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CAPP*aper*

n. 189 | June 2024

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Technology access for poor households in six European countries after Covid-19 pandemic crisis[1]

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Abstract

The growing importance of technology diffusion and digitalization processes in the global economy has accelerated further in the wake of the Covid-19 pandemic. However, this diffusion varies according to socioeconomic context and different types of technology. This study analyzes the impact of the Covid-19 pandemic on the digitalization process of poor households, focusing on Internet access and computer ownership. To this end, we implement a Probit model with a difference-in-differences approach using EU-SILC data for six European countries. The analysis considers several socioeconomic factors and household characteristics, also examining heterogeneity across countries and equivalised income deciles. We find a significant positive association between lack of digitalization and poverty. Covid-19 is confirmed as a driver of digitalization. Its effect on the economically struggling population depends on the technology considered: it is accentuated for Internet connection, while it is almost zero for computer ownership.

Keywords: Digitalization; poverty; technology access; difference-in-differences.

JEL classification codes: I32; O33.

[1] We are grateful to Antonella Caloffi, Chiara Mussida, and participants at the 3rd General Meeting MUSA (May 2024) for their useful and constructive comments. The usual caveat applies: The views expressed here are those of the authors and do not reflect those of the institutions with which the authors are affiliated.

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1. Introduction

Technology diffusion and digitalization processes are becoming increasingly important in global economic dynamics, especially after the recent boost due to the Covid-19 pandemic (Oldekop et al., 2020). This process involved various industries and sectors (Giordani and Rullani, 2020; Kudyba, 2020; Amankwah-Amoah et al., 2021) but also the families (Copson et al., 2022). Digital transformation has accelerated to such an extent that homes have gradually become a workspace for many (Watson et al., 2021). Despite the potential negative consequences due to increased reliance on technology, including privacy and surveillance issues (Livingstone, 2020), the crisis has also highlighted the potential of digital networks to support families and enhance digital learning (Hodges et al., 2020).

The process of technological diffusion has also been fostered by the proactive action of governments, which have invested substantially in projects to promote computer literacy and Internet access, convinced that this promotes economic growth, reduces poverty, and mitigates inequality (Acco Tives Leão and Canedo, 2018).

Moreover, access to technology for individuals and households has become progressively more feasible and easier over time, thanks to lower relative prices of technological goods and rising incomes (OECD, 2007). This diffusion process has meant that currently computers, the Internet, and telephony have become everyday tools for communicating, working, and accessing information. However, this is not a homogeneous phenomenon, as it depends on the technology considered (for example, Internet access in households has spread much faster than computers have) but especially on different socioeconomic variables (such as the average age of the population, level of education, gender) and from country context (OECD, 2007). So, the digital transformation has also highlighted the existing digital divide, particularly among poor families, who face challenges such as digital poverty, literacy, and exclusion (Chadwick et al., 2022).

The objective of this paper is to analyze whether a process of digital convergence is taking place for poor households and whether this has strengthened in the wake of the 2020 pandemic crisis. The main contribution is the introduction of the Covid-19 pandemic in explaining digital adoption for different socioeconomic strata.

For the analysis, we used the European Union Statistics on Income and Living Conditions (EU-SILC) database, which collects data on the socioeconomic status of households and individuals in the European Union, updated to 2022. We select six countries based on the digitalization clusters identified in Lucendo-Monedero et al. (2019) according to the household and individual digital development index (HIDDI). For each of the three clusters, we select the two most populous countries. They are Spain (ES), France (FR), Italy (IT), Netherlands (NL), Poland (PL) and Sweden (SE). In particular, the Netherlands and Sweden belong to the same cluster that recorded the highest level of HIDDI; intermediate values of HIDDI are recorded in Poland and France, which belong to the same cluster; finally, Italy and Poland belong to the southeastern cluster, the one that recorded the lowest HIDDI values. Moreover, these countries have been chosen in light of their belonging to different European welfare regimes according to the existing literature on the topic (Esping Andersen, 1990; Ferrera, 1996; Whelan and Maître, 2010). Specifically, the Mediterranean regime is represented by Italy and Spain; the Continental regime by France; the Scandinavian/Nordic regime by Sweden;

the Eastern European regime is represented by Poland; and the Netherlands represents a hybrid model between the continental and social democratic models.

With this extensive dataset, we build an econometric strategy utilizing a Probit model that applies a difference-in-differences approach (Angrist and Krueger, 1999) to examine technology household adoption. The degree of household digitalization is measured through two variables: the ability to have an Internet connection for personal use at home and the ownership of a computer within the household. Specifically, we compare the rate of digital technology adoption by poor households before and after Covid-19. The control group is non-poverty households. Households in poverty are defined through the ability to make ends meet indicator. To further examine the relationship between digitalization and poverty, we also consider other variables in the regression model that may influence technology adoption, such as gender, age, education level, and household composition (Venkatesh and Brown, 2001; Wareham et al., 2004; Korupp and Szydlik, 2005; Demoussis and Giannakopoulos, 2006; Nishijimaa et al., 2017). The analysis is also conducted by assessing heterogeneity by country and for the households' equivalised disposable income decile distribution. We also propose a sensitivity analysis by replacing the ability to make ends meet (which is a self-reported measure of poverty) with the At-Risk-Of Poverty or Social Exclusion (AROPE) indicator (which is a more objective measure of poverty).

The results differ depending on the outcome variable considered. In the model where the dependent variable is the probability of not having an Internet connection, we find that there is an association between poverty and not having access to technology. Before Covid-19, people perceived to be poor were almost 7.7% more likely to not have Internet than the non-poor. Covid-19 reduced the probability of not having internet by almost 7.0%. Among those perceived to be poor, this effect is even stronger: the probability of not having an Internet connection is reduced by 9.8%. Regarding computer ownership within the household, the effects are slightly different. Again, poverty status is associated with a higher probability of not having access to technology and Covid-19 has been a driver of digitalization, albeit with smaller effects. For poor households, however, this effect is almost zero, that is, the probability of not having a computer in the home is higher for the poor than for the non-poor. This is probably because the increased adoption of the Internet, as opposed to the computer, is not due to business needs, but more to entertainment needs. The process of convergence highlights the fact that digital media have increasingly become necessities, replacing other goods previously considered essential.

The rest of the article is structured as follows. The next section presents a review of the literature on the topic. Section 3 describes the data sets, and the definition of the variables of interest, and provides some descriptive statistics. Section 4 reports the econometric strategy. Section 5 presents the results and heterogeneity checks. Section 6 is for the sensitivity analysis and Section 7 provides concluding remarks.

2. Literature review

The relationship between socioeconomic factors and access to technology is widely documented in the literature (Bucy, 2000; Pick and Azari, 2008; Qureshi, 2009; Tambotoh et al., 2015). The adoption of digital technologies is influenced by several macroeconomic (income per capita, services sector, foreign direct investment), demographics, infrastructural (telephone density, electricity consumption), institutional (regulation, government effectiveness), and human capital (years of schooling, illiteracy) factors, that appear to be relevant in explaining cross-country ICT disparities (Chinn and Fairlie, 2007; Billon et al., 2009; Cruz-Jesus et al., 2012; Pick and Nishida, 2015). Barriers to access at the national level have resulted in significantly lower diffusion of digital technologies in lower-middle-income countries than in higher-income countries, and this gap has grown over time (World Bank). This explains the persistence of the deep digital divide (Van Deursen and Helsper, 2015; Van Deursen and Mossberger, 2018; Dutton and Reisdorf, 2019).

According to some studies (Tipton, 2002; Olaniran and Agnello, 2008; Beckman et al., 2008) income disparity is the primary driver of the digital divide across countries. In particular, there is a strong connection between GDPs per capita and the patterns of digitalization. The GDP, for example, is positively correlated with Internet diffusion (Quibria et al., 2003; Zhang, 2013) and with the usage of computers (Quibria et al., 2003).

Other studies focus on the disparity in ICT access at household and individual levels, highlighting the significance of socioeconomic and demographic factors (Hoffman and Novak, 1998; TELEC and TIO, 1999; Venkatesh and Brown, 2001; Wareham et al., 2004; Korupp and Szydlik, 2005; Demoussis and Giannakopoulos, 2006; Cruz-Jesus et al., 2012; Nishida et al., 2014; Pick and Nishida, 2015; Nishijimaa et al., 2017). Again, income is a very important variable. Households with access to ICT devices, indeed, are usually those richer and better educated (TELEC and TIO, 1999; Demoussis and Giannakopoulos, 2006; Nishida et al., 2014; Nishijimaa et al., 2017). Vodoz et al. (2007), for example, found that individuals with high education levels are likely to adopt digital technologies faster than people with low or no education at all. Conversely, households from disadvantaged social groups are less likely to be digitally included (Hoffman and Novak, 1998). The occupational structure also matters: persons employed as sales and executive professionals are more likely to own an ICT device (Wareham et al., 2004; Narayana, 2011). Demographic features such as age, gender, and family size also play a role in influencing households' decision to own ICT devices (Schumacher and Morahan Martin, 2001; Venkatesh and Brown, 2001; Korupp and Szydlik, 2005; Demoussis and Giannakopoulos, 2006; Nishijimaa et al., 2017).

