0312***	0.0371***	0.0213**	0.0419***	0.0203***	0.0279***	0.0243***	0.0228**	0.0195**
	(0.00894)	(0.00879)	(0.00989)	(0.00869)	(0.00783)	(0.00889)	(0.00923)	(0.00944)	(0.00952)
U - Density of universities	2.224***	2.906***	2.290***	3.111***	0.669***	1.418**	2.363***	2.762***	1.769***
	(0.655)	(0.640)	(0.657)	(0.646)	(0.255)	(0.652)	(0.655)	(0.659)	(0.665)
C - Density of social facilities		1.057***							
		(0.244)							
C - Volunteering in NPOs			0.588***						
			(0.127)						
C - Digital Civilian Service projects				-0.00339**					
				(0.00171)					
C,S - Code Week initiatives					-0.0161				-0.0166
					(0.0170)				(0.0172)
S - Teacher training on ICT						-0.255***			-0.221***
						(0.0293)			(0.0318)
S - Schools' outreach events							-0.242***		
							(0.0394)		
S - Schools-NPOs collaborations								-0.208***	-0.0961**
								(0.0375)	(0.0399)
Constant	0.337***	0.358***	0.267***	0.368***	0.267***	0.412***	0.406***	0.382***	0.436***
	(0.0190)	(0.0180)	(0.0287)	(0.0179)	(0.0159)	(0.0230)	(0.0250)	(0.0236)	(0.0257)
Observations	2,632	2,632	2,632	2,632	2,856	2,632	2,632	2,632	2,632
R-squared	0.040	0.037	0.038	0.031	0.021	0.052	0.040	0.038	0.055

Robust SE in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4. Results

Our hypothesis is that the activism of civil society (C), schools (S), libraries (L), and universities (U) has a positive impact on the level of citizens' DC. We also look at joint activism of multiple actors, thanks to the variable on Code Week initiatives and also by means of interactions among variables.

We start exploring these hypotheses with simple OLS specifications (Table 4.1). Overall, the coefficients for C, L, and U confirm our hypothesis – except for the variable on *Servizio Civile Digitale* –, while all variables related to schools (S) seem to have a negative relationship with DigComp. Interestingly, the Code Week variable is the only one never significant in OLS.

We move now to a more robust panel approach.

4.1. Panel data analysis

We start implementing our pseudo-panel approach by performing routine tests to identify the correct model specification to include the temporal dimension.

4.1.1. Results of the diagnostic tests

Pooled OLS vs Fixed Effects

First, we need to rule out the hypothesis that our pseudo-panel is just a pooled version of cross-sectional data. Hence, we implement a series of Wald tests to contrast a fixed effects (LSDV) approach with a pooled OLS approach (Table A1). To do so, we use only time-variant independent variables and controls, to enable the comparison with RE alternatives. The results rule out the Pooled OLS hypothesis: explanatory variables leave individual effects unexplained.

Heteroskedasticity and serial correlation

In the models illustrated so far, we have always used heteroskedasticity-robust standard errors, although we have not displayed any test showing the presence of heteroskedasticity. We provide evidence in this direction in Table A2, where we also investigate the presence of serial correlation.

Given the nature of our data, it is very likely that both are indeed present, as it is confirmed by the test results. Several variables in our dataset display outliers, skewness, or are the result of data transformations; furthermore, we cannot exclude omitted variable bias or conditional variation in the variance of residuals (e.g., the measurement error in DigComp could depend on income levels). These are all sources of heteroskedasticity (Wooldridge, 2019).

The same reasoning applies to auto-correlation. We are observing phenomena characterized by stickiness, with little volatility over time. For most of our variables, we can easily assume that the value at time t is highly determined by the value at time $(t - 1)$.

As a result, we must use clustered standard errors and we must resort to the Mundlak approach to choose between FE and RE models.

Fixed vs Random effects: Mundlak approach

As Table A3 shows, we reject the null hypothesis of the test: the coefficients of the panel-level means are not jointly zero, hence the FE assumptions are satisfied.

Mundlak's approach indicates we should go for a FE model, which once again is something we could expect: given the phenomenon under exam – competences –, we could assume that unobservable, time-invariant, unit-specific effects (e.g., cultural traits that are common within UoAs) were playing a role.

However, this result does not come at no cost for our analysis: FE models do not estimate the impact of time-invariant variables, which is the case of all the variables measuring our key constructs, with the only exception of Code Week. This implies finding a way to include time-invariant in our model, in order to reach some fruitful answer for our research questions.

The following section illustrates our solution, which makes use of interactions to assess the moderating role of variables on civil society (C), schools (S), libraries (L), and universities (U).

4.1.2. Fixed Effects specifications

A Fixed Effects model enables to argue for causal effects starting from observational data; FE assume that time-invariant individual-specific effects play a crucial role and that by managing that source of heterogeneity we can identify causal impacts.

Thus, we start from time-varying variables – with the main focus on Code Week initiatives – to extend the model in order to include year fixed effects and relevant control variables. In a second step we include also time-invariant factors that are crucial for our research question, by means of interactions.

FE models with year fixed effects and different sets of control variables

As we have seen in section 2, observations are clustered by year. Hence, we add a year FE to capture all the period-specific dynamics, such as variations in DigComp measurement, pure temporal trends or specific shocks (e.g., Covid-19). To support the hypothesis that year FE are always present, we implement for all specifications in Table 4.2 a Wald test for their joint significance.

As we can see from the results, not only year FE are present, but their explanatory power is much higher than the Code Week variable: in the simplest models (1 and 2), variations in DigComp is mainly driven by temporal trends. The coefficients of the year FE have a quite stationary trend: DigComp is significantly higher in 2015 and 2020 with respect to 2013, but significantly lower in 2016, 2017, and 2018. At least in such simple configuration, the passing of time is not driving citizens' digital skills up.

To add further control variables, we use a forward selection procedure and include at least one control for each relevant construct surveyed by Scheerder et al. (2017) – including alternatives to the initial set of controls (configurations 7 and 10).

