

Anticipating digital skills policy outcomes: a pseudo-panel evaluation of outreach initiatives in Italy

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Abstract

Scholars and policymakers have long identified stakeholders whose activities should help reduce digital inequalities; these include “outreach initiatives”, where organizations proactively go beyond their traditional boundaries to reach marginalized citizens. However, few studies have attempted to quantitatively evaluate the impact of this approach.

Our research fills this gap, employing both a static and dynamic analysis of a pseudo-panel dataset relating to Italy, a country that is experimenting with different policies to boost basic digital skills. We aggregate data from a representative national survey for the years 2014 to 2020, and we proxy outreach through the number of public events promoted to spread digital literacy.

The static model highlights the role of systemic variables: employment, broadband take-up, education, and social connectedness. The dynamic model shows that outreach – together with library activism – creates positive fluctuations around the trend but reaches a plateau.

We conclude that a policy mix is needed: outreach is a helpful policy tool to stimulate local communities in the short term, but other more structural interventions are needed to close the digital skills gap.

Keywords

digital skills; inequality; policy impact; panel data; Italy.

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1. INTRODUCTION

In an interview released in May 2021, Google CEO Sundar Pichai stated that the digital divide is “easier to bridge than most people think” and that “people are actually hungry to be part of the digital economy” (La Roche, 2021). However, many citizens still lack basic digital skills – defined as the ability to use “digital technology, communications tools, and/or networks to access, manage, integrate, evaluate, and create information *in order to function in a knowledge society*” (International ICT Literacy Panel, 2002, p. 16). Digital skills are scarce and unevenly distributed, with significant inequalities between and within countries (Livingstone et al., 2022; Van Deursen et al., 2017). Even in high- and upper-middle-income countries, such as the US and the EU, about 10% of the population does not even use the Internet (World Bank, 2022). In the EU, only 54% of the population is equipped with basic digital skills, with no substantial change since 2015 (European Commission, 2022).

The reality is that, more than 20 years after the term *digital divide* was coined (Hoffman et al., 2001), scholars “are only just beginning to formulate a theory explaining the phenomenon” and “they are not yet in a position to offer concrete policy directions” (van Dijk, 2020, p. 102).

Policymakers, however, have been trying to deal with the issue. van Dijk & van Deursen (2014, p. 172) have identified five types of strategies followed globally to improve digital skills: 1) strategies based on *awareness and organization*, i.e., on mobilizing multiple stakeholders, creating partnerships, and improving digital skills monitoring and measurement; 2) strategies based on *design improvement*, to increase accessibility and usability of hardware and software, especially for vulnerable categories; 3) strategies leveraging on *technology provision*, i.e., improving the infrastructure and providing devices and access points; 4) strategies based on *content development*, i.e., trying to standardize and certify skills and curricula, improving the quality of educational software; and 5) more traditional *educational strategies*, emphasizing teacher training, curriculum change, and new digitally-oriented courses for lifelong learning.

Nevertheless, despite the efforts put into analyzing these policy strategies, we have virtually zero evidence about the effectiveness of the policy interventions implemented so far and it is not clear, both from a theoretical and from a policy perspective, to what extent the different dimensions of the digital divide and the different policy approaches overlap and interact with each other.

Focusing on Europe, Helsper & van Deursen (2015, p. 142) underline that, together with limited theory, unstable measurement frameworks and poor interdepartmental and cross-sector collaboration imply that “the evaluation of policy effectiveness beyond infrastructure provision, related to digital skills and engagement, is poor” if not completely absent.

In this paper we deepen a policy approach that puts together, under the umbrella of *outreach*, different strategies: awareness initiatives; stakeholder organization; public-private partnerships; public access provision; special tools for the differently abled, seniors, low literates, and migrants; targeted contents; personal guidance (van Dijk & van Deursen, 2014). Taking stock of the theory and measurement frameworks available, we start overcoming the obstacles that so far have hindered evaluations to produce a preliminary impact assessment of a national policy package aimed at improving basic digital skills. Taking advantage of the data available for one European country – Italy – and of the policies it is experimenting with, we pursue the following research question: *Do local outreach initiatives have a positive impact on the digital skills of citizens?*

Operationally, we follow the examples of Bourguignon & Ferreira (2003) and Todd & Wolpin (2011) and we simulate the implementation of the policy throughout the years to anticipate its effects.

Since most of the extant literature underlines the role of social and cultural determinants of the skills divide, outreach initiatives are supposed to foster skills by targeting underserved communities and by overcoming the structural constraints that hinder access to digital technologies. This should be particularly true for policies that have multisector support and are integrated across the work of a variety of actors. Such hypotheses, however, should be validated empirically, both because it is unclear whether such multi-stakeholder alliances are effective, in the end, in delivering their interventions, and because we do not have any measure of the magnitude, heterogeneity, and duration of such potential effects.

2. THEORETICAL BACKGROUND

In this work we focus on the set of skills “that are required when using ICT and digital media to perform tasks; solve problems; communicate; manage information; collaborate; create and share content; and build knowledge effectively, efficiently, appropriately, critically, creatively, autonomously, flexibly, ethically, reflectively for work, leisure, participation, learning and socializing” (Ferrari, 2012, p. 3).

Differences in digital skills and usage are at the heart of van Dijk's (2020) Resource and Appropriation Theory of the Digital Divide: according to the authors, skills and usage are not only affected by pre-existing inequalities but can also affect participation outcomes such as economic well-being, social connectedness, location, political participation, nature of institutions (van Deursen & van Dijk, 2014). These social offline and online outcomes further fuel a cycle of digital inequalities, impacting personal and positional categories as well as individuals' initial resources through a *loop of reinforcement* (Blank & Groselj, 2014; Helsper, 2010; Mossberger et al., 2003). Scheerder et al. (2017) provide a comprehensive overview of the socioeconomic determinants of digital skills, uses, and outcomes.

Public policies can intervene here, to break the vicious loop of reinforcement both by acting directly on skills “by all kinds of educational means” (Van Dijk & Van Deursen, 2009) and by coupling digital inclusion with social inclusion strategies (Mervyn et al., 2014; Ragnedda, 2018; Reisdorf & Rhinesmith, 2020).

We focus in particular on so-called *digital skills for all* policies, i.e., on the development of skills for low-level users of ICT, with initiatives that “aim to raise public awareness of digital inclusion issues and publicize the need for digital skills” (Atchoarena et al., 2017, p. 38). Thus, we do not investigate other relevant policy areas such as computer skills for all children and young people (Resnick et al., 2009), specialized skills for all professionals (Sostero & Tolan, 2022), or soft and complementary skills, such as 21st-century skills (van Laar et al., 2017).

Policies for basic skills put particular emphasis on marginalized citizens, since individuals that belong to ICT-rich social networks – characterized by high levels of access, usage, and skills – are more inclined to use digital technologies (Mariën & Van Audenhove, 2010). van Deursen et al. (2014) and Asmar et al., (2020) show that patterns of support-seeking have a strong influence on digital skills development, the benefits one can attain from the internet, and the quality of the support received.

However, for proper policymaking on these topics, it is fundamental to understand that digital inclusion can flourish in manifold environments (Asmar et al., 2020). Wong et al. (2009) and van Dijk & van Deursen (2014) suggest that the strategy to bridge the digital gap should be a multi-stakeholder one, with governments collaborating with civil society and the private sector. The community-level capacity of volunteers, peers, and leaders can compensate for limited e-leadership at the national level (Graham & Hanna, 2011), especially for underserved groups, such as the elderly (Sourbati, 2009).

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). Outreach services are provided as close as possible to the underserved community and they are usually voluntary, meaning that it is not mandatory for customers to participate (Dewson et al., 2006).

What type of stakeholders are typically involved in this approach? School-community partnerships are often pivotal for a multi-stakeholder strategy (Valli et al., 2016), since 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 are ideally positioned to lead the way in this direction 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), which can provide both internet connection and devices (Jaeger et al., 2012) and have the employees necessary to provide assistance and training (Kinney, 2010). Universities, instead, have often limited themselves to tackling the shortage of digitally competent graduates, benefiting the economic system rather than society as a whole (Davenport et al., 2020; Johnston, 2020). However, in the last decades, the concept of university outreach has expanded

to services, programs, and partnerships that achieve full engagement with their communities (Leong, 2013; Slagter van Tryon, 2013).

Furthermore, many other local facilities are equipped to 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), municipal ICT schools (Hartviksen et al., 2002), vocational colleges (Ngqulu et al., 2019), senior centers (Lenstra, 2017), internet cafés (Ferlander & Timms, 2006), makerspaces (Kafai et al., 2014; Ratto, 2011).

Notwithstanding the potential of this wide network of organizations and the theoretical alignment of this approach with the sociopolitical nature of digital inequalities (Selwyn, 2004), we know very little about the effectiveness and the concrete impact that all these activities have on the population. Most of the available studies provide rich overviews of the activities performed by an actor in a specific region and of the difficulties encountered (e.g., Wong et al., 2009), or offer suggestions about the role that an actor might be able to play within a community (e.g., Martinez, 2019), also thanks to interviews and short surveys delivered to representatives of such organizations (e.g., Unterfrauner et al., 2020; Yilmaz & Cevher, 2015). Other works have focused on the pedagogy of specific initiatives, trying to optimize the learning experience (e.g., Kumpulainen et al., 2020).

3. DATA AND SAMPLE

3.1. The Italian case

Italy is a promising context to test the validity of an outreach-oriented approach. Despite being the 3rd largest country in the EU in terms of GDP and population, in fact, Italy has been lagging behind at the bottom of the European rankings for digital skills since these have been surveyed by Eurostat in the early 2010s (European Commission, 2022). Furthermore, Italy couples the overall lack of basic digital skills with relevant internal inequalities: almost 20 percentage points separate the best- and the worst-performing regions in terms of digitally skilled population (Istat, 2023).

This scenario, together with the strong impact that Covid has had on the country, has pushed the Italian government towards asking for relevant financial support from the European Commission in this area. As a result, Italy now displays the biggest EU-backed investment in basic skills in the Union.

These allocations include a 200M support for two “twin” policies explicitly aiming at boosting citizens’ basic digital skills: a national policy – the *Digital Civilian Service* – and a set of regional policies – the *Networks of eFacilitation Services* (Italiadomani, 2022). These policies scale up interventions that have been experimented with in some Italian regions over the last 15 years, resorting either to volunteers or to professional “eFacilitators” to help citizens become autonomous in the use of basic digital applications: digital identity, eHealth platforms, internet browsers, personal devices, basic software. This is pursued either through different forms of user support desks or through short (offline) informal courses. The target is ambitious: reaching and improving the skills of 2M citizens over 5 years.