As the literature shows, the poor are therefore less likely to have access to technology. This is confirmed by a study by Gabriels and Horn (2014), limited, however, to districts in South Africa only. Through a correlation analysis, they find a negative relationship between access to technology and poverty. In other words, in districts characterized by high levels of poverty, access to technology is lower.

In any case, the adoption of digital technologies in households has significantly increased over time, leading to changes in media usage, social behavior, and the structure of households (Ley et al., 2014). This important diffusion has become progressively more feasible and easier over time thanks to lower relative prices of technological goods and rising incomes (OECD, 2007), which encouraged access to technology even to the poorest segments of the population. In an article by De Silva and Zainudeen (2007) a representative population survey of five emerging Asian countries (Pakistan, India, Sri Lanka, the Philippines, and Thailand) is conducted to test the level of access to technology of the poorest population (at the bottom of the pyramid). The researchers found that access to technology is widespread even among the poor population, but there remains a significant gap in equipment ownership. This is because the opportunity cost of these goods is very high, implying a strong tradeoff between technology goods and necessities. For this reason, according to Dunga (2019), increased access to technology by the poor may exacerbate their degree of poverty.

The Covid-19 pandemic has further accelerated the adoption of digital technologies, also in poor households (Giordani and Rullani, 2020; Kudyba, 2020; Oldekop et al., 2020; Amankwah-Amoah et al., 2021; Copson et al., 2022). In some cases, this has contributed to highlighting existing digital exclusion and poverty, particularly for people with intellectual disabilities (Chadwick, 2022) and for developing countries (Ofosu-Ampong, 2021).

The acceleration of the process is due to pandemic containment measures that have led to long periods of home isolation, turning homes into workspaces and leading to a forced increase in the use of digital technologies (Maalsen and Dowling, 2020; Watson et al., 2021). The impact has varied depending on several factors such as place of residence, infrastructure, and demographics (Mikhaylova et al., 2021). Jahangir Rony et al. (2021) also underscores that the impact of the pandemic on technology adoption has particularly concerned working women in developing countries.

Our study adds to the existing body of knowledge by examining the changing dynamics of the association between poverty and household digitization levels over time, including the possible effect of the Covid-19 pandemic. However, while the existing literature provides an overview of digital disparities based on socioeconomic and demographic factors, this essay specifically examines the possible role of pandemic Covid-19 in influencing the degree of household digitalization, distinguishing by economic status. In addition, through a country analysis, we can distinguish the effects based on the country's welfare system and degree of technological adoption. To the best of our knowledge, we are the first to examine digitalization from this perspective. Using a DiD econometric approach, we present empirical evidence showing variability in technology adoption across socioeconomic strata. In addition, our results contribute to the literature by highlighting important policy implications. Considering our observation that post-Covid-19 digitalization is more pronounced among poorer households, we identify a novel role for technology. It becomes an essential good, although perhaps this implies a substitution of goods that were essential before the Covid-19 pandemic.

3. Data

For our analyses, we use data collected in the Statistics on Income and Living Conditions for European Countries (EU-SILC) survey in its cross-sectional version. The SILC database collects demographic and socioeconomic information on individuals and households in 27 European countries. Within it, there is monetary and nonmonetary information, useful in providing a detailed representation regarding the living conditions of households. Also collecting data regarding material deprivation, it contains information on the affordability of certain digital technologies.

Only six countries are considered for the analysis, selected based on the digitalization clusters identified in Lucendo-Monedero et al. (2019). To provide an overview as representative as possible, for each of the three clusters we select the two most populous countries. As specified in the introduction, these countries represent different European welfare regimes according to the existing literature on the topic (Esping Andersen, 1990; Ferrera, 1996; Whelan and Maître, 2010). They are

Spain (ES),[3] France (FR), Italy (IT), Netherlands (NL), Poland (PL) and Sweden (SE). Following this sample selection, we obtain a dataset consisting of 800,266 households. In Table A1 in the Appendix, we can observe in detail the yearly distribution among countries.

The target population of the survey is households residing in the country at the time of data collection. For each household, we consider data on their head member. Data have been collected since 2004, but our analysis is limited to looking at data from 2013 to 2022. This is because our dependent variables, which measure household digitalization likelihood, have been available since 2013. Specifically, these are two variables derived from two questions one regarding ownership of a computer and the other availability of an Internet connection for personal use. Possible answers are: 1: Yes; 2: No - cannot afford it; 3: No - other reason. From these, we compute a dummy variable for each question by grouping answers 2 and 3. This will be equal to 1 if the household answers negatively and equal to 0 otherwise. They represent a proxy for the lack of technology adoption in the family.

We have also another key variable, that identifies the economic status of the household. This is the Ability to make ends meet. In this case, the family is asked whether it can make ends meet, that is, pay the necessary expenses. The goal is to gauge respondents' feelings about the level of difficulty the family faces in making ends meet. Families can answer these questions with six possible answers. 1: With great difficulty; 2: With difficulty; 3: With some difficulty; 4: Fairly easily; 5: Easily; 6: Very easily. From this, we compute the economic distress dummy variable that is equal to 1 if the family answers 1 or 2 and 0 otherwise. For simplicity, we will henceforth define poor or economically distressed households as all households for which the dummy 'economic distress' equals 1.

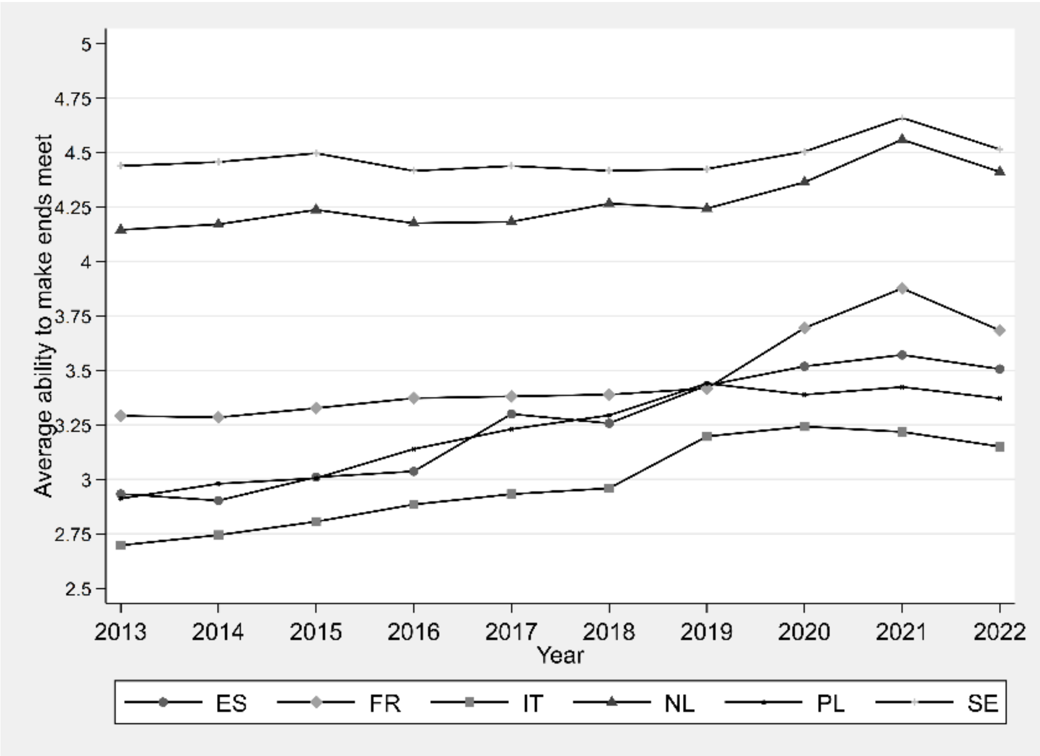
We use the ability to make ends meet as a measure of economic hardship because it is a measure of subjective poverty. Subjective poverty measures are based on individual feelings, subjective circumstances, and social context. They are therefore less dependent on income and actual conditions of material deprivation. Therefore, we expect to find, albeit decreasingly, households that report not being able to make ends meet across the income distribution. In this way, we can broaden our field of observation and at the same time avoid using arbitrary and standardized measures in a comparison between countries with different incomes and living standards.