All things considered, configurations (2), (5), (6), (7), and (10) will be used as reference in the remaining part of the analysis. Alternative control variables have been used also to replicate the tests performed in paragraph 4.1.1. The initial test results are confirmed, hence the choice of FE with clustered standard errors remains unchanged.

Regarding control variables, we see that those representing material and motivational determinants (broadband take-up, frequency of computer use) and human capital (share of tertiary graduates and of lower secondary graduates) are relevant. Some of the social determinants (participation in society and household type) have a significant influence on the outcome variable – as expected from the analysis of the literature – while others (childcare density, trust, and spread of separate waste collection practices) are generally not significant. Among economic determinants (income, inequality, firms, employment), only employments exert a positive impact on DC. Regarding cultural variables, the density of museums is not significant, while religiosity has a significant negative effect. Social wellbeing (health and life satisfaction) and demographics (fertility) are not significant. In the configurations, we keep also not significant variables because marginally improve the model fit.

We should note, however, that the only time-varying independent variable included in such specifications – density of Code Week initiatives – is not significant. Hence, we have to investigate whether we should conclude that OOOs activism, proxied by this single variable, has no impact on DC, or that its impact is conditional on observing the whole picture – i.e., looking also at civil society, schools', libraries', and universities' activism per se. These constructs are measured by time-invariant variables, thus we move to the final full specification, including also interacted regressors.

Table 4.2: Fixed effects models with year FE, using different control variables

VARIABLES	(1) DigComp	(2) DigComp	(3) DigComp	(4) DigComp	(5) DigComp	(6) DigComp	(7) DigComp	(8) DigComp	(9) DigComp	(10) DigComp
C,S - Code Week initiatives	0.0152**	-0.000376	0.00410	0.00279	0.00182	0.000269	-0.00149	0.00213	0.00297	-0.00207
	(0.00758)	(0.00948)	(0.00905)	(0.00951)	(0.00942)	(0.00957)	(0.00846)	(0.00936)	(0.00972)	(0.00857)
Average taxable income (log)			-0.0793	-0.0166	-0.0448	-0.0492		-0.0224	-0.0427	
			(0.107)	(0.108)	(0.105)	(0.104)		(0.107)	(0.105)	
Broadband take-up (%)			0.00173*	0.00190**	0.00192**	0.00199**	0.00180**	0.00179**	0.00191**	0.00174**
			(0.000902)	(0.000903)	(0.000888)	(0.000928)	(0.000743)	(0.000885)	(0.000925)	(0.000752)
Tertiary graduates (%)			0.282***	0.263***	0.259***	0.256***		0.260***	0.258***	
			(0.0191)	(0.0198)	(0.0193)	(0.0194)		(0.0193)	(0.0191)	
Population density (log)				0.0233	0.0230	0.0228	-0.00794	0.0245*	0.0237*	-0.00700
				(0.0142)	(0.0141)	(0.0139)	(0.0110)	(0.0141)	(0.0139)	(0.0108)
Participation in society				0.118***	0.123***	0.122***	0.105***	0.123***	0.126***	0.108***
				(0.0199)	(0.0194)	(0.0195)	(0.0181)	(0.0193)	(0.0194)	(0.0182)
People with no friends (%)					-0.117*	-0.118*		-0.116*	-0.119*	
					(0.0630)	(0.0637)		(0.0632)	(0.0612)	
Religious practice (%)					-0.0796***	-0.0791***	-0.0536***	-0.0804***	-0.0798***	-0.0546***
					(0.0171)	(0.0170)	(0.0159)	(0.0170)	(0.0172)	(0.0158)
Museum density (‰)						0.0208				0.00615
						(0.0266)				(0.0241)
Separate waste collection (%)						0.00613				
						(0.0220)				
Trust						0.0156				
						(0.0183)				
Gini index (regional)						-0.190				-0.147
						(0.180)				(0.153)
Employment rate (%)							0.369***			0.370***
							(0.0436)			(0.0433)
Lower secondary graduates (%)							-0.290***			-0.288***
							(0.0170)			(0.0168)

VARIABLES	(1) DigComp	(2) DigComp	(3) DigComp	(4) DigComp	(5) DigComp	(6) DigComp	(7) DigComp	(8) DigComp	(9) DigComp	(10) DigComp
One-person households (%)							-0.110*			-0.115*
							(0.0653)			(0.0655)
Share of medium-large companies (%)								8.99e-05		
								(9.57e-05)		
Health status (%)								-0.0448		
								(0.0613)		
Childcare density (%)								0.0741*		0.0516
								(0.0412)		(0.0366)
Firms' digital maturity index									0.0133	
									(0.0189)	
Fertility rate									-2.38e-05	
									(0.0363)	
Life satisfaction index									0.0343*	0.0282
									(0.0204)	(0.0200)
Constant	0.244***	0.217***	0.965	0.277	0.575	0.664	0.234***	0.365	0.539	0.261***
	(0.00103)	(0.00292)	(1.047)	(1.058)	(1.036)	(1.017)	(0.0342)	(1.056)	(1.041)	(0.0560)
Observations	2,856	2,856	2,856	2,856	2,856	2,856	2,856	2,856	2,856	2,856
Number of id (clusters)	357	357	357	357	357	357	357	357	357	357
R-squared	0.001	0.534	0.570	0.583	0.589	0.590	0.634	0.590	0.590	0.635
Adjusted R-squared	0.00113	0.532	0.568	0.581	0.587	0.587	0.632	0.587	0.587	0.632
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic (Wald test)		273.6003	99.9917	96.2485	95.0801	82.5878	101.5646	92.8765	93.2427	92.3929
Prob > F		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

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

Preferred specifications in grey

FE models including interactions for time-invariant variables

As illustrated in paragraph 3.1.3, we can include time-invariant variables in a FE model by interacting them with one or more time-varying variables. In such setting, the role of time-invariant factors should be then interpreted as *moderators* of the impact that time-varying factors exert.

An alternative could be represented by applying again the Mundlak approach to time-invariant variables in a RE model by splitting them between the average effect (panel-means) and the effect of group-means deviations (group-means deviations). However, this approach is valid only if all the coefficients of group-means are all equal to zero, meaning that time-invariant unobservable are not related to our regressor. We have seen in paragraph 4.1.1 that Mundlak coefficients do not pass such test, hence we are left with only one strategy.