More importantly, however, both policies adopt a bottom-up approach and finance heterogeneous initiatives promoted by a wide network of local governments, non-profits, cooperatives, schools, libraries, universities, and local health authorities. This is designed in order to impact “non-users’ social environment, including the local community, workplace, and neighborhood” (Park, 2014).

This approach is not completely novel in high-income countries (IFLA, 2020; Jaeger et al., 2012; Martin, 2017) and, for example, different States in the US have experimented with similar programs employing either AmeriCorps volunteers (Duvivier, 2023) or so-called *Digital Navigators* (NDIA, 2022) to promote digital equity in underserved communities. The Italian one, however, is the first systematic attempt to use it as a policy tool to reduce digital inequalities at the national level in a country possessing both the right scale and the data to test out hypotheses. Hence, our study aims at assessing whether there is hope for success, using data on past digital-related outreach initiatives to evaluate ex-ante the expected impact of policies with the same rationale.

3.2. Dependent variable and pseudo-panel approach

The first step of our analysis is represented by the construction of the dependent variable measuring individuals' digital skills. Outside an experimental or quasi-experimental setting, any causal claim requires longitudinal data to cancel the effect of unobservable individual characteristics out (Wooldridge, 2010). However, longitudinal surveys on digital skills are currently not available in European countries. Thus, we opted for a pseudo-panel approach.

Pseudo-panel methods are one way of making up for the lack of panel data and have been employed in different fields (Guillerm, 2017). Their use dates back to Deaton (1985), who first acknowledged their advantage in terms of data availability and time coverage. When the same individuals cannot be followed, types of individuals can be followed, referred to as “cohorts” or “cells”.

In our case, Eurostat and national statistical offices in the EU estimate the digital skills level of individuals from the type of usage and the number of online activities that citizens self-declare when answering multi-purpose household surveys (Eurostat, 2022). As for Italy, this information is collected through the survey *Aspetti della Vita Quotidiana* (AVQ). The survey sample is built with the purpose of being representative of the Italian population by: 1) gender; 2) region of residence; 3) municipality type; 4) age group; 5) education level.

Despite the richness and representativeness of the dataset, however, AVQ remains a repeated cross-section dataset. Thus, we have identified synthetic cohorts, balancing representativeness and statistical power, aggregating the stratified AVQ sample using the triplet: region (r) – 20 items; municipality type (m) – 3 categories; age group (a) – 7 groups. These cells can be followed over the years and can also be linked with data coming from other sources, as depicted in Figure 1. Table A1 shows how observations distribute over each cell.

The dependent variable resulting from this process is a composite index built following the Eurostat methodology and the DigComp 2.1 framework (JRC, 2017), aggregating 22 dichotomous indicators grouped in the following competence areas: information and data literacy, communication and collaboration, digital content creation or software skills, and problem solving. Each area weighs 25% and the score of each area is the arithmetic average of the dummies belonging to the area.

We use the 2.1 version of DigComp, not the more recent 2.2 version, since we need to harmonize data from waves of the AVQ survey where variables included in the latest update were not available. This implies the exclusion of the competence area related to safety. Furthermore, not all DigComp variables were surveyed every year, hence we substituted the missing variables with their closest match identified minimizing the Hamming distances between variables (Hamming, 1980) in the years when all AVQ variables were available.

Table A2 lists all the indicators used, while Figure A1 shows the distributions of the DigComp Index.

Figure 1. Synthesis of the pseudo-panel approach

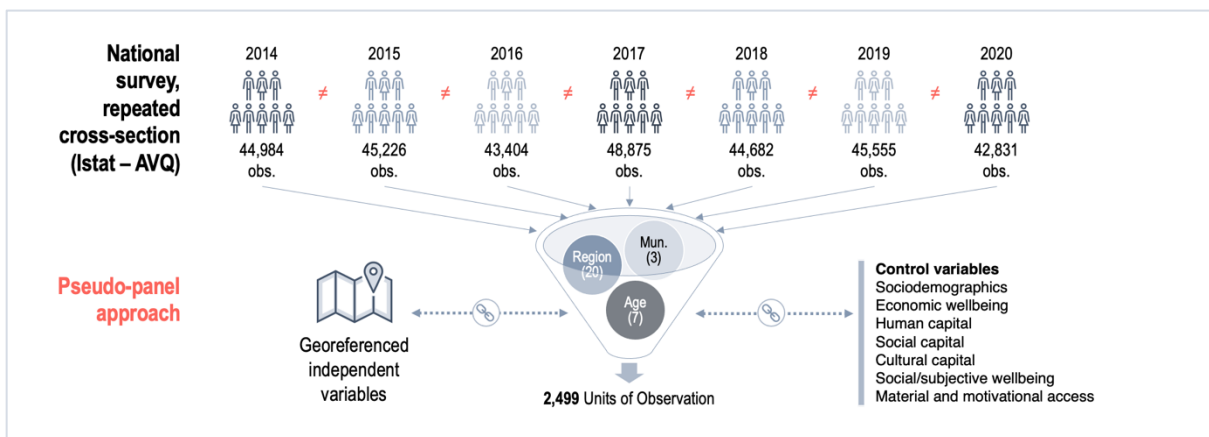
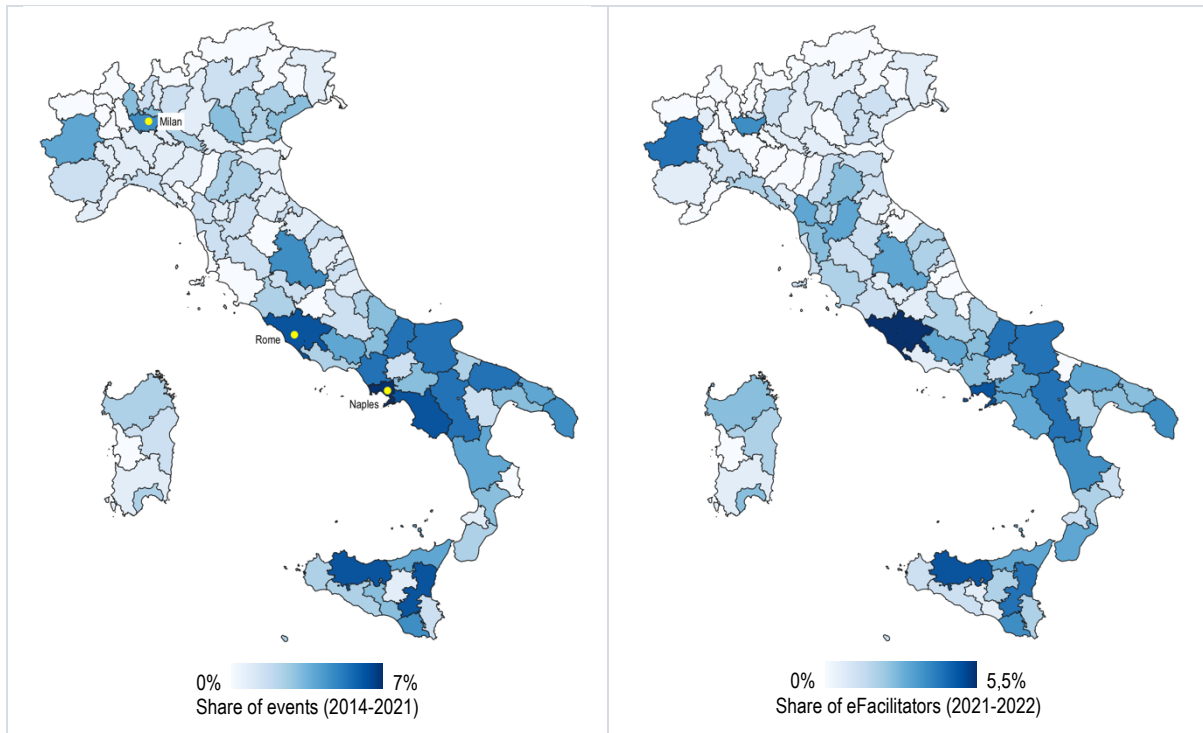


Figure 2. Geographical distribution of Code Week events (left) and of Digital Civilian Service eFacilitators (right)



Source: Authors' elaboration on data provided by EU Code Week organizers and by the Department for Youth Policies and the Civilian Service of the Italian Government.

3.3. Measuring outreach through digital skills-related events

Data availability has always been an issue in digital divide studies (Dimaggio et al., 2004), not only with respect to skills measurement but especially when evaluating policy interventions aimed at reducing digital (skills) inequalities. In particular, very few datasets cover multiple years.

A relevant exception is represented by the Code Week (CW), an international initiative supported by the European Commission that spreads digital awareness through volunteer events and activities. Launched in 2014, the Code Week is a grassroots initiative that aims to bring coding and digital literacy to everybody in a fun and engaging way (CodeWeek.eu, 2023).

Despite its name, CW is not only about coding. Activities also include other general digital-related topics such as motivation and awareness raising, promoting diversity, or using art and creativity. Basic programming skills and other topics – such as, e.g., robotics or mobile app development – are just the tip of the iceberg of a broader movement aiming at empowering local communities in the digital world. Moreover, the CW is not only about a week; events span mainly over the whole month of October and, more importantly, they are often followed up throughout the year with complementary activities.

Between 2014 and 2020, more than 550,000 events have been promoted only in Italy, one of the most active countries together with Poland and Turkey. Schools are the main organizers: 97% of the events overall feature a school or a teacher as the main promoter. However, it is important to note that, even when the organizer is a school, each event must be organized in collaboration with other organizations; hence, being active in the network implies being able to count on a receptive local community made of non-profit organizations, libraries, firms, and volunteers. Furthermore, CW events are typically open to the public: they can target school students, individuals in higher education, employed or unemployed adults, the elderly, or just the whole population. Organizers also have incentives to provide information

about their activities and have them featured within the CW network, since they receive support from the partners and sponsors in the form of learning resources, toolkits, training, and also certifications.

We use the number of CW events per 1,000 inhabitants held in Italy as a proxy of how proactive a cohort is in trying to reduce barriers between citizens and digital technologies. CW organizers do so by going beyond their traditional boundaries and by leveraging upon inter-organizational collaboration.

To show that the distribution of this variable is, in fact, a good proxy also of how eFacilitation is developing, Figure 2 compares the distribution of all CW events promoted between 2014 and 2021 with the distribution of volunteers in the first two years of implementation of the *Digital Civilian Service*. The similarity between the two maps supports the choice of this measure for an ex-ante impact evaluation of these policies. Table A3, in the Appendix, displays the results of a simple OLS model showing that the correlation between the distribution of eFacilitators and CW activities is not just driven by population size or by other drivers of the choice to apply for a volunteer position, such as being unemployed or being enrolled in university.

The appendix also provides further information on how CW activities actually develop, using the example of the city of Naples.