Figure 1 shows the average ability to make ends meet for the six selected European countries. There are two distinct groups of countries based on economic conditions. The first is composed of the Netherlands and Sweden, for which there is an average score above 4 for the entire period. This means that households in these two countries report on average being able to make ends meet with some ease. The second group of countries consists of France, Spain, Poland, and Italy, with the latter recording the lowest average scores. For this group of countries, the average score is between 2.70 and 3.75, except for France, which scores between 3.75 and 4 between 2020 and 2022. In general, we can say that families in these countries on average have difficulty or some difficulty making ends meet. For all countries, there is a slow improvement that becomes more substantial from 2019 onward and then worsens again in 2022, aided by the high inflation that has characterized the economic system since 2021.

[3] Spain is chosen for the cluster of central European regions, despite Germany being the most populous country. However, several variables needed for the analysis were not available for the latter.

Figure A1 in the Appendix shows the share of households in economic distress from 2013 to 2022. For Italy, Spain, and Poland, this share decreased substantially from 2013 to 2019 and then remained constant. For the Netherlands, a gradual decrease is observed. Sweden and France, on the other hand, have a constant share of economically distressed households throughout the period, with France that return to 2014 levels in 2022. Figure A2 shows how the share of households that declared themselves to be in economic distress is distributed across the deciles of households' equivalised disposable income. It is clear from the graphs that, as obvious, the share of households declaring themselves to be in economic distress is highest in the lowest deciles of the equivalised income distribution. In 2022, this share is the lowest for each country in each decile.

Figure 1. Average ability to make ends meet for six European countries from 2013 to 2022

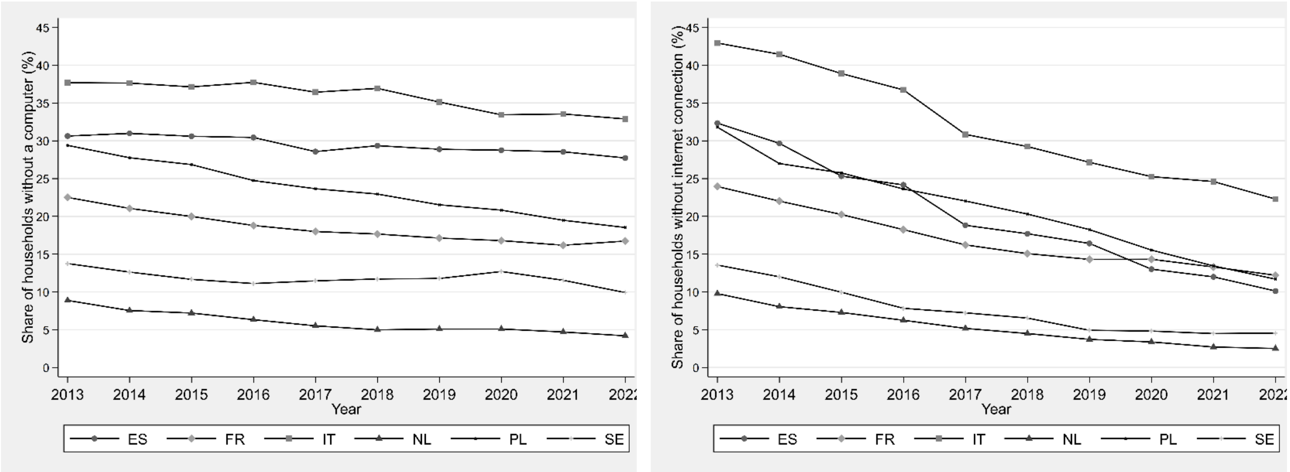


Source: Elaborations by the authors on EU-SILC data.

As already found in the literature, we observe that there is a strong relationship between economic conditions and digitalization (Hoffman and Novak, 1998; Demoussis and Giannakopoulos, 2006; Nishida et al., 2014; Nishijimaa et al., 2017). From Figure 2, we see that households in countries that report the most economic difficulties are also the least digitalized, and vice versa. Again, Sweden and the Netherlands form a group by themselves. The share of non-digitalized households in these countries is very low, especially in terms of Internet connection for personal use, which is less than 5% in 2022. France, which has average levels of economic distress, also has average levels of non-digitalization. Again, the share of households without an Internet connection declines steadily over time. Italy, Spain, and Poland, instead, present the highest levels of non-digitalized households.

Figure 2. Share of non-digitalized households in six European countries from 2013 to 2022

Panel A: Share of households without a computer *Panel B: Share of households without Internet connection*



Source: Elaborations by the authors on EU-SILC data.

Italy is the worst off, especially in terms of computer ownership (in 2022, 32.9% of households still don't have a computer). Spain shows roughly constant levels throughout the period, while Poland shows the greatest progress. The picture is better regarding the Internet connection. The share of households without Internet access has declined consistently over time for all countries, especially for Poland and Spain which are rapidly converging with France. In Italy, however, almost 1/4 of households in 2022 are still without an Internet connection for personal use.

From Tables 1 and 2, the relationship between poverty (measured through the economic distress condition derived from the ability to make ends meet indicators') and household digitalization is even clearer. From the first four columns of these tables, it is possible to observe the degree of digital technology adoption according to the economic status of households for each country over time. In addition, the last two columns show the share of digitalized households among poor and non-poor households. In general, more digitalization is evident among households not in a poverty condition. For all countries, the digitalization process is driven by non-poor households.

From 2013 to 2022, digital technology adoption increased further for non-poor households in all countries. For poor households, it is necessary to distinguish between computers and Internet access. In the former case, there were slight increases in France (+1.0 pp) and Poland (+5.4 pp). For all others, there is a decrease in the share of poor households with a computer.

Table 1. Share of households by poverty condition and computer ownership – 2013, 2018, 2022

Year 2013						
Country	No computer, poor	No computer, not poor	Computer, poor	Computer, not poor	% Computer among the poor	% Computer among the non-poor
Spain	13.9	16.8	22.8	46.5	62.2	73.5
France	5.1	17.4	14.6	62.9	74.2	78.3
Italy	17.8	19.8	22.1	40.2	55.3	66.9
Netherlands	2.1	6.8	14.5	76.6	87.4	91.9
Poland	14.0	15.4	19.4	51.2	58.1	76.9
Sweden	1.3	12.4	6.3	79.9	82.8	86.5
Total	11.0	16.6	18.4	54.0	62.7	76.5
Year 2018						
Country	No computer, poor	No computer, not poor	Computer, poor	Computer, not poor	% Computer among the poor	% Computer among the non-poor
Spain	11.5	17.9	14.8	55.9	56.3	75.8
France	4.3	13.3	12.8	69.5	74.8	83.9
Italy	15.9	21.0	14.4	48.6	47.5	69.8
Netherlands	1.2	3.8	10.0	85.0	89.1	95.8
Poland	9.3	13.6	12.0	65.1	56.1	82.7
Sweden	1.8	9.9	6.2	82.1	77.2	89.3
Total	9.1	15.4	13.0	62.6	58.9	80.3
Year 2022						
Country	No computer, poor	No computer, not poor	Computer, poor	Computer, not poor	% Computer among the poor	% Computer among the non-poor
Spain	9.0	18.7	12.7	59.5	58.5	76.1
France	5.0	11.7	15.2	68.1	75.2	85.3
Italy	10.7	22.2	11.6	55.5	52.0	71.4
Netherlands	1.4	2.8	6.7	89.1	83.0	96.9
Poland	6.2	12.4	10.7	70.7	63.5	85.1
Sweden	1.7	8.2	5.4	84.6	75.9	91.2
Total	7.0	15.0	12.1	65.9	63.5	81.4

Source: Elaborations by the authors on EU-SILC data.

Regarding Internet access, there is a consistent and generalized increase especially for Spain (+27.4 pp), Poland (+21.1 pp), and Italy (+20.1 pp). For these countries, the increase compared to 2013 is greater for the poor population than for the non-poor population. Thus, a consistent process of convergence is emerging. It is noteworthy that an increasing share of poor households equipped with Internet access reflects a shift in consumption patterns. The Internet is progressively emerging as a fundamental commodity, attributed to its affordability and accessibility. Nevertheless, among the most financially vulnerable households, a significant challenge arises in the form of a substitution effect with other goods that were traditionally deemed essential.