As a result, we use the Code Week variable to provide a time-variant interaction term for time-invariant independent variables, and such interactions should be interpreted as describing how the impact of joint schools-NPOs initiatives (Code Week) on citizens' DC varies by degrees of civil society / school / library / university activism, i.e., by factors that do not move over time but across units.

Table 4.3 reports the results of different specifications for the full model (columns 3 to 6). Column (1) displays the basic model for comparison; Column (2) reports the model with interactions but without controls. All models include year FE and clustered standard errors.

As we had seen before, if taken individually the role of Code Week initiatives is not significant, but it becomes so when considering the moderation of the role of OOOs. However, its absolute coefficient is negative: this might either mean that such initiatives target units in higher need for support, or that they are not able to sustain an improvement in digital skills. Nonetheless, since the FE model focuses on variations within units, the latter hypothesis seems the most plausible: taken per se, an increase in Code Week activism is associated to lower growth rates in DC over time, for the same units.

This dynamic, however, is contrasted and moderated by the role of OOOs. According to our results, when joint schools-NPOs initiatives are carried on in OOOs-rich units, the overall effects of activism for citizens' digital skills is positive. In particular, units characterized by schools more active in the digital field – as measured by ICT-related teacher training – and by a higher density of universities, witness a more marked improvement in citizens' DC. Community centers and libraries seem to exert no significant moderation effect. Considering the copresence of other forms of activism, the overall effect of joint schools-NPOs initiative is positive.

For example, a 10% increase in Code Week initiatives on average, *ceteris paribus*, is associated to a slight decrease in DC (-0.4%). But when this increase is coupled with a 10% increase in the share of schools providing teacher training courses in ICT, DC increase on average by 2.7%. The positive impact on DC raises to 3.0% if such increments are coupled also with a 10% increase in exposure to universities.

The significance of control variables was not affected by the introduction of interaction terms. The full models confirm the high relevance of social determinants, but also of specific economic determinants (employment rate), human capital variables (lower secondary graduates and tertiary graduates) and cultural determinants (religiosity).

Also in this case we can see how the joint action of OOOs' activism and other determinants translates into DC improvements. The simultaneous action of civil society, schools, and universities, together with a 10% increase in the participation index moves DC up by 4.5%. If, instead, OOOs' initiatives are accompanied by a 10% decrease in the share of population having at most a lower secondary diploma, DC increase by 9.7 percentage points.

In the following section we perform several tests to check whether such results are robust to alternative model specifications.

Table 4.3: Full FE model with interactions to include time-invariant dependent variables

VARIABLES	(1) DigComp	(2) DigComp	(3) DigComp	(4) DigComp	(5) DigComp	(6) DigComp
Code Week initiatives	**-0.000376**	**-0.226*** **	**-0.188*** **	**-0.184*** **	**-0.193*** **	**-0.188*** **
	(0.00948)	**(0.0671)**	**(0.0618)**	**(0.0592)**	**(0.0536)**	**(0.0536)**
Code Week # Community centers (C)		**-0.525**	**-0.466**	**-0.834**	**-0.356**	**-0.589**
		(0.771)	**(0.756)**	**(0.777)**	**(0.682)**	**(0.706)**
Code Week # ICT teacher training (S)		**0.308*** **	**0.281*** **	**0.286*** **	**0.266*** **	**0.271*** **
		(0.0903)	**(0.0830)**	**(0.0822)**	**(0.0730)**	**(0.0735)**
Code Week # Library density (L)		**-0.0227**	**-0.0130**	**-0.0109**	**-0.0184**	**-0.0160**
		(0.0202)	**(0.0193)**	**(0.0195)**	**(0.0170)**	**(0.0169)**
Code Week # University density (U)		**3.007***	**2.843***	**2.675***	**2.318***	**2.128***
		(1.702)	**(1.584)**	**(1.573)**	**(1.277)**	**(1.270)**
Average taxable income (log)			-0.0637	-0.0603		
			(0.117)	(0.115)		
Broadband take-up (%)			0.00170	0.00201*	0.00161	0.00178*
			(0.00117)	(0.00121)	(0.000989)	(0.000996)
Tertiary graduates (%)			0.244***	0.241***		
			(0.0202)	(0.0203)		
Population density (log)			0.0249*	0.0248*	-0.00548	-0.00435
			(0.0137)	(0.0133)	(0.0106)	(0.0106)
Participation in society			0.121***	0.120***	0.0973***	0.0996***
			(0.0215)	(0.0215)	(0.0201)	(0.0201)
People with no friends (%)			-0.103	-0.104		
			(0.0757)	(0.0768)		
Religious practice (%)			-0.0718***	-0.0713***	-0.0466***	-0.0474***
			(0.0176)	(0.0175)	(0.0163)	(0.0163)
Museum density (‰)				0.00396		
				(0.112)		
Separate waste collection (%)				-0.000751		
				(0.0240)		
Trust				0.0122		
				(0.0206)		
Gini index (regional)				-0.304		-0.238
				(0.199)		(0.165)
Employment rate (%)					0.366***	0.368***
					(0.0454)	(0.0453)
Lower secondary graduates (%)					-0.299***	-0.297***
					(0.0169)	(0.0168)
One-person households (%)					-0.129*	-0.133*
					(0.0742)	(0.0777)
Childcare density (%)						0.0494
						(0.0412)
Life satisfaction index						0.0334*
						(0.0195)
Constant	0.217***	-0.265	0.379	0.449	-0.0381	0.0775
	(0.00292)	(0.481)	(1.221)	(1.209)	(0.457)	(0.461)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,856	2,632	2,632	2,632	2,632	2,632
Number of id (clusters)	357	329	329	329	329	329
R-squared	0.534	0.541	0.590	0.591	0.641	0.642
Adjusted R-squared	0.532	0.539	0.586	0.586	0.637	0.639

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

4.2. Robustness checks

We verify the robustness of our results by using alternative configurations, both for dependent and independent variables. In particular, we focus on changes in:

- the configuration used to measure digital competences;
- the number and the type of independent variables employed;
- the time-series relationships among our variables.