3.4. Civic engagement and outreach-oriented organizations

The CW variable is not only meant to capture dynamics related to schools' outreach or to public events, but is to be interpreted as a signaling device, the tip of the iceberg indicating that a cell is proactive in promoting awareness about digital technologies. However, there might be other relevant drivers of digital and social inclusion that are not captured by the collaboration between schools and other community organizations. Hence, we include in our model also other variables accounting for voluntarism and for the activity of relevant "outreach-oriented" organizations: local associations, libraries, and universities.

Also in these cases, we hypothesize that density is a good indicator of activism, following the approach adopted by quantitative migration studies to proxy the strength of social networks (Åslund & Fredriksson, 2009; Dustmann et al., 2013; Siciliano et al., 2020). Thus, we measure social participation (*part*) as the share of individuals who are active either in associations, unions, or political parties. Second, we measure exposure to the activities of libraries (*lib*) as the number of active public libraries per 1,000 inhabitants, as recorded by the national registry of libraries (ICCU, 2023). Lastly, we measure university outreach (*tm*) – also taking into account its quality – through the multi-year assessment of third mission activities promoted by Italian higher education institutions, focusing on the indicators evaluating public engagement (Anvur, 2021).

Figure A3 illustrates the territorial distribution of these three independent variables, which enter the models also in the form of interactions with the main treatment variable.

3.5. Control variables

We include in our models also a set of control variables, drawing from the categorization of the determinants of digital divides made by Scheerder, van Deursen and van Dijk (2017).

First, we account for population density to control for the intensity of social interactions that are often correlated with higher returns from possessing digital skills (Courtois & Verdegem, 2016; Helsper, 2012; van Deursen et al., 2014). Second, we account for economic well-being, in terms of employment rate, since we expect more affluent cohorts to be more skilled and we also expect this skill premium to be mirrored by the local labor market (Lissitsa et al., 2017; Van Deursen & Helsper, 2015; Yoon, 2018).

Both of these variables also capture some dynamics related to the individuals' material and motivational access to digital technologies. However, we also included a direct measure of access, which is broadband take-up by households, one of the key indicators of digital inequality and a driver of skill acquisition (Lee et al., 2015).

Digital skills are also correlated with other types of (formal) skills (García-Mora & Mora-Rivera, 2021; Litt, 2013). Hence, we account for human capital through the share of individuals who possess at most

a lower secondary school diploma – which we expect to be negatively correlated with the outcome variable. Since we focus on basic skills, we prefer this indicator to other indicators looking at higher education levels – e.g., tertiary graduates, that we would expect to have a positive sign.

Lastly, since we are also investigating the links between social inclusion and digital inclusion, we include three relevant sets of social and individual determinants identified by Scheerder, van Deursen and van Dijk (2017): social capital – in terms of friendship, household composition, and trust in others –, cultural capital – looking at religiosity and at exposure to museums –, and subjective well-being – as measured by the subjective health status and in terms of how satisfied one is with one's life.

Table A4 in the Appendix lists the definitions and sources of this data and provides further details on their granularity in terms of the triplet region-municipality type-age group.

4. METHODS

We started from the basic ordinary least squares model:

$$DigComp_{it} = \beta_0 + \beta_1 CW_{it} + \gamma Z_{it} + u_{it} \quad (1)$$

Where: $i = 1, \dots, N$ is the number of units of observation (r, m, a) available each year; t is the time index; $DigComp_i \in [0,1]$ is the index of citizens' digital skills; CW_{it} is the independent variable measuring digital skills-related outreach; Z_{it} is the set of control variables; $u_{it} = v_i + \varepsilon_{it}$ is the error.

We first extend this basic model to include a matrix X of further independent variables – $X = \{part, lib, tm\}$ – together with their interactions with the main treatment variable (CW):

$$DigComp_{it} = \beta_0 + \beta_1 CW_{it} + \delta_x X_{it} + \theta_x (CW_{it} \times X_{it}) + \gamma Z_{it} + u_{it} \quad (2)$$

We move now to the panel specification, starting from the static model, to eliminate the potential bias from unobserved individual effects (v_i) and to include time fixed effects:

$$DigComp_{it} = \beta_0 + \beta_1 CW_{it} + \delta_x X_{it} + \theta_x (CW_{it} \times X_{it}) + \gamma Z_{it} + \lambda_t + \varepsilon_{it} \quad (3)$$

The vector λ_t represents the year fixed effects while only random observation-specific errors (ε_{it}) are now left in the model.

Lastly, since digital skills are accumulated over time, following the traditional dynamic path of human capital accumulation (see Heckman, Lochner and Taber, 1998), we estimate also a dynamic model. Digital skills in a cohort depreciate over time but are not reset in every period, hence the skills level at time t depends on previous levels or lags, according to the following model:

$$DigComp_{it} = \beta_0 + \alpha_l DigComp_{il} + \beta_1 CW_{it} + \delta_x X_{it} + \theta_x (CW_{it} \times X_{it}) + \gamma Z_{it} + \lambda_t + \varepsilon_{it} \quad (4)$$

Where $DigComp_{il}$ represents the auto-regressive component and $l = 1, 2, \dots, L$ is the number of lags we choose to include.

We use the Generalized Method of Moments (GMM) to estimate the dynamic model, in order to control for endogeneity of the lagged dependent variable, for omitted variable bias, and for unobserved panel heterogeneity; GMM models are also designed for situations characterized by heteroskedasticity, serial correlation, and arbitrarily distributed fixed effects (Wooldridge, 2001).

Furthermore, GMM models are appropriate when the number of groups ($N = 357$) is strictly larger than the time span ($t = 7$) considered (Blundell & Bond, 1998). Importantly, GMM uses instrumental variable estimation and requires instruments to be non-larger than the number of groups; this implies using model specifications that are more parsimonious in the number of variables employed, to reduce the number of instruments and strengthen overidentification tests (Roodman, 2009).

We use system GMM since it corrects endogeneity by introducing more instruments, thus improving efficiency. These instruments are transformed in order to make them uncorrelated with the fixed effects (Blundell & Bond, 1998). Given the clustering of our data, we use a two-step GMM estimator.

To sum up, the focus of our study is on equations (3) and (4), and mainly on the β_1 coefficient. Understanding potential channels for impact and moderating or moderating variables, however, implies focusing also on the coefficients of the other independent variables ($\delta_1, \delta_2, \delta_3$), of the interaction terms ($\theta_1, \theta_2, \theta_3$), and on the vector γ , i.e., on the concurrent role of other potential determinants.

Table 1. Static fixed-effects panel models, without interactions

VARIABLES	(1) DigComp Index	(2) DigComp Index	(3) DigComp Index	(4) DigComp Index	(5) DigComp Index	(6) DigComp Index
Digital outreach (cw)	0.000268 (0.00634)	4.55e-05 (0.00610)	-0.00189 (0.00622)	0.000125 (0.00608)	0.000104 (0.00608)	-0.00196 (0.00620)
Employment rate		0.210*** (0.0530)	0.213*** (0.0526)	0.209*** (0.0532)	0.208*** (0.0529)	0.210*** (0.0528)
Broadband take-up		0.106*** (0.0151)	0.105*** (0.0153)	0.106*** (0.0151)	0.104*** (0.0154)	0.104*** (0.0154)
Population density		-0.000140 (0.000289)	-0.000156 (0.000298)	-0.000136 (0.000288)	-0.000172 (0.000291)	-0.000192 (0.000300)
Secondary education		-0.207*** (0.0181)	-0.208*** (0.0180)	-0.207*** (0.0181)	-0.205*** (0.0182)	-0.207*** (0.0182)
No friends			-0.0611 (0.0792)			-0.0622 (0.0772)
One-person households			-0.159* (0.0815)			-0.160** (0.0807)
Trust			0.0108 (0.0202)			0.00902 (0.0201)
Religiosity				-0.000901 (0.0200)		-0.00184 (0.0202)
Museum density				0.0560 (0.101)		0.0595 (0.102)
Health status					0.0528 (0.0639)	0.0719 (0.0635)
Life satisfaction					0.0343 (0.0236)	0.0323 (0.0238)
Constant	0.250*** (0.00189)	0.209*** (0.0235)	0.257*** (0.0347)	0.203*** (0.0258)	0.168*** (0.0511)	0.198*** (0.0569)
Observations	2,499	2,499	2,499	2,499	2,499	2,499
R-squared	0.573	0.624	0.626	0.624	0.625	0.626
Number of groups	357	357	357	357	357	357
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

5. RESULTS

5.1. Static analysis

Table 1 and Table 2 display the results of the static panel analysis: models 1 to 6 report the estimation coefficients without including interactions, while models 7 to 12 report the specifications illustrated by equation (3).

We always use fixed-effects estimation, i.e., we focus on variation within units, given the nested structure of our data and the presence of time fixed-effects – the definition of the DigComp Index varies slightly depending on the years and we have seen that this results in different distributions (Figure A1). We test the assumption on fixed effects using the Mundlak (1978) approach, since we also hypothesize heteroskedasticity and serial correlation. The results of all the diagnostic tests are reported in Table A5. Since they confirm our hypotheses, we always estimate equation (3) using clustered standard errors.

Table 2. Static fixed-effects panel models, with interactions

VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
	DigComp Index	DigComp Index	DigComp Index	DigComp Index	DigComp Index	DigComp Index
Digital outreach (<i>cw</i>)	0.00610 (0.0179)	0.00835 (0.0170)	0.00427 (0.0176)	0.00735 (0.0176)	0.00827 (0.0166)	0.00229 (0.0178)
Employment rate		0.214*** (0.0577)	0.216*** (0.0572)	0.214*** (0.0577)	0.210*** (0.0576)	0.211*** (0.0572)
Broadband take-up		0.0957*** (0.0147)	0.0950*** (0.0148)	0.0957*** (0.0146)	0.0943*** (0.0148)	0.0936*** (0.0149)
Population density		-0.000310 (0.000323)	-0.000328 (0.000333)	-0.000308 (0.000324)	-0.000357 (0.000324)	-0.000379 (0.000336)
Secondary education		-0.193*** (0.0184)	-0.195*** (0.0182)	-0.193*** (0.0184)	-0.191*** (0.0184)	-0.193*** (0.0182)
No friends			-0.0697 (0.0800)			-0.0711 (0.0775)
One-person households			-0.136 (0.0828)			-0.142* (0.0819)
Trust			0.00680 (0.0201)			0.00476 (0.0201)
Religiosity				-0.00851 (0.0191)		-0.0106 (0.0193)
Museum density				0.0121 (0.105)		0.0257 (0.105)
Health status					0.0794 (0.0634)	0.0959 (0.0635)
Life satisfaction					0.0373 (0.0227)	0.0362 (0.0229)
Social participation (<i>part</i>)	0.121*** (0.0300)	0.0879*** (0.0278)	0.0862*** (0.0280)	0.0881*** (0.0279)	0.0891*** (0.0280)	0.0877*** (0.0282)
Third Mission (<i>tm</i>)	-0.00384 (0.00239)	-0.00153 (0.00225)	-0.000911 (0.00231)	-0.00145 (0.00225)	-0.00129 (0.00226)	-0.000520 (0.00232)
Library activism (<i>lib</i>)	-0.731 (0.464)	-0.461 (0.485)	-0.530 (0.487)	-0.473 (0.488)	-0.479 (0.481)	-0.567 (0.485)
Interaction 1 (<i>cw</i> * <i>part</i>)	0.0498 (0.0602)	0.0358 (0.0589)	0.0401 (0.0583)	0.0375 (0.0578)	0.0410 (0.0578)	0.0479 (0.0560)
Interaction 2 (<i>cw</i> * <i>tm</i>)	0.00430 (0.00345)	0.00218 (0.00331)	0.00165 (0.00336)	0.00213 (0.00331)	0.00183 (0.00329)	0.00124 (0.00334)
Interaction 3 (<i>cw</i> * <i>lib</i>)	-0.117 (0.113)	-0.109 (0.109)	-0.0941 (0.110)	-0.104 (0.114)	-0.113 (0.106)	-0.0890 (0.112)
Constant	0.352*** (0.0740)	0.271*** (0.0848)	0.322*** (0.0906)	0.273*** (0.0857)	0.214** (0.0955)	0.260*** (0.0996)
Observations	2,499	2,499	2,499	2,499	2,499	2,499
R-squared	0.594	0.635	0.636	0.635	0.636	0.637
Number of id_panel	357	357	357	357	357	357
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Moving on to the analysis of our models, the first relevant result is that in the static configuration our main independent variable, i.e., our measure of digital-related outreach, is never significant, with or without the inclusion of the other independent variables.