Table 2. Share of households by poverty condition and adoption of an Internet connection for personal use – 2013, 2018, 2022

Country	No internet, poor	No internet, not poor	Internet, poor	Internet, not poor	% Computer among the poor	% Computer among the non-poor
Year 2013						
Spain	15.0	17.4	21.7	46.0	59.1	72.6
France	5.5	18.5	14.2	61.8	72.1	77.0
Italy	21.1	21.9	18.9	38.2	47.2	63.6
Netherlands	2.4	7.4	14.2	76.1	85.4	91.2
Poland	15.3	16.5	18.2	50.0	54.3	75.2
Sweden	1.4	12.1	6.2	80.2	81.5	86.9
Total	12.3	17.7	17.0	52.9	58.0	74.9
Year 2018						
Country	No internet, poor	No internet, not poor	Internet, poor	Internet, not poor	% Computer among the poor	% Computer among the non-poor
Spain	6.8	10.9	19.4	62.9	74.0	85.3
France	3.1	12.0	14.1	70.8	82.1	85.5
Italy	13.6	15.6	16.7	54.0	55.1	77.6
Netherlands	0.9	3.6	10.3	85.2	91.7	96.0
Poland	8.4	11.9	12.9	66.8	60.7	84.8
Sweden	0.9	5.6	7.1	86.3	88.7	93.9
Total	7.0	11.8	15.0	66.2	68.2	84.9
Year 2022						
Country	No internet, poor	No internet, not poor	Internet, poor	Internet, not poor	% Computer among the poor	% Computer among the non-poor
Spain	2.9	7.2	18.8	71.0	86.5	90.8
France	3.3	8.9	16.9	70.8	83.8	88.8
Italy	7.3	15.0	15.0	62.7	67.4	80.7
Netherlands	0.5	2.0	7.6	89.9	93.3	97.9
Poland	4.2	7.5	12.8	75.6	75.4	90.9
Sweden	0.8	3.8	6.4	89.1	89.1	95.9
Total	4.0	9.2	15.0	71.7	78.8	88.6

Source: Elaborations by the authors on EU-SILC data.

4. Econometric strategy

In this section, we set up the econometric strategy through two models. The first one is called 'Base model', and it is useful to identify the general relationship between economic conditions and digitalization. According to the literature, we expect to find a positive relationship between poverty and lack of digitalization, measured as either absence of computer or absence of Internet connection.

In the second one, we want to identify the impact of Covid-19 on the degree of households' digitalization deficit. After the pandemic crisis, we expect an increased reliance on technology use due to social distancing measures. This is expected to have a negative effect on the lack of access to technology, leading to greater digitalization.

However, the potential positive effect may be obscured by economic factors that, as reported in the literature, are obstacles to households' adoption of digital technologies. Furthermore, it is presumed that the impact of social distancing measures did not uniformly affect the digitalization of households. Indeed, an increase in the use of digital technologies is likely to be higher for workers who have the option of remote work facilitated by technology, typically individuals with higher qualifications and thus not in a poverty situation.

An analysis of the pandemic impact on the actual degree of households' digitalization deficit, therefore, cannot overlook these implications. To this end, we have developed a Difference-in-Differences (DiD) identification strategy based on the premise that, while the social distancing measures resulting from the pandemic affected everyone equally, the change in technological adoption was not uniform for all. It consists of a DiD strategy where the dummy variable "being economically distressed" (our treatment) iterates with the variable Covid-19 (our pre-post factor).

To summarize, we estimate the causal effect of the pandemic on the probability of being a not-digitalized family, comparing the rate of technological adoption by poor households from six European countries (Spain, France, Italy, Netherlands, Poland, and Sweden) before (2013-2019) and after (2020-2022) Covid-19 pandemic crisis.

For both models, we analyze the digitalization of households in economic distress using a discrete choice (Probit) model:

$$P\left(Y_{it} = 1 \middle| X_{it}, Y_{i,t} = 0\right) = \Phi(Z), \tag{1}$$

where $Y_{it} = 1$ if the household *i* is not digitally equipped at year *t* and $Y_{it} = 0$ if the household is digitalized. We state that a household is not digitalized if don't have an internet connection for personal use or doesn't have a computer. For this reason, we have two specifications of the models, one for each dependent variable. Given that the models are non-linear, after maximum likelihood estimations, average marginal effects are computed for different specifications. All estimates are based on robust standard errors and household sample weights are considered.

Specifically, as for the 'Base model', we assume that the probability of being non-digitalized is driven by the following equation:

$$Z = \alpha + \beta T + \gamma H + \delta W, \tag{2}$$

where the dummy *T* identifies economically distressed households (defined through the ability to make ends meet indicator). This is equal to 1 if the family declares an ability to make ends meet "with difficulty" or "with great difficulty". In addition, the model includes the vector *H* containing householder's characteristics (i.e. gender, age group, education level) and the vector *W* containing household well-being related variables (i.e. household composition, tenure status, logarithm of equivalised income, and a dummy that is equal to 1 if all household members earn a wage). In this model, we also have country and time fixed effects.

In the 'DiD model' it is necessary to add the shock event, thus the Covid-19 dummy. In this case, the probability of being non-digitalized at time *t* is therefore driven by the following equation:

$$Z = \alpha + \beta T + \gamma P + \delta T \cdot P + \theta H + \vartheta W, \tag{3}$$

where the Covid-19 dummy (pre-post) *P* is equal to 1 for the period 2020-2022 (and 0 for the pre-pandemic period, 2013-2019). Like before, the dummy that identifies an economic distressed household (treatment) is *T*. The interaction of the Covid-19 dummy and the poor household dummy represents the DiD term. Also in this case we includes the two vectors *H* and *W*, as well as country fixed effects.

A complete description of all the variables in the models is provided in Table A2 in the Appendix.

As indicated in the previous sections, to investigate potential heterogeneity within the EU, we estimate separate regression models for each of six selected European countries. Similarly, we perform a heterogeneity analysis by decile group of the household equivalised disposable income to explore to what extent estimated results change along the national income distribution. In Section 6 we also provide a sensitivity analysis replacing the ability to make ends meet dummy (a subjective measure of poverty) with a more objective measure of economic hardship, thus the At-Risk-Of Poverty or Social Exclusion (AROPE) indicator. The AROPE condition embeds three other social indicators composing the EU Social Protection Committee's portfolio: the at-risk-of-poverty (AROP) rate, the (quasi-)joblessness, and the severe material deprivation. According to the AROP indicator, an individual is poor if his/her household income is below the 60% of the national equivalised median income. According to the (quasi-)joblessness indicator, an individual is poor if he/she lives within a household with very low work intensity (i.e. on average, household members aged 18-59 work less than 20% of their total work potential). Finally, according to the severe material deprivation indicator, an individual is poor if he/she lives within a household who cannot afford at least four items out of a list of nine.[4] The AROPE condition represents a combination of the previous three indicators, so that the AROPE indicator equals 1 if at least one of the three indicator is 1 and 0 otherwise.

5. Results

We estimate the probability of being a non-digitalized family before and after the Covid-19 pandemic using different specifications. In all models, we emphasize the role of living an economic distress condition, but the list of covariates shown in Table A2 is also included.

5.1. Effect of Covid-19 on non-computer ownership

To see the effect of Covid-19 on the digitalization of families, we estimate the DiD model based on the equation (3). Marginal effects are shown in Table 3. The positive relation between economic distress and non-possession of a computer is confirmed by the positive sign and statistical significance of the coefficient of the economic distress dummy in the Base model (equation (2)). The DiD model also shows that, before the pandemic, a poor household had a higher probability to don't have a computer. After the Covid-19 pandemic, a push toward digitalization has been observed. The coefficient associated with the dummy variable 'Covid-19 period' is negative, indicating that after the spread of the virus, the probability of not owning a computer in all households significantly decreases.

[4] The nine items are the following: I) face unexpected expenses; II) afford a one-week annual holiday away from home; III) avoid arrears (mortgage or rent, utility bills or hire purchase instalments); IV) afford a meal with meat, chicken, fish or vegetarian equivalent every second day; V) afford keeping home adequately warm; VI) have a washing machine; VII) have a colour TV; VIII) have a telephone; IX) have access to a personal car.

Table 3. Marginal effects of Covid-19 on non-computer ownership

Variables	Base model	DiD model
Economic distress	0.068***	0.066***
	(0.001)	(0.002)
Covid-19 period		−0.017***
		(0.001)
Interaction term		0.012***
		(0.003)
Observations	800,278	800,278

*Notes: The model specifications also include all the other covariates listed in Section 4. Full estimates are provided in Table A3 in the Appendix. SE in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaborations on EU-SILC data.*

The interaction term indicates that this reduction in the probability of being non-digitalized does not occur for families in economic distress though. Once the coefficients of the Covid-19 dummy and the interaction term are added together, the overall pandemic effect for poor households is not statistically different from zero. This dynamic could be attributed to the fact that purchasing a computer after the pandemic is still perceived as a high cost by poor households. In addition, it could depend on the fact that these households may perceive less of a need for a computer for work purposes, presumably because working in less skilled occupations or working less in general.