Overall, our main results are confirmed, but the robustness checks highlight some relevant caveats.

4.2.1. Alternative measures of digital competence

As explained in section 2.2, different configurations of the DC index differ either in terms of variable selection, or in terms of aggregation into competence area scores, or in terms of composition into the overall index. Hence, we have three main alternatives to our preferred configuration (*DigComp4*):

1. Threshold-based perfect-match configuration (*DigComp1*);
2. Averaged perfect-match configuration (*DigComp2*);
3. Threshold-based configuration with proxies (*DigComp3*).

For all these alternatives, the final index should be interpreted as a measure of the average DC level in a unit. We have also two additional alternatives, in which the final index consists in the share of population with above-basic DC, as defined by Eurostat:

1. Threshold-based perfect-match configuration, above-basic digital skills (*DigComp1 - AB*);
2. Threshold-based configuration with proxies, above-basic digital skills (*DigComp3 - AB*).

Table 4.4 illustrates the results of such alternative specifications, starting from model (5) in Table 4.3.

As we can see, the choice of the DC index strongly impacts on the magnitude, sign, and significance of all independent variables. Control variables are impacted only in specifications (1) and (4).

4.2.2. Choice of the independent variables

Alternative indicators about school activism

Regarding schools, we tested (1) different alternatives for the single variable to be interacted with Code Week intiatives, but also (2) kept two interaction terms for schools, trying different combinations.

Only the variable about ICT projects for students is not significant when interacted alone, while only the variable about ICT training for teachers remains significant when we use two interaction terms for schools. It seems that ICT-related activities for teaching are a better predictor for the impact on DC.

Alternative time-varying dependent variable

We can check if results change if instead of Code Week initiatives we use an alternative time-varying independent variable – the share of individuals who volunteered in the past 12 months (Table A5).

Also in this model we obtain significant positive interaction terms and controls behave similarly to Table 4.3. Hence, the impact of Third Sector activism is once again conditional on the behavior of other OOOs.

Employing a subset of independent variables

We check the effect of excluding independent variables about libraries and universities; they are of secondary importance since they are both time-invariant and not digital-related. We test both the models with one and the ones with two variables measuring school activism (Table A6).

The results are very similar to those illustrated so far, although eliminating libraries and universities makes a second school variable significant in 2 out of 3 cases. Schools' ICT-related projects for students, however, are never significant.

4.2.3. *Time series approach: Leading Indicator and ARDL models*

In Table A7 we verify the presence of relevant time-series dynamics in our data. According to our results, both specifications are plausible, although not equally justifiable according to the theory.

When using Leading Indicators, the impact of OOOs' activism is overall negative, and some controls lose significance. This model is more difficult to justify theoretically, also because .

When using autoregressive models, instead, we obtain results again very similar to those obtained with the reference specifications. The lag term is positive and significant, while the negative raw impact of Code Week initiatives is counterbalanced by the moderation effect of ICT training for teachers.

Table 4.4. FE models using alternative measures of digital competence

VARIABLES	DigComp4	(1) DigComp1	(2) DigComp1 AB	(3) DigComp2	(4) DigComp3	(5) DigComp3 AB
Code Week initiatives	**-0.193*****	**0.0108**	**0.103**	**-0.0709**	**-0.364**	**-0.291*****
	(0.0536)	**(0.277)**	**(0.108)**	**(0.0587)**	**(0.369)**	**(0.0995)**
Code Week # Community centers (C)	**-0.356**	**3.471**	**-1.035**	**-0.274**	**10.48****	**-0.745**
	(0.682)	**(3.333)**	**(1.079)**	**(0.669)**	**(4.242)**	**(1.354)**
Code Week # ICT teacher training (S)	**0.266*****	**-0.0552**	**-0.0706**	**0.106**	**0.460**	**0.493*****
	(0.0730)	**(0.344)**	**(0.138)**	**(0.0790)**	**(0.474)**	**(0.118)**
Code Week # Library density (L)	**-0.0184**	**0.0494**	**0.0451***	**0.00501**	**0.0599**	**-0.0370**
	(0.0170)	**(0.0763)**	**(0.0270)**	**(0.0157)**	**(0.119)**	**(0.0348)**
Code Week # University density (U)	**2.318***	**12.28***	**3.454**	**2.808****	**19.70****	**1.219**
	(1.277)	**(6.866)**	**(2.625)**	**(1.257)**	**(8.611)**	**(2.297)**
Employment rate (%)	0.366***	0.345	0.424***	0.419***	0.333	0.260***
	(0.0454)	(0.302)	(0.0943)	(0.0495)	(0.395)	(0.0922)
Broadband take-up (%)	0.00161	-0.00196	-0.000760	0.00118	-0.000947	0.00147
	(0.000989)	(0.00575)	(0.00213)	(0.00121)	(0.00706)	(0.00195)
Lower secondary graduates (%)	-0.299***	-0.869***	-0.448***	-0.353***	-0.701***	-0.377***
	(0.0169)	(0.110)	(0.0335)	(0.0183)	(0.137)	(0.0384)
Population density (log)	-0.00548	-0.258***	-0.0748***	-0.0368***	-0.165*	-0.0186
	(0.0106)	(0.0673)	(0.0221)	(0.0106)	(0.0936)	(0.0214)
Participation in society	0.0973***	0.325***	0.111**	0.0627***	0.697***	0.164***
	(0.0201)	(0.119)	(0.0488)	(0.0225)	(0.132)	(0.0477)
One-person households (%)	-0.129*	-1.008**	-0.364***	-0.214***	-1.572***	-0.208
	(0.0742)	(0.394)	(0.136)	(0.0725)	(0.533)	(0.198)
Religious practice (%)	-0.0466***	-0.124	-0.0846**	-0.0687***	-0.0373	0.000771
	(0.0163)	(0.0885)	(0.0355)	(0.0172)	(0.144)	(0.0387)
Constant	-0.0381	-0.0258	-0.389	0.0411	-0.980	-0.750
	(0.457)	(2.298)	(1.057)	(0.632)	(2.674)	(1.003)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,632	2,619	2,632	2,632	2,619	2,632
Number of id (clusters)	329	329	329	329	329	329
R-squared	0.641	0.446	0.561	0.732	0.584	0.573

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

Reference model

5. Conclusions

The effectiveness of an organization's activism is conditional to the simultaneous presence and proactive approach of a wide network of organizations in the same territory. Joint schools-NPOs initiatives do not exert a positive impact, if taken per se. However, when we factor in the autonomous activities of other OOOs, the overall impact is positive. Schools and universities, in particular, act as relevant moderators.