What matters, instead, are more structural drivers of the economy (employment, education, and connectivity), all moving in the expected direction. Units that improve over time in terms of economic well-being display growing levels of digital skills among their population (coefficient $\approx +0.21$). Human capital is positively correlated, too: units where a decreasing share of the population holds at most a secondary school diploma, i.e., increase their human capital, witness improvements in basic digital

skills (coefficient ≈ -0.20). Lastly, cohorts where broadband take-up increases over time are able to translate this into more frequent and arguably skilled use of the internet (coefficient between $+0.094$ and $+0.107$).

Other control variables are generally not significant, except for one of the sociodemographic characteristics of our cells: the share of households composed of only one individual is negatively correlated with the outcome variable (coefficient between -0.16 and -0.14), signaling that being embedded in a family network might exert a positive influence on the digital skills of individuals.

The analysis of Table 2 reveals another link between social and digital inclusion. When we extend the model to the full set of independent variables considered in equation (3), social participation is positive and highly significant (coefficient between $+0.087$ and $+0.089$). This means that the units where the population is more active in society over time see their digital literacy increase, although there seems to be no significant interaction between this phenomenon and school-led digital outreach.

In the static analysis, lastly, the two variables concerning the role of universities and libraries are not significant, as are their interactions with our main treatment variable.

Table 3. Dynamic panel models, system GMM estimation

VARIABLES	(1) DigComp Index	(2) DigComp Index	(3) DigComp Index	(4) DigComp Index
DigComp Index = L1	0.485** (0.229)	0.555*** (0.205)	0.531*** (0.193)	0.534*** (0.181)
DigComp Index = L2	-0.430** (0.168)	-0.381** (0.154)	-0.368*** (0.128)	-0.345*** (0.124)
Digital outreach (<i>cw</i>)	0.565* (0.294)	0.458* (0.253)	0.463** (0.233)	0.407** (0.205)
Employment rate	0.243* (0.128)	0.198 (0.121)	0.213* (0.111)	0.210** (0.102)
Broadband take-up	0.914*** (0.344)	0.857*** (0.307)	0.839*** (0.308)	0.734*** (0.275)
Secondary education	0.0261 (0.414)	0.0993 (0.365)	0.104 (0.359)	0.0229 (0.337)
One-person households	0.0788 (0.549)	-0.212 (0.453)	-0.0667 (0.399)	-0.0446 (0.372)
Social participation (<i>part</i>)	-0.153 (0.419)	-0.110 (0.418)	-0.0912 (0.376)	-0.176 (0.326)
Third Mission (<i>tm</i>)	0.00989 (0.0112)	0.00757 (0.0110)	0.00530 (0.00956)	0.00485 (0.00848)
Library activism (<i>lib</i>)	0.995*** (0.367)	0.754** (0.340)	0.691** (0.292)	0.677** (0.275)
Interaction 1 (<i>cw * part</i>)	-2.183 (1.334)	-2.029* (1.183)	-2.179* (1.128)	-1.830** (0.929)
Interaction 2 (<i>cw * tm</i>)	-0.0430 (0.0343)	-0.0304 (0.0334)	-0.0236 (0.0289)	-0.0246 (0.0252)
Interaction 3 (<i>cw * lib</i>)	-0.404 (0.881)	-0.0998 (0.912)	-0.113 (0.802)	-0.0855 (0.769)
Constant	-0.604* (0.339)	-0.565* (0.294)	-0.542* (0.301)	-0.435 (0.276)
Instrumented lags for <i>lib</i> (l_1 l_2):	(2 2)	(2 3)	(2 4)	(2 5)
Observations	1,785	1,785	1,785	1,785
Wald Prob > χ^2	0	0	0	0
N. of instruments	32	36	39	41
AR1 Prob > χ^2	0,0009	0,0004	0,0003	0,0002
AR2 Prob > χ^2	0,2168	0,2127	0,1389	0,1374
Hansen test of overid. Prob > χ^2	0,1342	0,203	0,293	0,173

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

5.2. Dynamic analysis

Serial correlation in the outcome variable is not only coherent with the laws of human capital accumulation (Becker, 1962) but it also emerges clearly from the data (Table A5). Hence, we proceed with the estimation of dynamic models using system GMM (**Error! Reference source not found.**).

We include in models 1 to 4 two lags of the dependent variable, the main explanatory variable (*CW*), the other independent variables with their interactions, and the controls that were significant in the static models. For all specifications, we use cluster-robust standard errors and apply the backward orthogonal deviations transform to the instruments for the transformed equation.

Only year dummies are considered strictly exogenous, while all other variables are considered as endogenous regressors and used as GMM-style internal instruments. These are divided into two groups – a key empirical solution for the robustness of our configurations:

1. Library activism (*lib*) is instrumented using the lags from lib_{t-2} to lib_{t-5} ;
2. All the remaining regressors – lags of y , outreach, social participation, third mission, and the four control variables – are instrumented using only the second lag. For them, we also use the *collapse* option to reduce the number of instruments.

The resulting models pass the diagnostic test for autocorrelation: we reject the null hypothesis of no first-order serial correlation and we fail to reject the null hypothesis of no second-order serial correlation. Moreover, the models also pass the test for overidentification, with all the p-values of the Hansen test in the comfortable range between 0.10 and 0.30.

Overall, the resulting picture confirms some of the conclusions already drawn for the static configuration, but at the same time highlights several relevant differences.

First, when taking into account dynamic fluctuations over the trend, digital outreach (*CW*) becomes positive and significant, with a coefficient ranging from +0.41 to +0.57. Becoming more active in promoting digital awareness increases the likelihood of a positive fluctuation.

Second, the dynamic of the lagged outcome variables, significant with opposite signs, gives support to the overall coherence of the models, since it implies that there is no compound exponential trend at play, the second lag creating a plateauing effect when a territory might witness consecutive improvements over multiple years.

Third, libraries play a relevant role, too. The coefficient of library activism (between +0.68 and +0.99) is even larger than the one estimated for digital outreach, signaling that an increased presence of libraries captures an increased interest in digital technologies.

Fourth, we identify a significant (negative) interaction between social participation and digital outreach, while social participation per se is not impacting the dynamic trend. This might seem counterintuitive, but also in this case the variable acts as a moderator: when social participation is already high, an increase in digital skills-oriented proactiveness of local actors is less effective since part of the job related to digital/social inclusion is already taken care of.

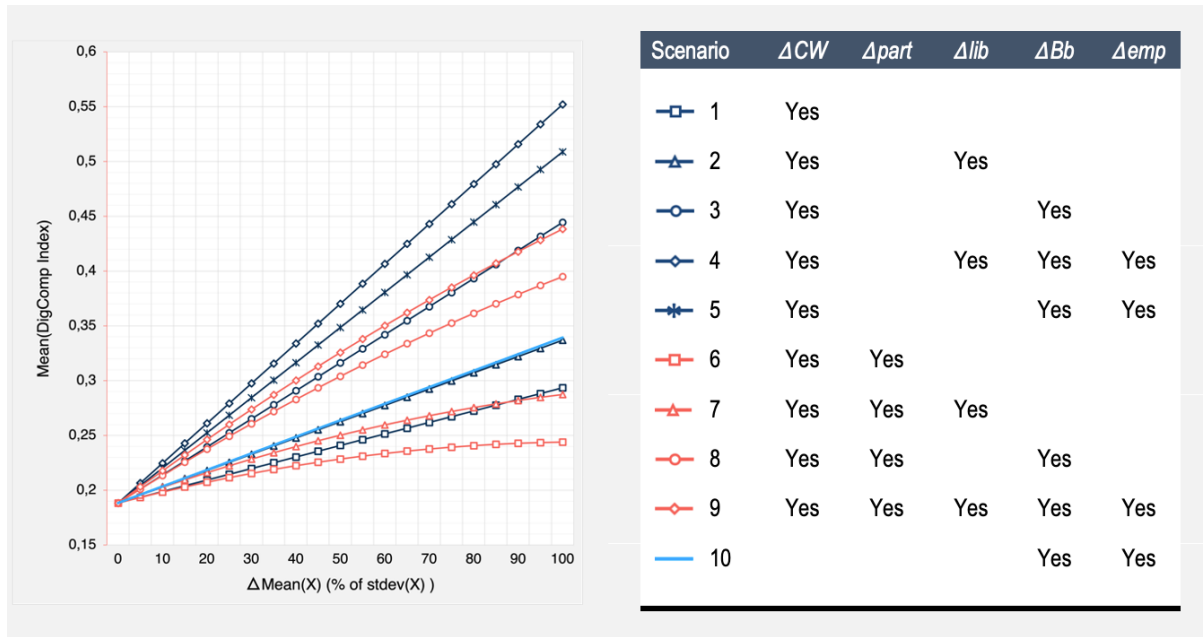
Lastly, the most impactful variable is again broadband take-up (between +0.74 and +0.91), more than employment, while education and social connectedness do not play a role in boosting the trend upward.

How large is the impact of these dynamics on the level of basic digital skills? The simulations illustrated in Figure 4 help us get a more concrete idea of the size of the effect. We simulate how the mean outcome across cohorts (vertical axis) would move if we increased the mean of any of the significant regressors by a share of its standard deviation (horizontal axis).