5.1.1. Heterogeneity by country

We can also analyze the Covid-19 effect on non-computer ownership assessing for country heterogeneity. Marginal effects are shown in Table 4. In general, we find similar results in signs to the overall model, with the notable exception of Spain, where the coefficient associated with the dummy variable 'Covid-19 period' is positive. This suggests that, for this country, the pandemic has not contributed to the household digitalization process. This finding is further accentuated, as evidenced by the interaction term, in the case of economically distressed households. Table 4 highlights that the positive and significant effect of the interaction term on the dependent variable is mainly driven by France, the Netherlands, and Sweden, while it is insignificant in Italy and Poland. As a consequence, poor and non-poor households followed the same digitalization pattern after pandemic in the latter two countries, where however we also observe the greatest association between poverty and non-digitalization (together with Spain).

5.1.2. Heterogeneity along income distribution

We can also assess the distribution by decile of household equivalised disposable income (Table 5). This heterogeneity analysis firstly confirms that the relationship between subjective poverty and digitalization is not necessarily related to the household income, as the coefficient of the adopted poverty indicator presents a positive and significant effect on the probability of being non-digitalized in each decile group. Also, except for the first decile, the magnitude of this relationship is quite stable along the income distribution.

For the II, III, and IV deciles of the distribution, the same sign pattern found in the general model is confirmed. The impact of Covid-19 in encouraging household digitalization persists up to the median decile. From the median decile onward, the effect of Covid-19 is no longer significant even if negative (expect for the last decile). The interaction term is positive and significant only for families in the II, III, and IV deciles. For economically distressed households that belong to these deciles, the digitalization brought by Covid-19 is mitigated. For these households, in which subjective economic hardship coincides with objective economic hardship, purchasing a computer represents a high opportunity cost. From the fifth decile onward, the interaction term is never significant (except for the eighth decile).

Table 4. Marginal effects of Covid-19 on non-computer by country

Variables	Spain		France		Italy		Netherlands		Poland		Sweden	
	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model
Economic distress	0.079***	0.073***	0.033***	0.026***	0.093***	0.096***	0.024***	0.015***	0.069***	0.072***	0.036***	0.019***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.006)
Covid-19 period		0.017***		−0.035***		−0.015***		−0.021***		−0.029***		−0.008**
		(0.003)		(0.003)		(0.003)		(0.002)		(0.003)		(0.003)
Interaction term		0.021***		0.025***		−0.010		0.039***		0.000		0.054***
		(0.006)		(0.006)		(0.007)		(0.006)		(0.005)		(0.010)
Observations	153,450	153,450	120,064	120,064	196,809	196,809	120,534	120,534	148,528	148,528	60,893	60,893

*Notes: Models also include all the other covariates listed in Section 4. SE in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaborations on EU-SILC data.*

Table 5. Marginal effects of Covid-19 on non-computer ownership by households' equivalised disposable income distribution deciles

Variables	I		II		III		IV		V	
	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model
Economic distress	0.106***	0.100***	0.044***	0.039***	0.045***	0.037***	0.050***	0.045***	0.039***	0.037***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Covid-19 period		−0.026***		−0.017***		−0.032***		−0.019***		−0.020***
		(0.007)		(0.006)		(0.006)		(0.006)		(0.005)
Interaction term		0.016		0.021**		0.032***		0.023**		0.013
		(0.010)		(0.009)		(0.009)		(0.009)		(0.010)
Observations	68,893	68,893	74,829	74,829	77,478	77,478	79,554	79,554	81,523	81,523

	VI		VII		VIII		IX		X	
	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model
Economic distress	0.050***	0.047***	0.046***	0.045***	0.042***	0.036***	0.042***	0.043***	0.044***	0.046***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Covid-19 period		−0.003		−0.003		−0.001		−0.004		0.000
		(0.005)		(0.005)		(0.004)		(0.004)		(0.003)
Interaction term		0.016		0.014		0.031***		−0.002		−0.008
		(0.010)		(0.010)		(0.011)		(0.010)		(0.009)
Observations	81,829	81,829	82,687	82,687	83,250	83,250	84,555	84,555	85,680	85,680

*Notes: Models also include all the other covariates listed in Section 4. SE in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaborations on EU-SILC data.*

5.2. *Effect of Covid-19 on non-adoption of internet connection for personal use*

Following the model based on equation (3), this time we evaluate the effect of Covid-19 on households' digitalization using the likelihood of not having an Internet connection for personal use within the household as a dependent variable (Table 6).

Table 6. Marginal effects of Covid-19 on non-adoption of Internet connection for personal use

Variables	Base model	DiD model
Economic distress	0.065***	0.077***
	(0.001)	(0.001)
Covid-19 period		−0.070***
		(0.001)
Interaction term		−0.028***
		(0.003)
Observations	800,278	800,278

*Notes: The model specifications also include all the other covariates listed in Section 4. Full estimates are provided in Table A4 in the Appendix. SE in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaborations on EU-SILC data.*

Also, in this case, we can see by the Base model a positive relation between economic distress and non-digitalization probability. The positive sign of the dummy 'economic distress' means that a household in economic hardship has a higher probability of not having access to an internet connection for personal use. By the DiD model, we can see that this was also true before the Covid-19 pandemic, but things changed after it. The coefficient associated with the dummy variable 'Covid-19 period' is negative and this means that this event has a negative impact on the lack of internet connection for all households. The interaction term has, also, a negative sign. This suggests that this reduction in the probability of being non-digitalized is more pronounced for economically distressed households. These means that, despite the positive relation between poverty and lack of digitalization, there is an important internet connection diffusion dynamic pushed by the Covid-19 pandemic that is strongest for families in economic difficulty. Unlike the computer, the post-pandemic Internet connection is an increasingly relevant commodity for households, regardless of their economic situation. In other words, Internet connection increasingly assumes the role of a primary good. Its success is probably due to its relatively low cost, the ability to access it from any device, and its essential role in new forms of entertainment. It also represents a useful digital good outside of work, a role with which the computer is instead more closely associated.

5.2.1. *Heterogeneity by country*

We can analyze the marginal effects assessing for country heterogeneity. In general, the results are similar to the overall model in the signs, with the dummy 'economic hardship' that increases the probability of not having an Internet connection in each country before the pandemic. From Table 7 we can see that the effect is mainly driven by Italy, where being poor (in general, but especially before Covid-19) increases the probability of not having an Internet connection for personal use more than in other countries. Instead, for countries such as France, Netherlands, and Sweden, with already high initial levels of digitalization and low shares of economically distressed households, the effect of the dummy variable ‘economic distress’ before Covid-19 is very low. For all countries, the Covid-19 period led to an increase in Internet connection, with a particularly high contribution in Spain, Italy, and Poland, that are countries with low initial levels of digitalization. The negative sign of the interaction term suggests that, in these countries, the Covid-19 effect is greater for households in economic distress, while is laughable or not statistically significant for France, the Netherlands, and Sweden. In particular, after the pandemic crisis, the probability of a poor household not having an Internet connection for personal use was reduced by −11.8% in Spain, −13.7% in Italy, and −10.0% in Poland. As in the non-computer ownership case, it seems that, for these countries, it is very difficult to reach the non-digitalized poor households, that are probably those most in need.

5.2.2. Heterogeneity along income distribution

Assessing for decile distribution of equivalised disposable income (Table 8), the heterogeneity analysis confirms the relationship between subjective poverty and digitalization for the first five deciles. The impact of Covid-19 on households’ digitalization decreases as one moves toward the higher deciles of the distribution. This means that households with higher incomes are less affected by the post-pandemic digitalization process. This is probably because they already had an Internet connection or do not consider it necessary, not so much for economic reasons. The interaction variable is U-shaped. Adding up the coefficients of the Covid-19 dummy and the interaction term for the first five deciles (the significant ones), we deduce a decreasing L-shaped Covid-19 effect for economically distressed households. This means that digitalization because of the pandemic for self-declared economically distressed households while remaining relevant, decreases as we move toward higher deciles (until the fifth). In other words, the effect of Covid-19 on digitalization is greatest for those households where objective and subjective poverty coincide.