Our study also confirms how relevant is the nexus between digital inequality and social inclusion: variables measuring the impact of social networks, social capital, and economic determinants are always significant and sizeable. Digital equality cannot be pursued without focusing on network ties

5.1. Theoretical, policy, and managerial implications

From a theoretical perspective, we highlight three key messages:

1. network ties among organizations matter. When evaluating the impact of OOOs on digital competences, an ecosystem approach should be adopted. Focusing on single actors separately does not provide relevant feedback both in terms of research and in terms of policy;
2. network ties among individuals matter. Digital competences require full inclusion in society, in terms of participation in social life, extent of the personal network, and access to education;
3. the measurement approach is not neutral. As usual, the use of composite indices opens a broad range of analytic scenarios, e.g., with respect to the choice of scales and specific thresholds.

The major implication for practitioners in OOOs is the importance of searching for (scalable and effective) partnerships on the territory rather than focusing on solitary initiatives. This implies being equipped for collaboration, for enhancing each other's capacity, but also understanding that project success is strongly dependent on contextual factors and interconnections among local stakeholders.

As for policymakers, our research points to the need to incentivize collaboration among entities, e.g., when selecting or evaluating outreach initiatives. Furthermore, policymakers must carefully allocate funds among different actors within networks, balancing different typologies of organizations and initiatives though still preserving the adequate scale to yearn for impact.

5.2. Limitations and Agenda for future research

The main limitation of our work lies in our rich but still incomplete dataset. This can be improved by:

- including time-varying dependent variables that specifically address digital-related activism for all OOOs under exam.
- the measurement approach used to operationalize the construct of digital competence has a non-negligible impact; a stable and comprehensive framework, with variables available for all years, should be adopted to measure the main construct under exam;
- the granularity of control variables can be improved, since they are often available only at the region-municipality level, or only at the regional level; full coherence with the triplet constituting our unit of analysis would ensure more robust results.

In addition to improving the quality of data, future research should explore more complex and complete time-series models, such as the autoregressive models we have experimented.

Policy would also benefit from the replication of such study in a different geographical context, to test whether our conclusions – very connected with the social and cultural environment – are actually robust to different national contexts.

So far, research has confirmed or strengthened the close link between (offline) interconnectedness among organizations and individuals, and online outcomes. Further evidence is needed to provide more powerful feedback to be transformed in relevant policy responses.

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Appendix

Table A1: Wald tests for the Pooled OLS hypothesis

VARIABLES	(1)	(2)	(3)	(4)	(5)
Code Week initiatives	Yes	Yes	Yes	Yes	Yes
Average taxable income (log)		Yes	Yes	Yes	Yes
Broadband take-up (%)		Yes	Yes	Yes	Yes
Tertiary graduates (%)		Yes	Yes	Yes	Yes
Population density (log)			Yes	Yes	Yes
Participation in society			Yes	Yes	Yes
People with no friends (%)				Yes	Yes
Religious practice (%)				Yes	Yes
Museum density (‰)					Yes
Separate waste collection (%)					Yes
Trust					Yes
Gini index					Yes
F-statistic	4.69	423.20	289.20	227.63	163.14
Prob > F	0.0304	0.0000	0.0000	0.0000	0.0000

Table A2: Results of tests for heteroskedasticity and serial correlation

VARIABLES		(1)	(2)	(3)	(4)	(5)
Code Week initiatives		Yes	Yes	Yes	Yes	Yes
Average taxable income (log)			Yes	Yes	Yes	Yes
Broadband take-up (%)			Yes	Yes	Yes	Yes
Tertiary graduates (%)			Yes	Yes	Yes	Yes
Population density (log)				Yes	Yes	Yes
Participation in society				Yes	Yes	Yes
People with no friends (%)					Yes	Yes
Religious practice (%)					Yes	Yes
Museum density (‰)						Yes
Separate waste collection (%)						Yes
Trust						Yes
Gini index						Yes
Modified Wald test for groupwise heteroskedasticity	$\bar{\chi}^2(357)$	26030.97	48709.14	61601.84	38979.10	32074.93
	$Prob > \bar{\chi}^2$	0.0000	0.0000	0.0000	0.0000	0.0000
Wooldridge test for autocorrelation	$F(1, 356)$	318.424	194.348	255.333	243.427	205.959
	$Prob > F$	0.0000	0.0000	0.0000	0.0000	0.0000

Table A3: Results of the Mundlak approach for FE vs RE estimators

VARIABLES*		(1)	(2)	(3)	(4)	(5)
Code Week initiatives		Yes	Yes	Yes	Yes	Yes
Average taxable income (log)			Yes	Yes	Yes	Yes
Broadband take-up (%)			Yes	Yes	Yes	Yes
Tertiary graduates (%)			Yes	Yes	Yes	Yes
Population density (log)				Yes	Yes	Yes
Participation in society				Yes	Yes	Yes
People with no friends (%)					Yes	Yes
Religious practice (%)					Yes	Yes
Museum density (‰)						Yes
Separate waste collection (%)						Yes
Trust						Yes
Gini index						Yes
Region FE		Yes	Yes	Yes	Yes	Yes
Municipality type FE		Yes	Yes	Yes	Yes	Yes
Age group FE		Yes	Yes	Yes	Yes	Yes
Wald test on panel-level means	$\bar{\chi}^2(n)$	3.50	424.30	568.33	577.37	660.59
	$Prob > \bar{\chi}^2$	0.0614	0.0000	0.0000	0.0000	0.0000

* All the variables listed are included both as panel-level means and as mean deviations. n = number of regressors.