If the distribution of outreach activities moves right by 1 standard deviation (which means doubling them, on average), basic digital skills would increase by 5-35 percentage points on average, depending on the simultaneous dynamics of other relevant regressors. We can also see the plateau effect caused by increased social participation (dark blue vs red scenarios).

Overall, the effect of an increase in outreach and in library activity is comparable to that of increasing broadband take-up and employment by the same extent (Scenario 2 vs Scenario 10).

Figure 3. Simulating the impact of increasing outreach



6. DISCUSSION

Our study suggests that local digital-oriented outreach initiatives can exert a positive impact on the digital skills of citizens, in terms of stimulating positive fluctuations in the structural trend of digital skills development. Cohorts that increase the number of events dedicated to digital awareness witness higher rates of improvements in basic digital skills, once we account for the time-series dynamics.

The interaction between different actors, never explored so far by other studies, is significant only for one variable – social participation – in the GMM configurations and enters the model with a negative sign. This implies a moderation effect signaling how outreach becomes less and less effective to boost basic digital skills the higher the social capital – a sort of saturation effect.

Among the other variables, library activism displays a sizeable effect in the dynamic setting but broadband take-up takes the lion's share, being constantly positive and significant in both configurations. Employment is relevant, too, though to a lesser extent, while education and household composition are significant only in the static models. Other regressors such as population density, trust, cultural capital, and subjective well-being are not significant.

In our view, the static and dynamic models provide two complementary perspectives (Figure 4) that require integration among three of the strategic pillars identified by van Dijk & van Deursen (2014): awareness and organization (i.e., multisector support), technology provision, and education.

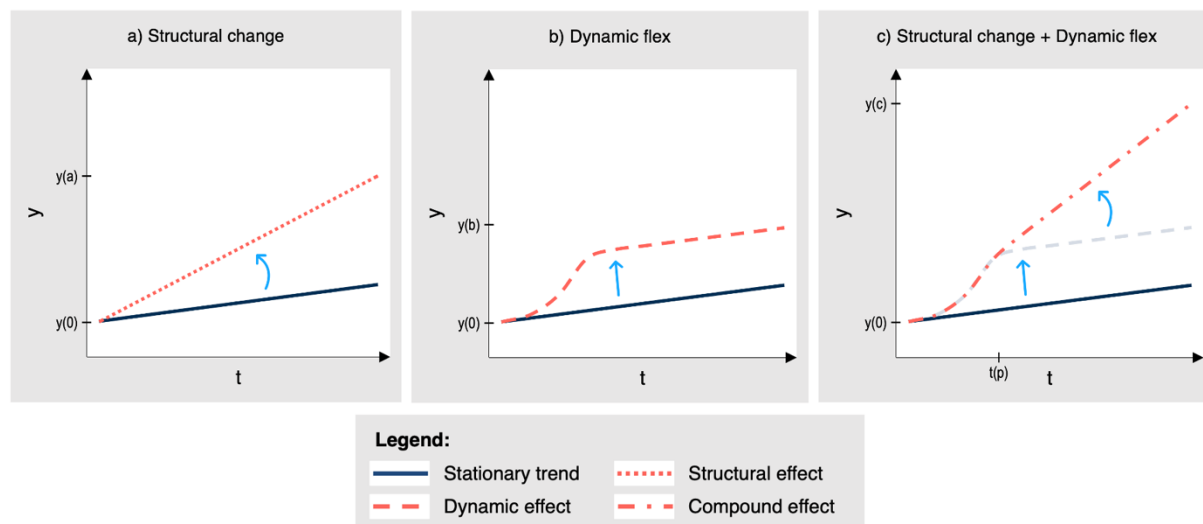
On the one hand, the static fixed-effects model identifies variables that structurally impact citizens' basic digital skills. From the viewpoint of policymakers, this implies that, if one wants to change the trajectory of the structural trend for (digital) skills development, she should aim at triggering traditional (digital) policy levers: active labor policies to stimulate employment; education policies to endure basic (literacy and numeracy) skills for all; strengthening broadband coverage and facilitating its take-up.

Social capital matters, too: more dense social networks facilitate digital inclusion. As Warschauer (2003) put it, technologies are socially embedded and we must take into account "people's ability to make use of those technologies to engage in meaningful social practices."

On the other hand, the dynamic GMM model identifies variables that can cause positive fluctuations in the structural trend. These include policy levers that can be activated also in the short term: outreach initiatives promoted by schools, non-profits, libraries, and other actors that animate local communities; incentives for broadband take-up and use.

The optimal strategy would be a mixed approach: effective short-term stimulus could open up a window of opportunity until $t(p)$ that may be used to implement structural interventions.

Figure 4. Synthesis between static and dynamic analysis



7. CONCLUSIONS

Overall, our contribution provides relevant insight for academics and practitioners with respect to the determinants of basic digital skills improvements. Our ex-ante evaluation concludes that outreach is a helpful policy tool to stimulate local communities in the short term, but other more structural interventions are needed to close the digital skills gap. This confirms van Dijk's theory according to which the digital divide cannot be closed without reducing existing social inequalities.

From a methodological point of view, both the pseudo-panel approach and the variables used to operationalize the key constructs can prove useful to assess the impact of digital skills policies, in the absence of experimental and quasi-experimental evaluations.

Our study, however, is only a first perfectible attempt to answer a very ambitious research question that will require further investigations. Our data is limited to the most relevant observable outreach dynamics: unfortunately, adequate longitudinal data is not currently available for other potentially relevant local actors that are also involved in the policy. Future studies should broaden the focus to all actors, employing the empirical methods appropriate for a larger set of variables.

The static approach could be improved in robustness by means of instrumental variable estimation, to support causal inference. Preliminary attempts have proved encouraging but not sufficiently consistent.

Replications are welcome (and possible, especially for European countries), in particular, to check the external validity of GMM results. In particular, future studies could combine structural and dynamic approaches to obtain a more general framework.

Research should focus on how to impact the policy levers identified in the two models, in order to trigger generalized improvements and scale up valuable activities. We should never forget that our estimates also depend on the way we measure digital skills and on the skill level we focus on: it is essential to investigate higher-order competencies, too. Lastly, future studies should improve the measurement of the role played by outreach-oriented actors – such as universities – that were included in the study with second-best indicators, e.g., by resorting to social network analysis and improving measures of public engagement.

References

- Anvur. (2021). *VQR*. Valutazione Della Qualità Della Ricerca. <https://www.anvur.it/attivita/vqr/>
- Arifoglu, A., Afacan, G., & Er, E. (2012). An Analysis of Public Internet Access Points (PIAPs). *The Journal of Community Informatics*. <https://doi.org/10.15353/joci.v9i1.3192>
- Åslund, O., & Fredriksson, P. (2009). Peer effects in welfare dependence: Quasi-experimental evidence. *Journal of Human Resources*. <https://doi.org/10.3368/jhr.44.3.798>
- Asmar, A., van Audenhove, L., & Mariën, I. (2020). Social support for digital inclusion: Towards a typology of social support patterns. *Social Inclusion*. <https://doi.org/10.17645/si.v8i2.2627>
- Atchoarena, D., Selwyn, N., Chakroun, B., Miao, F., West, M., & de Coligny, C. (2017). *Digital skills for life and work*. <https://www.broadbandcommission.org/wp-content/uploads/2021/02/WG-Education-Report2017.pdf>
- Basler, T. G. (2005). Community outreach partnerships. In *Reference Services Review*. <https://doi.org/10.1108/00907320410519441>
- Becker, G. S. (1962). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy*, 70(5), 9–49. <https://doi.org/10.1086/258724>
- Blank, G., & Groseelj, D. (2014). Dimensions of Internet use: Amount, variety, and types. *Information Communication and Society*, 17(4), 417–435. <https://doi.org/10.1080/1369118X.2014.889189>
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115–143. [https://doi.org/10.1016/S0304-4076\(98\)00009-8](https://doi.org/10.1016/S0304-4076(98)00009-8)
- Bourguignon, F., & Ferreira, F. H. G. (2003). Ex Ante Evaluation of Policy Reforms Using Behavioral Models. *The Impact of Economic Policies on Poverty and Income Distribution Evaluation Techniques and Tools*.
- Childhope Philippines. (2021). *Defining, Building, and Joining an Outreach Program*. <https://childhope.org.ph/community-outreach-program-definition/>
- CodeWeek.eu. (2023). *#CodeWeek About*. <https://codeweek.eu/about>
- Courtois, C., & Verdegem, P. (2016). With a little help from my friends: An analysis of the role of social support in digital inequalities. *New Media and Society*. <https://doi.org/10.1177/1461444814562162>
- Davenport, J. H., Crick, T., & Hourizi, R. (2020). The institute of coding: A university-industry collaboration to address the UK's digital skills crisis. *IEEE Global Engineering Education Conference, EDUCON*. <https://doi.org/10.1109/EDUCON45650.2020.9125272>
- Deaton, A. (1985). Panel data from time series of cross-sections. *Journal of Econometrics*. [https://doi.org/10.1016/0304-4076\(85\)90134-4](https://doi.org/10.1016/0304-4076(85)90134-4)
- Dewson, S., Davis, S., & Casebourne, J. (2006). *Maximising the Role of Outreach in Client Engagement*. <http://www.dwp.gov.uk/asd/asd5/rports2005-2006/rrep326.pdf>
- Dimaggio, P., Hargittai, E., Celeste, C., & Shafer, S. (2004). Digital inequality: From unequal access to differentiated use. In *Social Inequality*.
- DiMaggio, P., Hargittai, E., Russell Neuman, W., & Robinson, J. P. (2001). Social implications of the internet. *Annual Review of Sociology*. <https://doi.org/10.1146/annurev.soc.27.1.307>
- Dustmann, C., Frattini, T., & Preston, I. P. (2013). The effect of immigration along the distribution of wages. *Review of Economic Studies*. <https://doi.org/10.1093/restud/rds019>
- Duvivier, S. (2023). PARTNERING WITH AMERICORPS FOR DIGITAL EQUITY IN AFFORDABLE HOUSING. *National Housing Trust News*. <https://nationalhousingtrust.org/news/partnering-amicorps-digital-equity-affordable-housing>
- Elmborg, J. K. (2011). Libraries as the spaces between us: Recognizing and valuing the third space. *Reference and User Services Quarterly*. <https://doi.org/10.5860/rusq.50n4.338>
- Epstein, J. L., Sanders, M. G., Simon, B. S., Salinas, K. C., Jansorn, N. R., & Van Voorhis, F. L. (2019). *School, family, and community partnerships: Your handbook for action*.
- European Commission. (2022). *DESI by components - At least Basic Digital Skills*. Digital Scoreboard. <https://digital-agenda-data.eu/charts/desi-components>
- Eurostat. (2022). *Individuals' level of digital skills (from 2021 onwards) (isoc_sk_dskl_i21)*. ESMS Indicator Profile (ESMS-IP). https://ec.europa.eu/eurostat/cache/metadata/en/isoc_sk_dskl_i21_esmsip2.htm
- Ferlander, S., & Timms, D. (2006). Bridging the dual digital divide: A local net and an IT-Café in Sweden. *Information Communication and Society*. <https://doi.org/10.1080/13691180600630732>