Table 7. Marginal effects of Covid-19 on non-adoption of Internet connection for personal use by country

	Spain		France		Italy		Netherlands		Poland		Sweden	
Variables	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model
Economic distress	0.061***	0.075***	0.027***	0.028***	0.107***	0.132***	0.012***	0.011***	0.066***	0.076***	0.027***	0.021***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)
Covid-19 period		−0.092***		−0.059***		−0.073***		−0.040***		−0.081***		−0.044***
		(0.003)		(0.003)		(0.003)		(0.002)		(0.002)		(0.003)
Interaction term		−0.026***		0.001		−0.064***		0.012**		−0.019***		0.022**
		(0.006)		(0.006)		(0.006)		(0.006)		(0.005)		(0.009)
Observations	153,450	153,450	120,064	120,064	196,809	196,809	120,534	120,534	148,528	148,528	60,893	60,893

*Notes: Models also include all the other covariates listed in Section 4. SE in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaborations on EU-SILC data.*

Table 8. Marginal effects of Covid-19 on non-adoption of Internet connection for personal use by decile distribution of poor households

	I		II		III		IV		V	
Variables	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model
Economic distress	0.101***	0.119***	0.041***	0.056***	0.051***	0.061***	0.045***	0.055***	0.037***	0.048***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Covid-19 period		−0.097***		−0.077***		−0.069***		−0.057***		−0.051***
		(0.007)		(0.006)		(0.006)		(0.005)		(0.005)
Interaction term		−0.039***		−0.035***		−0.018*		−0.021**		−0.026***
		(0.010)		(0.009)		(0.009)		(0.009)		(0.010)
Observations	68,893	68,893	74,829	74,829	77,478	77,478	79,554	79,554	81,523	81,523

	VI		VII		VIII		IX		X	
	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model	Base model	DiD model
Economic distress	0.051***	0.057***	0.044***	0.049***	0.042***	0.046***	0.038***	0.041***	0.046***	0.049***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Covid-19 period		−0.043***		−0.039***		−0.027***		−0.031***		−0.025***
		(0.005)		(0.005)		(0.004)		(0.004)		(0.003)
Interaction term		−0.012		−0.007		−0.008		−0.003		−0.014*
		(0.010)		(0.010)		(0.009)		(0.010)		(0.008)
Observations	81,829	81,829	82,687	82,687	83,250	83,250	84,555	84,555	85,680	85,680

*Notes: Models also include all the other covariates listed in Section 4. SE in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaborations on EU-SILC data.*

6. Sensitivity analysis

We investigate whether the effect of Covid-19 on the lack of digitalization of households is sensitive to the definition of poverty. For this reason, we propose a second definition of poverty which is the AROPE.

The economic strategy is the same that we present in Section 4, with the only difference being that the variable that identifies if a family is in a difficult economic situation is the AROPE and not the economic distress derived from the Ability to make ends meet. The main difference between the two is that the AROPE is a more objective measure of poverty that depend on household income, work intensity and material deprivation, while the ability to make ends meet is self-declared and then might be driven by personality traits and heuristics in general. It is necessary to specify that the household income data used to define AROPE refer to the income reference period (*t-1*). Thus, the AROPE is a mixed indicator that assesses poverty status at both time *t* and time *t-1*. This represents an additional robustness check of our estimates, since in this case there is no simultaneity between poverty status and digitalization.

Following equations (2) and (3) we have that the dummy that identifies a poor household (treatment) T_i is equal to 1 if the family is At-risk-of poverty or social exclusion (is "at risk of poverty" or "severely material deprived" or "low work intensity").

Both the Base model and the general DiD model (Table 9) confirm the positive relation between economic conditions and non-possession of a computer. A household that is At-risk-of poverty or social exclusion has a higher probability of not having a computer (in general and before Covid-19). The pandemic crisis has little influenced this probability, but the effect is lower for those families that are in a difficult economic situation. This is evident from the positive sign of the interaction term, which signals that the Covid-19 effect is mitigated by the economic condition (even if it is higher than the one that we find in the model with the ability to make ends meet). As in the previous case, the explanation for this dynamic is probably the fact that the purchase of a computer involves high costs and is still not perceived as a necessary good for families in economic need.

Table 9. Marginal effects of Covid-19 on non-computer ownership

Variables	Base model	DiD model
At-risk-of poverty or social exclusion	0.075***	0.072***
	(0.002)	(0.002)
Covid-19 period		−0.023***
		(0.001)
Interaction term		0.012***
		(0.003)
Observations	800,278	800,278

*Notes: The model specifications also include all the other covariates listed in Section 4. Full estimates are provided in Table A5 in the Appendix. SE in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaborations on EU-SILC data.*

Table 10 shows the marginal effects for the case of Internet connection. The results shown in section 5.2 are confirmed. There is a positive relationship between poverty risk status and the probability of non-digitalization, meaning that poor households are more likely to be non-digitalized (in general and before Covid-19). Covid-19 is confirmed to be a driver of digitalization (the sign of the dummy variable 'Covid-19 period' is negative) especially for households at risk of poverty (the interaction term is negative). This implies and reiterates that Internet connection has a new role in the household consumption basket. It is now a primary good due to its special characteristics. It will be important to explore this new role further, especially to know what goods the Internet has replaced.

Table 10. Marginal effects of Covid-19 on non-adoption of Internet connection for personal use

Variables	Base model	DiD model
At-risk-of poverty or social exclusion	0.069***	0.072***
	(0.001)	(0.002)
Covid-19 period		−0.079***
		(0.001)
Interaction term		−0.015***
		(0.003)
Observations	800,278	800,278

*Notes: The model specifications also include all the other covariates listed in Section 4. Full estimates are provided in Table A6 in the Appendix. SE in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaborations on EU-SILC data.*

7. Conclusions

In this paper, we investigate the dynamics of household digitalization following the Covid-19 pandemic. Specifically, using a Probit model with a difference-in-differences approach, we examine the probability of non-adoption of digital technologies among households. For this purpose, we use two dependent variables that indicate the degree of non-digitalization: the absence of a computer and the lack of an Internet connection for personal use within the household. Our treatment group consists of economically distressed households, and our pre-post variable is the Covid-19 pandemic. The study uses the EU-SILC (European Union Statistics on Income and Living Conditions) database, focusing on six European countries representative of the Lucendo-Monedero et al. (2019) digitalization clusters and different European welfare regimes.

The results of the analysis show a generally positive relationship between economic hardship and lack of digitalization. This is confirmed by both the Base model, in a general sense, and by the DiD model when looking before the pandemic crisis. However, the advent of the Covid-19 pandemic played a key role as a catalyst for digitalization, significantly reducing the likelihood of not owning a computer or not having Internet access at home for personal purposes.

For economically distressed households, Covid-19 further contributed to the prevalence of Internet connection, while the effect is negligible for computer ownership. This dynamic is evident when looking at the sign of the interaction term, which is negative in the former case and positive in the latter.

Regarding computer ownership, the lower likelihood of digitalization in economically disadvantaged households could be attributed to the perceived excessive cost and the absence of a real need for this tool for professional purposes. Since it is not perceived as essential and has costs that cannot be underestimated, there is too high an opportunity cost problem for these households. This phenomenon is led by the Netherlands and Sweden, countries with already high rates of computer ownership. In these countries, reaching the few poor households that are not digitalized is particularly difficult. These households are probably the neediest, but purchasing a computer represents an excessively high opportunity cost for them. Examination of the distribution by decile of equivalised household income reveals that the effects found in the general model hold only for households with equivalised disposable income below the median, i.e., households in which subjective economic hardship coincides with objective economic hardship.

Regarding Internet connection, while before the pandemic poor households were more likely to lack Internet access (underscoring a pre-existing digital divide), there is subsequently evidence of a greater propensity to use this technology. This relation holds only in the first five deciles of the household's equivalised income distribution. From this heterogeneity analysis, we can note that the interaction term exhibits a U-shaped magnitude. Evaluating the effect of Covid-19 on economically distressed households we deduce a decreasing L-shaped pattern. It seems that the digitalization decision is stronger for families that also live in objective poverty conditions. The Internet connections increase for economically distressed households mainly in Spain, Italy, and Poland, while it is negligible in France, the Netherlands, and Sweden. As in the case of computer ownership, reaching non-digitalized poor households seems to be a challenge in these countries. Its growing importance has been aided by its ease of use, accessibility, and low cost. The Internet has taken on a role in entertainment, communication, and sociability not limited to the work environment. Having become part of the consumption basket of economically distressed households, we can say that it has assumed the role of a necessity good. It remains to be seen, however, under conditions of equal income, what other commodity of necessity it has replaced.