Table A4: FE models with alternative measures of school activism

VARIABLES	(1) DigComp	(2) DigComp	(3) DigComp	(4) DigComp	(5) DigComp	(6) DigComp	(7) DigComp
Code Week initiatives	**-0.193***** **(0.0536)**	**-0.0981** **(0.0724)**	**-0.221**** **(0.0918)**	**-0.204**** **(0.0853)**	**-0.202***** **(0.0720)**	**-0.285***** **(0.0908)**	**-0.264***** **(0.0861)**
Code Week # Community centers (C)	**-0.356** **(0.682)**	**-0.0420** **(0.690)**	**-0.00506** **(0.707)**	**-0.134** **(0.681)**	**-0.342** **(0.691)**	**-0.230** **(0.710)**	**-0.375** **(0.685)**
Code Week # ICT teacher training (S)	**0.266***** **(0.0730)**				**0.264***** **(0.0758)**	**0.224***** **(0.0723)**	**0.214***** **(0.0757)**
Code Week # Library density (L)	**-0.0184** **(0.0170)**	**-0.0222** **(0.0199)**	**-0.0138** **(0.0177)**	**-0.0130** **(0.0167)**	**-0.0193** **(0.0188)**	**-0.0165** **(0.0170)**	**-0.0134** **(0.0166)**
Code Week # University density (U)	**2.318*** **(1.277)**	**0.446** **(1.269)**	**0.445** **(1.188)**	**0.484** **(1.217)**	**2.231** **(1.402)**	**1.814** **(1.266)**	**1.927** **(1.319)**
Code Week # Students' ICT projects (S)		**0.240** **(0.227)**			**0.0441** **(0.220)**		
Code Week # School events (S)			**0.302**** **(0.135)**			**0.193** **(0.134)**	
Code Week # School-NPOs agreements (S)				**0.276**** **(0.124)**			**0.179** **(0.134)**
Employment rate (%)	0.366*** (0.0454)	0.358*** (0.0456)	0.361*** (0.0454)	0.359*** (0.0456)	0.366*** (0.0453)	0.367*** (0.0452)	0.364*** (0.0453)
Broadband take-up (%)	0.00161 (0.000989)	0.00217** (0.000987)	0.00206** (0.000995)	0.00180* (0.000997)	0.00161 (0.000989)	0.00162 (0.000989)	0.00148 (0.000995)
Lower secondary graduates (%)	-0.299*** (0.0169)	-0.299*** (0.0169)	-0.298*** (0.0171)	-0.300*** (0.0171)	-0.298*** (0.0168)	-0.297*** (0.0169)	-0.298*** (0.0169)
Population density (log)	-0.00548 (0.0106)	-0.00419 (0.0111)	0.00261 (0.0110)	0.00265 (0.0110)	-0.00495 (0.0109)	0.000827 (0.0109)	0.000634 (0.0110)
Participation in society	0.0973*** (0.0201)	0.0996*** (0.0204)	0.0947*** (0.0200)	0.0966*** (0.0200)	0.0979*** (0.0201)	0.0953*** (0.0198)	0.0967*** (0.0199)
One-person households (%)	-0.129* (0.0742)	-0.169** (0.0731)	-0.166** (0.0744)	-0.160** (0.0752)	-0.130* (0.0721)	-0.137* (0.0738)	-0.137* (0.0742)
Religious practice (%)	-0.0466*** (0.0163)	-0.0493*** (0.0169)	-0.0459*** (0.0162)	-0.0441*** (0.0162)	-0.0466*** (0.0163)	-0.0451*** (0.0160)	-0.0445*** (0.0161)
Constant	-0.0381 (0.457)	0.0192 (0.289)	-0.0831 (0.533)	0.427 (0.419)	0.233 (0.389)	-0.306 (0.527)	0.156 (0.461)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,632	2,632	2,632	2,632	2,632	2,632	2,632
Number of id (clusters)	329	329	329	329	329	329	329
R-squared	0.641	0.637	0.639	0.639	0.641	0.642	0.641

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Reference model

Table A5: Full FE model with alternative time-varying independent variable

VARIABLES	(1) DigComp	(2) DigComp	(3) DigComp	(4) DigComp	(5) DigComp	(6) DigComp	(7) DigComp
Volunteering in NPOs (C)	**0.0995**	**0.0996**	**-0.0841**	**-0.501**	**-0.446**	**-0.557**	**-0.466**
	(0.0764)	**(0.0763)**	**(0.612)**	**(0.690)**	**(0.682)**	**(0.624)**	**(0.616)**
Code Week initiatives (C,S)	**0.00187**	**-0.00137**	**-0.000465**	**0.00357**	**0.00268**	**0.00102**	**0.00113**
	(0.00941)	**(0.00845)**	**(0.0100)**	**(0.0103)**	**(0.0104)**	**(0.00913)**	**(0.00914)**
Volunteering # ICT teacher training (S)			**1.952***	**2.332****	**2.236****	**2.608****	**2.597****
			(1.098)	**(1.119)**	**(1.099)**	**(1.100)**	**(1.102)**
Volunteering # Library density (L)			**0.472***	**0.464***	**0.474***	**0.490****	**0.551****
			(0.254)	**(0.249)**	**(0.259)**	**(0.239)**	**(0.245)**
Volunteering # University density (U)			**42.66****	**43.14****	**43.70****	**35.48****	**39.19****
			(17.29)	**(16.93)**	**(17.25)**	**(15.61)**	**(16.27)**
Broadband take-up (%)	0.00187**	0.00174**		0.00214*	0.00230**	0.00211**	0.00214**
	(0.000886)	(0.000745)		(0.00110)	(0.00114)	(0.000893)	(0.000902)
Population density (log)	0.0234*	-0.00768		0.0214	0.0212	-0.00970	-0.00858
	(0.0140)	(0.0109)		(0.0150)	(0.0146)	(0.0118)	(0.0116)
Participation in society	0.121***	0.102***		0.120***	0.119***	0.0961***	0.0986***
	(0.0196)	(0.0182)		(0.0221)	(0.0222)	(0.0206)	(0.0206)
Religious practice (%)	-0.0796***	-0.0537***		-0.0764***	-0.0761***	-0.0513***	-0.0525***
	(0.0171)	(0.0159)		(0.0181)	(0.0180)	(0.0167)	(0.0167)
Average taxable income (log)	-0.0328			-0.0212	-0.0221		
	(0.105)			(0.122)	(0.121)		
Tertiary graduates	0.258***			0.246***	0.244***		
	(0.0192)			(0.0199)	(0.0200)		
People with no friends (%)	-0.119*			-0.109	-0.112		
	(0.0631)			(0.0761)	(0.0772)		
Museum density					0.0254		
					(0.110)		
Separate waste collection					0.00381		
					(0.0243)		
Trust					0.0137		
					(0.0202)		
Gini index (regional)					-0.216		-0.150
					(0.195)		(0.157)
Employment rate		0.370***				0.367***	0.370***
		(0.0434)				(0.0465)	(0.0463)
Lower secondary graduates		-0.290***				-0.301***	-0.299***
		(0.0169)				(0.0172)	(0.0171)
One-person households (%)		-0.106				-0.161**	-0.173**
		(0.0653)				(0.0733)	(0.0767)
Childcare density							0.0585
							(0.0418)
Life satisfaction index							0.0369*
							(0.0196)
Constant	0.448	0.223***	0.0297	0.199	0.246	0.175	0.204
	(1.033)	(0.0354)	(0.420)	(1.200)	(1.194)	(0.386)	(0.390)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,856	2,856	2,632	2,632	2,632	2,632	2,632
Number of id	357	357	329	329	329	329	329
R-squared	0.589	0.634	0.539	0.587	0.588	0.639	0.641