- Ferrari, A. (2012). *Digital Competence in Practice: An Analysis of Frameworks*. Joint Research Centre. <https://op.europa.eu/en/publication-detail/-/publication/2547ebf4-bd21-46e8-88e9-f53c1b3b927f/language-en>
- García-Mora, F., & Mora-Rivera, J. (2021). Exploring the impacts of Internet access on poverty: A regional analysis of rural Mexico. *New Media and Society*. <https://doi.org/10.1177/14614448211000650>
- Graham, G., & Hanna, N. (2011). Re-connect Canada: A Community-based e-development Strategy. *Journal of the Knowledge Economy*. <https://doi.org/10.1007/s13132-010-0025-4>
- Guillerm, M. (2017). Pseudo-panel methods and an example of application to Household Wealth data. *Economie et Statistique*. <https://doi.org/10.24187/ecostat.2017.491d.1908>
- Hamming, R. W. (1980). *Coding and Information Theory*. Prentice-Hall. <https://archive.org/details/codinginformatio0000hamm>
- Harding, J. (2008). Information literacy and the public library: We've talked the talk, but are we walking the walk? *Australian Library Journal*. <https://doi.org/10.1080/00049670.2008.10722480>
- Hartviksen, G., Akselsen, S., & Eidsvik, A. K. (2002). MICTS: Municipal ICT schools - A means for bridging the digital divide between rural and urban communities. *Education and Information Technologies*. <https://doi.org/10.1023/A:1020349509331>
- Heckman, J. J., Lochner, L., & Taber, C. (1998). Tax Policy and Human-Capital Formation. In *American Economic Review*.
- Helsper, E. J. (2010). Gendered internet use across generations and life stages. *Communication Research*, 37(3), 352–374. <https://doi.org/10.1177/0093650209356439>
- Helsper, E. J. (2012). A Corresponding Fields Model for the Links Between Social and Digital Exclusion. *Communication Theory*, 22(4), 403–426. <https://doi.org/10.1111/j.1468-2885.2012.01416.x>
- Helsper, E. J., & van Deursen, A. J. A. M. (2015). Digital skills in Europe: Research and policy. In *Digital Divides: The New Challenges and Opportunities of e-Inclusion*. <https://doi.org/10.1201/b17986>
- Hoffman, D. L., Novak, T. P., & Schlosser, A. E. (2001). The evolution of the digital divide: Examining the relationship of race to Internet access and usage over time. *The Digital Divide: Facing a Crisis or Creating a Myth*.
- ICCU. (2023). *Anagrafe delle Biblioteche Italiane - Open Data*. <https://anagrafe.iccu.sbn.it/it/open-data/>
- IFLA. (2020). *Libraries in Digital Skills Policies. Policy areas, mechanisms, practices. December*, 1–10. <https://www.ifla.org/publications/node/93525>
- International ICT Literacy Panel. (2002). *Digital Transformation: A Framework for ICT Literacy ICT*. <https://www.ets.org/Media/Research/pdf/ICTREPORT.pdf>
- Istat. (2023). *CITTADINI E ICT - ANNO 2022*. <https://www.istat.it/it/archivio/282257>
- Italiadomani. (2022). *Basic digital skills*. <https://www.italiadomani.gov.it/content/sogei-ng/it/en/Interventi/investimenti/competenze-digitali-di-base.html>
- Jaeger, P. T., Bertot, J. C., Thompson, K. M., Katz, S. M., & Decoster, E. J. (2012). The Intersection of Public Policy and Public Access: Digital Divides, Digital Literacy, Digital Inclusion, and Public Libraries. *Public Library Quarterly*. <https://doi.org/10.1080/01616846.2012.654728>
- Johnston, N. (2020). The Shift towards Digital Literacy in Australian University Libraries: Developing a Digital Literacy Framework. *Journal of the Australian Library and Information Association*. <https://doi.org/10.1080/24750158.2020.1712638>
- JRC. (2017). DigComp 2.1: The Digital Competence Framework for Citizens. In S. Carretero, R. Vuorikari, & Y. Punie (Eds.), *Publications Office of the European Union*. <https://doi.org/doi:10.2760/38842>
- Kafai, Y. B., Fields, D. A., & Searle, K. A. (2014). Electronic textiles as disruptive designs: Supporting and challenging maker activities in schools. *Harvard Educational Review*. <https://doi.org/10.17763/haer.84.4.46m7372370214783>
- Kinney, B. (2010). The internet, public libraries, and the digital divide. *Public Library Quarterly*. <https://doi.org/10.1080/01616841003779718>
- Kumpulainen, K., Kajamaa, A., Leskinen, J., Byman, J., & Renlund, J. (2020). Mapping Digital Competence: Students' Maker Literacies in a School's Makerspace. *Frontiers in Education*. <https://doi.org/10.3389/educ.2020.00069>
- Lee, H. J., Park, N., & Hwang, Y. (2015). A new dimension of the digital divide: Exploring the relationship between broadband connection, smartphone use and communication competence. *Telematics and Informatics*. <https://doi.org/10.1016/j.tele.2014.02.001>

- Lenstra, N. (2017). The Community-Based Information Infrastructure of Older Adult Digital Learning. *Nordicom Review*. <https://doi.org/10.1515/nor-2017-0401>
- Leong, J. H. T. (2013). Community Engagement - Building Bridges between University and Community by Academic Libraries in the 21st Century. *Libri*. <https://doi.org/10.1515/libri-2013-0017>
- Lissitsa, S., Chachashvili-Bolotin, S., & Bokek-Cohen, Y. (2017). Digital skills and extrinsic rewards in late career. *Technology in Society*, 51, 46-55. <https://doi.org/https://doi.org/10.1016/j.techsoc.2017.07.006>
- Litt, E. (2013). Measuring users' internet skills: A review of past assessments and a look toward the future. *New Media and Society*. <https://doi.org/10.1177/1461444813475424>
- Livingstone, S., Helsper, E. J., & Rahali, M. (2022). The digital lives of children and youth. In *Global Connectivity Report 2022* (pp. 138–151). ITU Publications. <https://www.itu.int/itu-d/reports/statistics/2022/05/30/gcr-chapter-9/>
- Mariën, I., & Van Audenhove, L. (2010). Embedding e-inclusion initiatives in people's daily reality: The role of social networks in tackling the digital divide. *Digitas Conference 'Digital Natives, Digital Immigrants; Digital Asylum Seekers: The Clash of Cultures*.
- Martin, C. (2017). Libraries as Facilitators of Coding for All. *Knowledge Quest*.
- Martinez, C. (2019). Promoting critical digital literacy in the leisure-time center: Views and practices among Swedish leisure-time teachers. *Nordic Journal of Digital Literacy*. <https://doi.org/10.18261/ISSN.1891-943X-2019-03-04-04>
- Mervyn, K., Simon, A., & Allen, D. K. (2014). Digital inclusion and social inclusion: a tale of two cities. *Information Communication and Society*. <https://doi.org/10.1080/1369118X.2013.877952>
- Mossberger, K., Tolbert, C. J., & Stansbury, M. (2003). *Virtual Inequality. Beyond the digital divide*. Georgetown University Press.
- Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica*. <https://doi.org/10.2307/1913646>
- NDIA. (2022). *The Digital Navigator Model. Adding Digital Equity to Our Social Safety Net*. <https://www.digitalinclusion.org/digital-navigator-model/>
- Ngqulu, N., Gumbo, S., & Nogwina, M. (2019). Modelling TVET Colleges as Alternative Centres to Deliver eSkills Training in Rural Communities of Eastern Cape. *2019 IST-Africa Week Conference, IST-Africa 2019*. <https://doi.org/10.23919/ISTAFRICA.2019.8764849>
- Park, S. (2014). The role of local intermediaries in the process of digitally engaging non-users of the internet. *Media International Australia*. <https://doi.org/10.1177/1329878x1415100118>
- Ragnedda, M. (2018). Tackling digital exclusion: Counter social inequalities through digital inclusion. In *Global Agenda for Social Justice: Volume one*.
- Ratto, M. (2011). Critical making: Conceptual and material studies in technology and social life. *Information Society*. <https://doi.org/10.1080/01972243.2011.583819>
- Reisdorf, B., & Rhinesmith, C. (2020). Digital inclusion as a core component of social inclusion. In *Social Inclusion*. <https://doi.org/10.17645/si.v8i2.3184>
- Resnick, M., Maloney, J., Monroy-Hernández, A., Rusk, N., Eastmond, E., Brennan, K., Millner, A., Rosenbaum, E., Silver, J., Silverman, B., & Kafai, Y. (2009). Scratch: Programming for all. *Communications of the ACM*. <https://doi.org/10.1145/1592761.1592779>
- Roodman, D. (2009). A Note on the Theme of Too Many Instruments. *Oxford Bulletin of Economics and Statistics*, 71(1), 135–158. <https://doi.org/10.1111/j.1468-0084.2008.00542.x>
- Scheerder, A., Van Deursen, A. J. A. M., & Van Dijk, J. A. G. M. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telematics and Informatics*, 34(8), 1607–1624. <https://doi.org/10.1016/j.tele.2017.07.007>
- Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *New Media and Society*. <https://doi.org/10.1177/1461444804042519>
- Siciliano, M. D., Carr, J. B., & Hugg, V. G. (2020). Analyzing the Effectiveness of Networks for Addressing Public Problems: Evidence from a Longitudinal Study. *Public Administration Review*, 00, 1–16. <https://doi.org/10.1111/puar.13336>
- Slagter van Tryon, P. J. (2013). The Instructional Designer's Role in Forming University-Community Partnerships in Digital Literacy. *TechTrends*. <https://doi.org/10.1007/s11528-012-0631-z>
- Sostero, M., & Tolan, S. (2022). Digital skills for all? From computer literacy to AI skills in online job advertisements. In *JRC Working Papers Series on Labour, Education and Technology* (No. JRC130291;

Issue 7).