It is important to point out some limitations of the work, due to the characteristics of the EU-SILC dataset. If this consists of few households residing in rural areas, it is possible that our results represent a lower-bound. This is because poverty is higher in rural areas (which would lead to a greater lack of access to digital technologies), but also because rural areas are the least digitalized (European Commission, 2022). In other words, the relationship between poverty and digitalization described by coefficient β should have a larger magnitude.

Although, the study contributes to the understanding of the relationship between poverty and digitalization, especially after the Covid-19 pandemic crisis. The effects are differentiated between countries and deciles equivalised income distribution. While computer ownership seems to be influenced mainly by perceived cost and lack of professional need, Internet connection has gained importance, becoming a primary good. Finally, the pandemic has shaped differentiated digitalization dynamics, highlighting the need to consider specific contexts and individual perceptions when analyzing digital transformation patterns.

In light of the results of this work, some implications and policy suggestions for bridging the current digital divide among households are reported. Given the various aspects that influence technological diffusion, it is crucial to take a multidimensional approach. First, initiatives to promote digital accessibility are essential, such as the implementation of a system of subsidies and tax incentives to make affordable the costs perceived as too high by financially struggling households. This involves establishing an infrastructure system that is accessible to all. So, in addition to hardware equipment, an adequate level of infrastructure is needed, for example, to enable network accessibility to the entire population, regardless of geographic location. Currently, however, in 14 of the 27 countries of the European Union, more than half of the households living in rural areas do not have access to FTTP or DOCSIS 3.1 coverage[5] (European Commission, 2022). At the same time, it is necessary to accompany the provision of hardware equipment with an appropriate level of digital literacy through the implementation of targeted programs. This proves critically important in a context where in only 11 out of 27 European countries does at least one-third of the population have overall digital skills above basic (Eurostat, 2023). Digitalization strategies must be developed on a national scale to be targeted to the specific country system. In countries with a high degree of digitalization, for example, interventions need to be tailored to identify and assist only poor households that are not digitalized. In contrast, large-scale interventions are needed in the most deficient countries (Spain, Italy and Poland in our study). Such digital deployment strategies need a robust contemporary system of ongoing monitoring and evaluation. Finally, a cultural change is needed regarding the role played by digital tools. They are now necessary for development and well-being and as such should be counted among the essential goods and services for households.

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[5] FTTP and DOCSIS 3.1 are two types of broadband telecommunications networks. A home is covered if it can be connected to one of these broadband infrastructures without requiring the construction of a new infrastructure and is available to be connected in reasonable time and cost.

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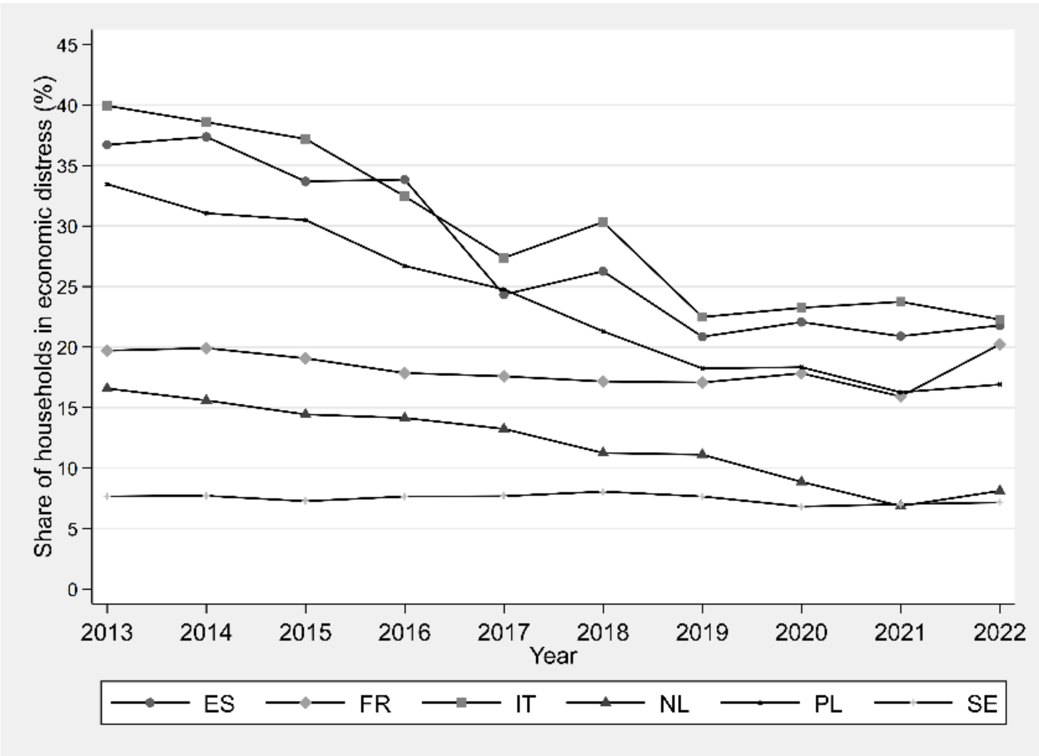
Appendix

Table A1. Households in the sample by country and year

Year	Spain	France	Italy	Netherlands	Poland	Sweden
2013	12,098	10,980	18,487	9,957	12,864	5,936
2014	11,945	11,256	19,663	10,026	12,928	5,539
2015	12,340	11,253	17,985	9,703	12,135	5,598
2016	14,216	11,279	21,325	12,288	11,830	5,548
2017	13,726	10,980	22,226	12,778	12,915	5,635
2018	13,339	10,809	21,173	12,004	15,002	5,519
2019	15,772	11,663	20,831	13,076	19,582	5,344
2020	14,956	10,801	14,240	12,624	15,026	5,418
2021	20,935	13,858	18,561	14,471	16,753	8,305
2022	24,111	17,185	22,318	13,607	19,493	8,051
Total	153,438	120,064	196,809	120,534	148,528	60,893

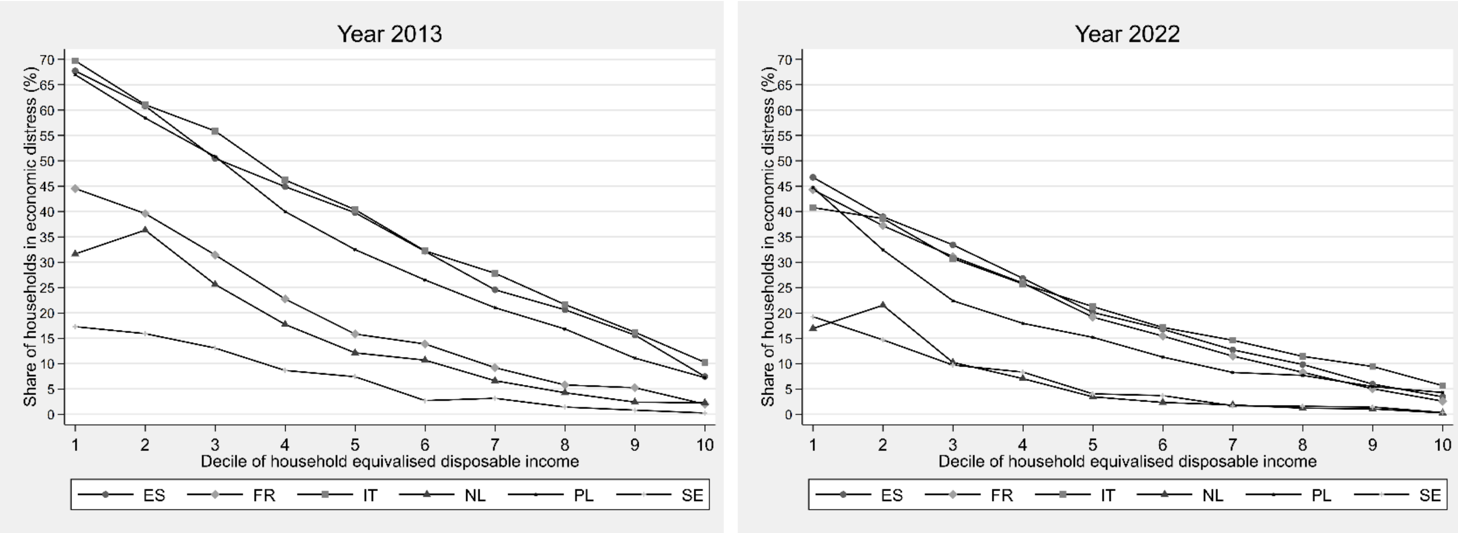
Source: Elaborations by the authors on EU-SILC data.

Figure A1. Share of households in economic distress for six European countries from 2013 to 2022



Source: Elaborations by the authors on EU-SILC data.