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

Table A6: Full FE model employing a subset of independent variables

VARIABLES	(1) DigComp	(2) DigComp	(3) DigComp	(4) DigComp	(5) DigComp	(6) DigComp	(7) DigComp
Code Week initiatives	**-0.100**** **(0.0395)**	**-0.0445** **(0.0432)**	**-0.195**** **(0.0875)**	**-0.173**** **(0.0810)**	**-0.121**** **(0.0524)**	**-0.235***** **(0.0888)**	**-0.211**** **(0.0862)**
Code Week # Community centers ©	**-0.847** **(0.651)**	**-0.448** **(0.630)**	**-0.265** **(0.690)**	**-0.400** **(0.640)**	**-0.796** **(0.648)**	**-0.570** **(0.713)**	**-0.711** **(0.667)**
Code Week # ICT teacher training (S)	**0.192***** **(0.0703)**				**0.185***** **(0.0709)**	**0.151**** **(0.0714)**	**0.139*** **(0.0743)**
Code Week # Students' ICT projects (S)		**0.225** **(0.209)**			**0.121** **(0.202)**		
Code Week # School events (S)			**0.313**** **(0.136)**			**0.248*** **(0.137)**	
Code Week # School-NPOs agreements (S)				**0.277**** **(0.125)**			**0.221*** **(0.134)**
Employment rate (%)	0.364*** (0.0465)	0.357*** (0.0459)	0.360*** (0.0456)	0.359*** (0.0459)	0.363*** (0.0463)	0.365*** (0.0460)	0.362*** (0.0462)
Broadband take-up (%)	0.00194** (0.000848)	0.00244*** (0.000842)	0.00231*** (0.000838)	0.00209** (0.000841)	0.00199** (0.000853)	0.00200** (0.000842)	0.00182** (0.000844)
Lower secondary graduates (%)	-0.302*** (0.0169)	-0.300*** (0.0168)	-0.299*** (0.0170)	-0.301*** (0.0170)	-0.300*** (0.0167)	-0.299*** (0.0169)	-0.300*** (0.0169)
Population density (log)	-0.00456 (0.0107)	-0.00363 (0.0110)	0.00406 (0.0109)	0.00389 (0.0110)	-0.00279 (0.0108)	0.00386 (0.0109)	0.00337 (0.0111)
Participation in society	0.0975*** (0.0204)	0.0995*** (0.0205)	0.0945*** (0.0200)	0.0966*** (0.0201)	0.0984*** (0.0203)	0.0947*** (0.0200)	0.0965*** (0.0201)
One-person households (%)	-0.129* (0.0735)	-0.174** (0.0718)	-0.168** (0.0739)	-0.160** (0.0750)	-0.137* (0.0715)	-0.141* (0.0734)	-0.138* (0.0741)
Religious practice (%)	- 0.0470*** (0.0164)	-0.0498*** (0.0168)	-0.0459*** (0.0161)	- 0.0440*** (0.0161)	- 0.0473*** (0.0164)	- 0.0449*** (0.0160)	- 0.0442*** (0.0162)
Constant	0.403 (0.350)	0.215** (0.105)	0.134 (0.422)	0.685** (0.299)	0.657*** (0.250)	0.148 (0.419)	0.590 (0.361)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,632	2,632	2,632	2,632	2,632	2,632	2,632
Number of id (clusters)	329	329	329	329	329	329	329
R-squared	0.638	0.637	0.639	0.639	0.639	0.640	0.640

Robust SE in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A7: FE models with Leading Indicator and with ARDL models