- Sourbati, M. (2009). Media literacy and universal access in Europe. *Information Society*. <https://doi.org/10.1080/01972240903028680>
- Todd, P., & Wolpin, K. I. (2011). Ex Ante Evaluation of Social Programs. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.931393>
- Unterfrauner, E., Hofer, M., Pelka, B., & Zirngiebl, M. (2020). A new player for tackling inequalities? Framing the social value and impact of the maker movement. *Social Inclusion*. <https://doi.org/10.17645/si.v8i2.2590>
- Valli, L., Stefanski, A., & Jacobson, R. (2016). Typologizing School–Community Partnerships: A Framework for Analysis and Action. *Urban Education*. <https://doi.org/10.1177/0042085914549366>
- van Deursen, A. J. A. M., Courtois, C., & van Dijk, J. A. G. M. (2014). Internet Skills, Sources of Support, and Benefiting From Internet Use. *International Journal of Human-Computer Interaction*. <https://doi.org/10.1080/10447318.2013.858458>
- Van Deursen, A. J. A. M., & Helsper, E. J. (2015). *The Third-Level Digital Divide: Who Benefits Most from Being Online?* 29–52. <https://doi.org/10.1108/s2050-206020150000010002>
- Van Deursen, A. J. A. M., Helsper, E. J., Eynon, R., & Van Dijk, J. A. G. M. (2017). The compoundness and sequentiality of digital inequality. *International Journal of Communication*, 11, 452–473.
- van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2014). The digital divide shifts to differences in usage. *New Media and Society*, 16(3), 507–526. <https://doi.org/10.1177/1461444813487959>
- van Dijk, J. A. G. M. (2020). *The digital divide*. Polity Press. <https://doi.org/10.1080/1369118X.2020.1781916>
- van Dijk, J. A. G. M., & van Deursen, A. J. A. M. (2014). *Digital skills: unlocking the Information Society* (1st ed.). Palgrave Macmillan US. <https://doi.org/10.1057/9781137437037>
- Van Dijk, J. A. G. M., & Van Deursen, A. J. A. M. (2009). Inequalities of digital skills and how to overcome them. In *Handbook of Research on Overcoming Digital Divides: Constructing an Equitable and Competitive Information Society*. <https://doi.org/10.4018/978-1-60566-699-0.ch015>
- van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*. <https://doi.org/10.1016/j.chb.2017.03.010>
- Warschauer, M. (2003). *Technology and Social Inclusion: Rethinking the Digital Divide*. MIT Press. <https://doi.org/https://doi.org/10.7551/mitpress/6699.001.0001>
- Wong, Y. C., Fung, J. Y. C., Law, C. K., Lam, J. C. Y., & Lee, V. W. P. (2009). Tackling the digital divide. *British Journal of Social Work*. <https://doi.org/10.1093/bjsw/bcp026>
- Wooldridge, J. M. (2001). Applications of generalized method of moments estimation. *Journal of Economic Perspectives*, 15(4), 87–100. <https://doi.org/10.1257/jep.15.4.87>
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). MIT Press.
- World Bank. (2022). *Individuals using the Internet (% of population) - United States, European Union*. World Development Indicators. <https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=US-EU>
- Yilmaz, B., & Cevher, N. (2015). Future of public libraries: Opinions of public librarians in Turkey. *IFLA Journal*. <https://doi.org/10.1177/0340035215608861>
- Yoon, S. C. (2018). Servicization with skill premium in the digital economy. *Journal of Korea Trade*. <https://doi.org/10.1108/JKT-10-2017-0094>

Appendix: What do Code Week activities actually look like?

Given the relevance of the CW variable for our study, we use the information publicly available online to complement its description with a concrete example; the purpose of this short qualitative analysis is to provide further details on how CW events actually unfold and develop within one of our cohorts. We focus in particular on the city of Naples (Figure A), which has been the most active over the years.

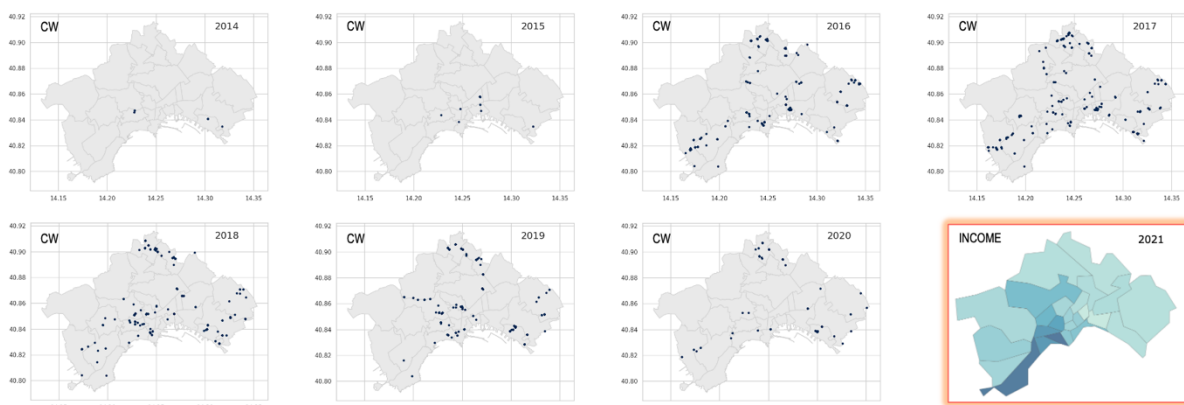
As we can see from the map, for the first two years of activity only a few events were organized, evenly split between richer and poorer neighborhoods. In 2014, activities were led by two primary schools: 3 events dedicated to basic coding skills were organized in Vomero, one of the most affluent neighborhoods in the city; 5 events dedicated to computational thinking were instead located in San Giovanni a Teduccio, one of the poorest neighborhoods in Italy, which since 2015 hosts a new campus of the University of Naples and an Apple Academy. Collaboration with university is in fact key: these activities were all part of a national program sponsored by the Ministry of Education and by the national consortium of universities for informatics. In 2015 also high schools get involved, with 8 activities dedicated to web development. Furthermore, four primary schools promote events dedicated to playful coding activities sponsored by TIM, the biggest Italian phone and internet company.

Thanks to the great emphasis put on digitalization efforts by the National Plan for Digital Schools (October 2015) and by the appointment of a national commissioner for the Italian Digital Agenda (September 2016), also CW activities grew significantly between 2016 and 2018. This can be seen also in the national map available in the Appendix (Figure A2), where we can note that new locations become involved every year, but they all tend to nest around locations that were involved previously.

Locally, however, the turnover rate of organizers is relatively high, with schools typically participating for two years in a row before exiting the network. Locations vary due to the high mobility of the teachers involved, to changes in the sources of funding, but also because collaborations evolve over time. School events become increasingly open to families and adults in the community, for example in the activities organized in the peripheral neighborhood of Cercola,¹ on the slopes of Vesuvius. With activities spreading across the city, CW initiatives also become a substitute for teacher training courses.

With the pandemic hitting in 2020, 56% of the activities were moved online, while less than 30% of the events had an online component until 2019. In the meantime, the network of collaborations has grown significantly to include local, national, and international organizations such as #CodeMooc,² linked to the University of Urbino, Associazione Dschola,³ and CoderDojo.⁴

Evolution of Code Week events in the city of Naples (2014-2020)



Source: Authors' elaboration on data provided by EU Code Week organizers and on MEF (2022).

¹ See: <https://codeweek.eu/view/12161/a-scuola-di-coding>

² See: <https://codemooc.org/codemooc-live-napoli/>

³ See: <https://archivio2022.icvittorinodafeltre.edu.it/dschola-coding-italian-scratch-festival-2017/>

⁴ See: <https://www.tecnosrl.it/assets/front/img/press/60e2bdefd099f.pdf>

Appendix – Tables

Table A1. Distribution of observations by cell (r,m,a) and year (2014-2020)

Cell	Observations		Municipality type	N	(%)
<i>Region</i>	<i>N</i>	<i>(%)</i>	1. Metropolitan areas	539	21.57
1. Piemonte	147	5.88	2. Other municipalities (pop. < 10k)	980	39.22
2. Valle d'Aosta	98	3.92	3. Other municipalities (pop. > 10k)	980	39.22
3. Lombardia	147	5.88	<i>Total</i> 2,499 100.00		
4. Trentino-Alto Adige	98	3.92	<i>Age group</i>	<i>N</i>	<i>(%)</i>
5. Veneto	147	5.88	1. Less than 15 years of age	357	14.29
6. Friuli Venezia Giulia	98	3.92	2. From 16 to 19 years of age	357	14.29
7. Liguria	147	5.88	3. From 20 to 29 years of age	357	14.29
8. Emilia-Romagna	147	5.88	4. From 30 to 39 years of age	357	14.29
9. Toscana	147	5.88	5. From 40 to 54 years of age	357	14.29
10. Umbria	98	3.92	6. From 55 to 64 years of age	357	14.29
11. Marche	98	3.92	7. More than 65 years of age	357	14.29
12. Lazio	147	5.88	<i>Total</i> 2,499 100.00		
13. Abruzzo	98	3.92	<i>Years</i>	<i>N</i>	<i>(%)</i>
14. Molise	98	3.92	2014	357	14.29
15. Campania	147	5.88	2015	357	14.29
16. Puglia	147	5.88	2016	357	14.29
17. Basilicata	98	3.92	2017	357	14.29
18. Calabria	98	3.92	2018	357	14.29
19. Sicilia	147	5.88	2019	357	14.29
20. Sardegna	147	5.88	2020	357	14.29
<i>Total</i> 2,499 100.00			<i>Total</i> 2,499 100.00		

Note: Observations do not sum to $(20 \times 3 \times 7)$ since not all Italian regions have a metropolitan area.

Table A2. DigComp index methodology, list of indicators

Comp. area	Indicators of online activity (performed in the last 3 months before the survey)	Year							
		2014	2015	2016	2017	2018	2019	2020	
1. Information and data literacy	Copied or moved files or folders	●	●	●	(a)	(a)	●	(a)	
	Saved files on Internet storage space	●	●	●	●	●	●	●	
	Obtained information from public authorities/services' websites	●	●	●	●	●	●	●	
	Finding information about goods or services	●	●	●	●	●	●	●	
	Seeking health-related information	●	●	●	●	●	●	●	
2. Communication and collaboration skills	Sending/receiving emails	●	●	●	●	●	●	●	
	Participating in social networks	●	●	●	●	●	●	●	
	Telephoning/video calls over the internet	●	●	●	●	●	●	●	
	Uploading self-created content to any website to be shared online	●	●	●	●	●	●	●	
3. Digital content creation skills	Used word processing software	(b)	●	●			●		
	Used spreadsheet software	●	●	●	(c)	(c)	●	(c)	
	Used software to edit photos, video or audio files		●	●			●		
	Created presentation or document integrating text, pictures, tables or charts	●	●	●	(d)	(d)	●	(e)	
	Used advanced functions of spreadsheet to organise and analyse data	(f)	●	●	(f)	(f)	●	(g)	
	Have written a code in a programming language	●	●	●	(h)	(h)	●	(h)	
5. Problem solving skills	Transferring files between computers or other devices	●	●	●	(i)	(i)	●		
	Installing software and applications (apps)	●	●	●	●	●	●	(j)	
	Changing settings of any software, including o.s. or security programs	(k)	●	●	(k)	(k)	●	(l)	
	Online purchases (in the last 12 months)	●	●	●	●	●	●	●	
	Selling online	●	●	●	●	●	●	●	
	Used online learning resources	(m)	●	●	●	(m)	●	●	
	Internet banking	●	●	●	●	●	●	●	

Authors' elaboration from (Eurostat, 2021).