Figure A2. Share of households in economic distress by decile of equivalized disposable income for six European countries



Source: Elaborations by the authors on EU-SILC data.

Table A2. Descriptive statistics for all variables in the model

Variable	Mean	Std. dev.	Min	Max
No computer	0.245	0.430	0	1
No internet	0.207	0.405	0	1
Economic distress	0.228	0.420	0	1
Ability to make ends meet	3.377	1.243	1	6
At-risk-of poverty or social exclusion	0.227	0.419	0	1
Home not adequately warm	0.092	0.289	0	1
Female	0.545	0.498	0	1
Aged 35 or less	0.167	0.373	0	1
Aged 36-45	0.185	0.388	0	1
Aged 46-55	0.191	0.393	0	1
Aged 56-65	0.183	0.387	0	1
Aged 66 or more	0.274	0.446	0	1
Local	0.944	0.231	0	1
Primary or less education	0.168	0.373	0	1
Lower secondary education	0.173	0.378	0	1
Upper secondary education	0.367	0.482	0	1
Bachelor or more	0.293	0.455	0	1
Single person	0.321	0.467	0	1
Two adults	0.283	0.451	0	1
Household without children	0.125	0.331	0	1
Household with one child	0.134	0.341	0	1
Household with 2+ children	0.137	0.343	0	1
All adult members earn	0.713	0.452	0	1
Home ownership	0.696	0.460	0	1
Rental house	0.245	0.430	0	1
Free accommodation	0.059	0.236	0	1
Household equivalised income	19,989	21,323	1	6,178,827

Source: Elaborations by the authors on EU-SILC data.

Table A3. Marginal effects of Covid-19 on non-computer ownership, full estimates

Variables	Base model	DiD model
Economic distress	0.068***	0.066***
	(0.001)	(0.002)
Female	0.014***	0.014***
	(0.001)	(0.001)
Aged 36-45	0.007***	0.007***
	(0.002)	(0.002)
Aged 46-55	0.016***	0.015***
	(0.002)	(0.002)
Aged 56-65	0.070***	0.069***
	(0.002)	(0.002)
Aged 66 or more	0.235***	0.233***
	(0.002)	(0.002)
Local	−0.051***	−0.051***
	(0.003)	(0.003)
Lower secondary education	−0.137***	−0.138***
	(0.002)	(0.002)
Upper secondary education	−0.230***	−0.230***
	(0.002)	(0.002)
Bachelor or more	−0.327***	−0.328***
	(0.002)	(0.002)
Two adults	−0.123***	−0.123***
	(0.002)	(0.002)
Households without children	−0.238***	−0.238***
	(0.002)	(0.002)
Household with one child	−0.203***	−0.202***
	(0.002)	(0.002)
Household with 2+ children	−0.202***	−0.202***
	(0.002)	(0.002)
All adult members earn	−0.019***	−0.018***
	(0.001)	(0.001)
Rental house	0.042***	0.041***
	(0.002)	(0.002)
Free accommodation	0.041***	0.041***
	(0.002)	(0.002)
Log(household equivalised income)	−0.017***	−0.017***
	(0.001)	(0.001)
Covid-19 period		−0.017***
		(0.001)
Interaction term		0.012***
		(0.003)
Year fixed effects	Yes	No
Country fixed effects	Yes	Yes
Observations	800,278	800,278

Source: Elaborations by the authors on EU-SILC data.

Table A4. Marginal effects of Covid-19 on non-adoption of internet connection for personal use, full estimates

Variables	Base model	DiD model
Economic distress	0.065***	0.077***
	(0.001)	(0.001)
Female	0.005***	0.004***
	(0.001)	(0.001)
Aged 36-45	0.017***	0.016***
	(0.002)	(0.002)
Aged 46-55	0.026***	0.024***
	(0.002)	(0.002)
Aged 56-65	0.071***	0.068***
	(0.002)	(0.002)
Aged 66 or more	0.238***	0.233***
	(0.002)	(0.002)
Local	−0.021***	−0.019***
	(0.003)	(0.003)
Lower secondary education	−0.118***	−0.123***
	(0.002)	(0.002)
Upper secondary education	−0.183***	−0.187***
	(0.002)	(0.002)
Bachelor or more	−0.256***	−0.261***
	(0.002)	(0.002)
Two adults	−0.118***	−0.117***
	(0.002)	(0.002)
Households without children	−0.223***	−0.223***
	(0.002)	(0.002)
Household with one child	−0.184***	−0.184***
	(0.002)	(0.002)
Household with 2+ children	−0.186***	−0.186***
	(0.002)	(0.002)
All adult members earn	−0.017***	−0.017***
	(0.001)	(0.001)
Rental house	0.028***	0.025***
	(0.002)	(0.002)
Free accommodation	0.031***	0.031***
	(0.002)	(0.002)
Log(household equivalised income)	−0.018***	−0.018***
	(0.001)	(0.001)
Covid-19 period		−0.070***
		(0.001)
Interaction term		−0.028***
		(0.003)
Year fixed effects	Yes	No
Country fixed effects	Yes	Yes
Observations	800,278	800,278

Source: Elaborations by the authors on EU-SILC data.

Table A5. Marginal effects of Covid-19 on non-computer ownership, full estimates

Variables	Base model	DiD model
At-risk-of poverty or social exclusion	0.075***	0.072***
	(0.002)	(0.002)
Female	0.015***	0.014***
	(0.001)	(0.001)
Aged 36-45	0.011***	0.011***
	(0.002)	(0.002)
Aged 46-55	0.018***	0.018***
	(0.002)	(0.002)
Aged 56-65	0.073***	0.072***
	(0.002)	(0.002)
Aged 66 or more	0.241***	0.240***
	(0.002)	(0.002)
Local	−0.047***	−0.047***
	(0.003)	(0.003)
Lower secondary education	−0.138***	−0.139***
	(0.002)	(0.002)
Upper secondary education	−0.232***	−0.233***
	(0.002)	(0.002)
Bachelor or more	−0.331***	−0.333***
	(0.002)	(0.002)
Two adults	−0.119***	−0.119***
	(0.002)	(0.002)
Households without children	−0.230***	−0.229***
	(0.002)	(0.002)
Household with one child	−0.195***	−0.195***
	(0.002)	(0.002)
Household with 2+ children	−0.196***	−0.196***
	(0.002)	(0.002)
All adult members earn	−0.009***	−0.009***
	(0.001)	(0.001)
Rental house	0.045***	0.045***
	(0.002)	(0.002)
Free accommodation	0.039***	0.040***
	(0.002)	(0.002)
Log_household equivalised income	−0.009***	−0.010***
	(0.001)	(0.001)
Covid-19 period		−0.023***
		(0.001)
Interaction term		0.012***
		(0.003)
Year fixed effects	Yes	No
Country fixed effects	Yes	Yes
Observations	800,278	800,278

Source: Elaborations by the authors on EU-SILC data.

Table A6. Marginal effects of Covid-19 on non-adoption of internet connection for personal use, full estimates

Variables	Base model	DiD model
At-risk-of poverty or social exclusion	0.069***	0.072***
	(0.001)	(0.002)
Female	0.005***	0.005***
	(0.001)	(0.001)
Aged 36-45	0.020***	0.020***
	(0.002)	(0.002)
Aged 46-55	0.029***	0.027***
	(0.002)	(0.002)
Aged 56-65	0.073***	0.071***
	(0.002)	(0.002)
Aged 66 or more	0.245***	0.239***
	(0.002)	(0.002)
Local	−0.018***	−0.016***
	(0.003)	(0.003)
Lower secondary education	−0.118***	−0.124***
	(0.002)	(0.002)
Upper secondary education	−0.185***	−0.191***
	(0.002)	(0.002)
Bachelor or more	−0.260***	−0.267***
	(0.002)	(0.002)
Two adults	−0.113***	−0.113***
	(0.002)	(0.002)
Households without children	−0.216***	−0.216***
	(0.002)	(0.002)
Household with one child	−0.177***	−0.176***
	(0.002)	(0.002)
Household with 2+ children	−0.180***	−0.180***
	(0.002)	(0.002)
All adult members earn	−0.009***	−0.010***
	(0.001)	(0.001)
Rental house	0.032***	0.030***
	(0.002)	(0.002)
Free accommodation	0.030***	0.030***
	(0.002)	(0.002)
Log(household equivalised income)	−0.011***	−0.012***
	(0.001)	(0.001)
Covid-19 period		−0.079***
		(0.001)
Interaction term		−0.015***
		(0.003)
Year fixed effects	Yes	No
Country fixed effects	Yes	Yes
Observations	800,278	800,278

Source: Elaborations by the authors on EU-SILC data.