	Leading Indicator models			*Autoregressive AR(1) models*		
VARIABLES	(1) $DigComp_{t+1}$	(2) $DigComp_{t+1}$	(3) $DigComp_{t+1}$	(4) $DigComp_{t}$	(5) $DigComp_{t}$	(6) $DigComp_{t}$
$\boldsymbol{DigComp_{t-1}}$				**0.137*** (0.0234)**	**0.137*** (0.0223)**	**0.100*** (0.0220)**
Code Week initiatives	**-0.140*** (0.0496)**	**-0.129** (0.0520)**	**-0.145*** (0.0506)**	**-0.154*** (0.0494)**	**-0.130** (0.0501)**	**-0.146*** (0.0474)**
Code Week # Community centers (C)	**0.357 (0.623)**	**0.0625 (0.630)**	**0.225 (0.584)**	**-0.902 (0.577)**	**-0.722 (0.597)**	**-0.713 (0.604)**
Code Week # ICT teacher training (S)	**0.0829 (0.0586)**	**0.0598 (0.0603)**	**0.0708 (0.0574)**	**0.195*** (0.0686)**	**0.170** (0.0678)**	**0.191*** (0.0651)**
Code Week # Library density (L)	**-0.0441*** (0.0163)**	**-0.0428*** (0.0163)**	**-0.0475*** (0.0158)**	**-0.0235 (0.0148)**	**-0.0180 (0.0155)**	**-0.0192 (0.0151)**
Code Week # University density (U)	**0.977 (1.203)**	**1.577 (1.246)**	**1.306 (1.178)**	**2.175 (1.404)**	**2.067 (1.349)**	**1.766 (1.276)**
Broadband take-up (%)		0.00230** (0.00110)	0.00224** (0.00109)		0.00171* (0.000967)	0.00164* (0.000912)
Population density (log)		0.0397*** (0.0117)	0.0244** (0.0102)		0.0204* (0.0108)	0.00377 (0.0105)
Participation in society		-0.0298 (0.0201)	-0.0440** (0.0192)		0.0998*** (0.0241)	0.0986*** (0.0230)
Religious practice (%)		-0.00658 (0.0162)	0.00838 (0.0160)		-0.00917 (0.0191)	-0.0117 (0.0183)
Average taxable income (log)		0.0793 (0.123)			-0.0266 (0.102)	
Tertiary graduates (‰)		0.0622*** (0.0231)			0.180*** (0.0215)	
People with no friends (%)		0.0738 (0.0648)			-0.0574 (0.0924)	
Employment rate (%)			0.329*** (0.0482)			0.226*** (0.0521)
Lower secondary graduates (%)			-0.0741*** (0.0163)			-0.227*** (0.0187)
One-person households (%)			-0.0381 (0.0800)			-0.0572 (0.0793)
Constant	-0.411 (0.523)	-0.828 (1.296)	-0.0771 (0.523)	-0.444 (0.398)	-0.0101 (1.055)	-0.128 (0.440)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,303	2,303	2,303	2,303	2,303	2,303
Number of id (clusters)	329	329	329	329	329	329
R-squared	0.601	0.607	0.619	0.614	0.640	0.657

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

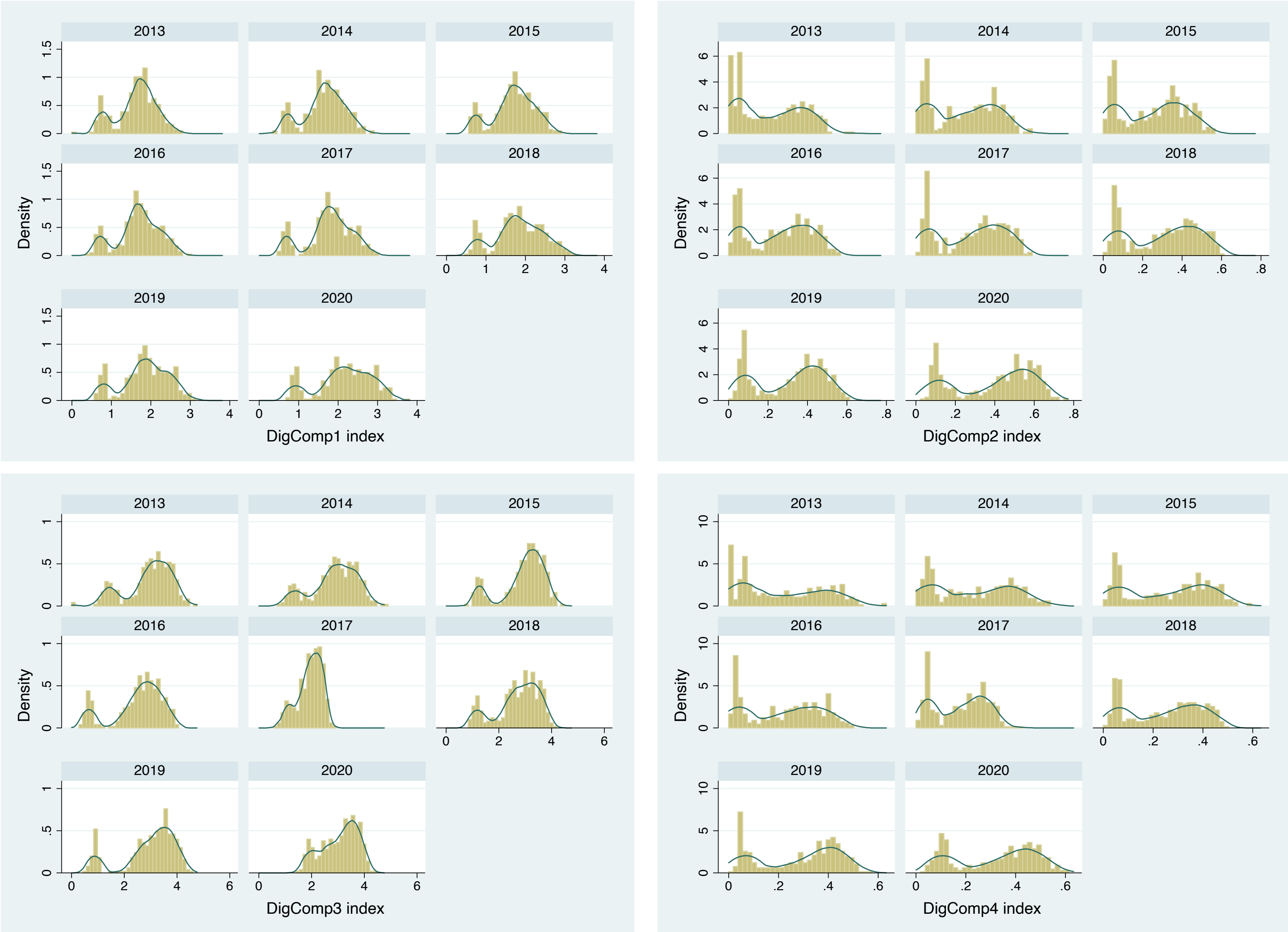

Figure A1. Distributions of the four different DigComp indexes