Circles identify perfect-matches. Proxies, when used, are indicated by footnotes in the parentheses:

- a) Read or download books online or ebooks;
- b) Change safety settings in a browser;
- c) Purchase or renew insurance policies online;
- d) Using online payment methods to buy goods or services;
- e) Watching Tv via streaming services;
- f) Participating in a professional social network online;
- g) Attending on online course;
- h) Playing or downloading games online;
- i) Looking for a job or sending a job application;
- j) Buying any of the following online services: music, films, books, games, software, health apps, other apps;
- k) Ordering or buying sports items online;
- l) Instant messaging;
- m) Looking for information on educational activities or courses.

Table A3. OLS modeling of the territorial distribution of *Digital Civilian Service* eFacilitators

VARIABLES	(1) eFacilitators (%)	(2) eFacilitators (%)	(3) eFacilitators (%)	(4) eFacilitators (%)
Code Week events (%)	0.783*** (0.0928)	0.713*** (0.0952)	0.577*** (0.102)	0.565*** (0.106)
Population share (%)		0.119 (0.121)	0.247** (0.119)	0.254** (0.121)
Employment rate (18-29 years)			-0.0177*** (0.00485)	-0.0147** (0.00700)
Share of residents enrolled in university				0.0755 (0.108)
Constant	0.202*** (0.0717)	0.157* (0.0921)	0.768*** (0.227)	0.455 (0.539)
Observations	107	107	107	107
R-squared	0.749	0.755	0.816	0.817

Robust standard errors in parentheses

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

Table A4. List of control variables by category of digital skills divide determinants and granularity

Variables by category of digital skills divide determinants	Source	Region	Mun. type	Age group
<i>Sociodemographics</i>				
Population density: number of inhabitants per squared-km	Istat	●	●	●
<i>Economic well-being</i>				
Employment rate	Istat	●		●
<i>Human capital</i>				
Secondary education: share (%) of individuals that possess at most a lower secondary school diploma	Istat-AVQ	●	●	●
<i>Social capital</i>				
No friends: share (%) of individuals who declare having no friends	Istat-AVQ	●	●	●
One-person households: share (%) of households composed by a single individual	Istat-AVQ	●	●	●
Trust: share (%) of individuals who claim to trust others	Istat-AVQ	●	●	●
<i>Cultural capital</i>				
Museum density: number of museums per 1000 inhabitants	Istat-ASC	●	●	
Religiosity: share (%) of individuals who have attended a place of worship at least weekly	Istat-AVQ	●	●	●
<i>Subjective well-being</i>				
Health status: share (%) of individuals who claim they are in good health	Istat	●	●	●
Life satisfaction: share (%) of individuals who declare to be highly satisfied with their personal life, in terms of leisure time, economics, health, environment, relationships	Istat-AVQ	●	●	●
<i>Material and motivational access</i>				
Broadband take-up: share (%) of households subscribing to broadband connection	Istat-AVQ	●	●	●

Sources: Digital skills divide determinants from Scheerder, van Deursen and van Dijk (2017). Data sources: Istat (2022c, 2022a, 2022b, 2022d); Istat-AVQ (2022); Istat-ASC (2022).

Table A5. Results of diagnostic tests, panel models with and without interactions

CONTROLS						
Employment rate	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Broadband take-up	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Population density	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Secondary education	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
No friends	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
One-person households	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Trust	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Religiosity	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Museums	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Health status	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Life satisfaction	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>

a) Test results for the correlation between time-invariant unobservables and model regressors (Mundlak approach)						
Parameters:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$\chi^2(n)$	6,5	34,94	145,74	114,48	858,01	806,95
(Prob > χ^2)	0,0108	0	0	0	0	0
Parameters:	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
$\chi^2(n)$	299,34	125,53	211,84	279,77	811,04	842,23
(Prob > χ^2)	0	0	0	0	0	0

b) Joint F-test for year fixed-effects						
Parameters:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$F(6, 328)$	339,98	251,42	247,88	225,03	198,04	177,63
Prob > F	0	0	0	0	0	0
Parameters:	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
$F(6, 328)$	332,65	241,63	237,72	224,92	195,33	181,35
Prob > F	0	0	0	0	0	0

c) Modified Wald test for groupwise heteroskedasticity						
Parameters:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$\chi^2(357)$	16667,66	44747,15	61754,1	39723,8	4724,87	8339,22
(Prob > χ^2)	0	0	0	0	0	0
Parameters:	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
$\chi^2(357)$	30574,61	44984,17	109576,14	25763,79	9512,76	13159,67
(Prob > χ^2)	0	0	0	0	0	0

d) Wooldridge test for autocorrelation						
Parameters:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$F(1, 356)$	325,77	327,25	325,8	312	323,88	297,78
Prob > F	0	0	0	0	0	0
Parameters:	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
$F(1, 356)$	383,46	395,51	395,72	352	381,34	326,01
Prob > F	0	0	0	0	0	0

■ = variable used in the model; □ = variable not used in the model.

Appendix – Figures

Figure A1. Distribution of the dependent variable (DigComp Index), 2014-2020

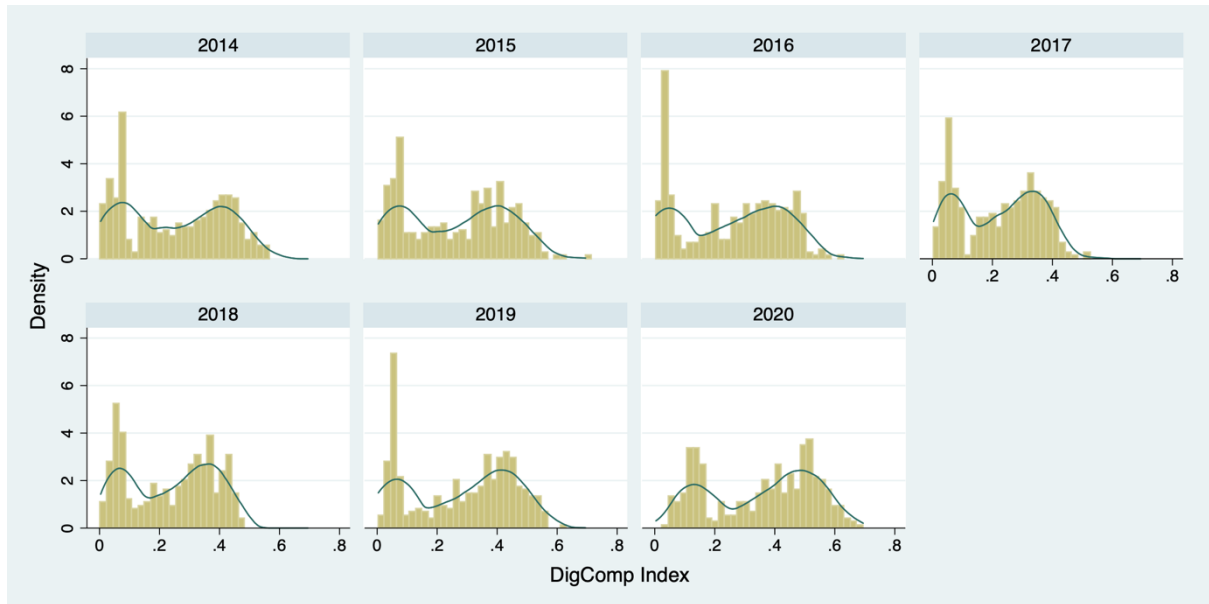


Figure A2. Evolution of Code Week events in Italy, 2014-2020

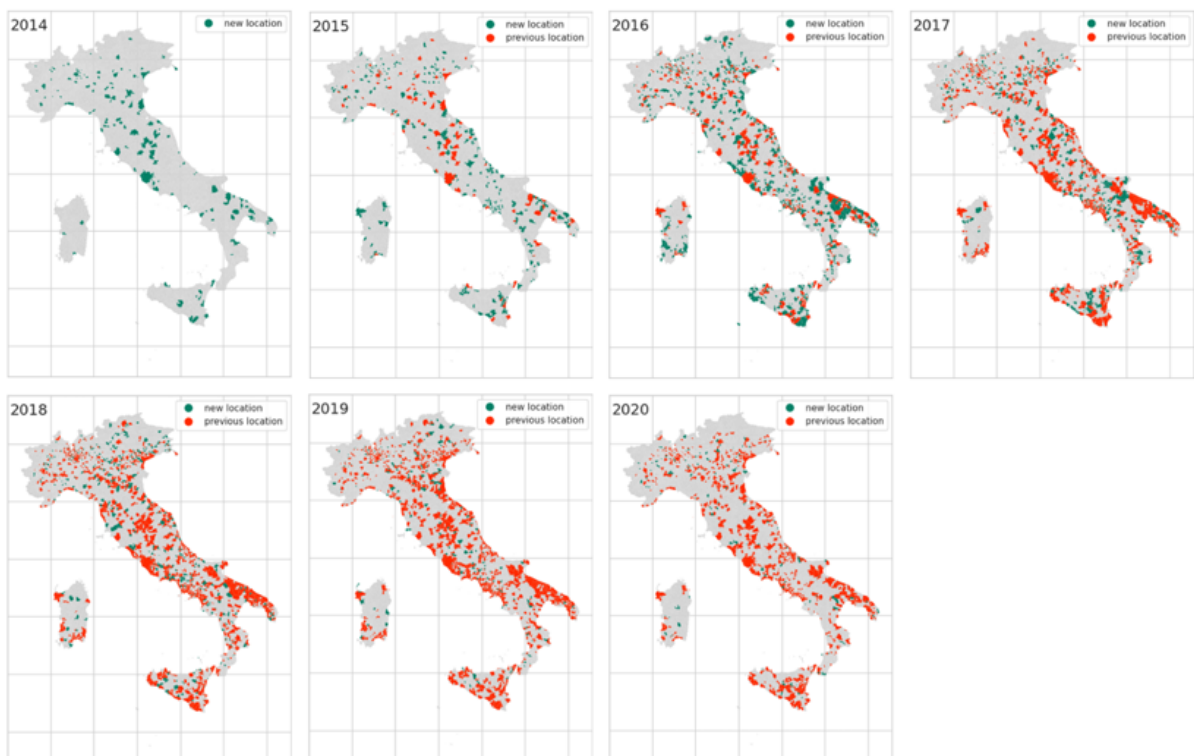


Figure A3. Territorial distribution of other relevant outreach-related variables, year 2019

