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Why do we consume as we do? The case of ICT spending in the Spanish market

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Why do we consume as we do?

The case of ICT spending in the Spanish market.

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Abstract

This paper presents the research on the last fourteen years household spending patterns on information and communication technology (ICT) and the associated use of digital services due to socioeconomic variables. We found that over the 14 years covered by the research, there is a gender gap in ICT spending that extends beyond the pandemic COVID-10 to the present day, as well as an income gap. Women spend less on ICT than men, although according to the most recent data, this difference is no longer significant. Furthermore, the expected income gap should not be ignored, as fewer resources invested in telecommunications means less ability to move up the labour market, and this may be another way of damaging the social ladder.

Keywords: ICT, online literacy, consumers, survey data, econometric models, behavioral economics.

1. Introduction

Impacts on the international economy are often reflected in consumer behavior and decisions; household ICT spending is no exception (Rojko, Lesjak & Vehovar, 2011; Rojko, Lesjak & Erman, 2022). Examples of these impacts on the economy could be the 2008 Crisis and the recent Covid-19 pandemic, which according to the data (INE, 2022) also entail changes in the ICT consumption of Spanish households.

The pandemic has meant a paradigm shift in the relationship between individuals and ICT. People, confined to their homes, have had to learn to use them to carry out activities that they used to do outside their homes, and this has meant a change in their relationships with their environment (Yang et al., 2020). This adaptation, which included the stimulation of online commerce, education and even work relationships, was a fundamental shift in their investment (Erman, Rojko & Lesjak, 2022).

The adoption of ICTs in households and the adaptability of individuals to innovations depend on more factors than the general economic situation. ICT adoption is highly dependent on culture, wealth, state investment capacity, existing infrastructure, etc. (Azeez & Erumban, 2006; Lee et al, 2016).

However, it is important to analyse the role of ICT investment and adoption in economic and sustainable growth, as proposed by Haldar et al. (2023). Incorporating an important perspective, especially in the global north, which is behavioral economics and how external social and psychological factors affect our consumption (Tomer, 2017).

In addition to leisure, other factors such as online education and teleworking have had a major influence on ICT adoption in Spain (INE, 2022) and around the world (Yang et al, 2020). Education and how young and educated people adapt to the accelerated adoption of innovation are a key part of studying the rise in spending and individuals' relationship with telecommunications (Lythreatis, Singh & El-Kassar, 2021; Siddiquah & Salim, 2017). Re-emphasising the role of internet skills and innovation in education in this process (Scheerder, Van Deursen & Van Dijk, 2017; Van Laar et al, 2017) is crucial in the 21st century.

Even so, this does not imply that there are no digital divides in this process, the study of the digital divide and its fundamental reasons: gender, purchasing power, education, age,

etc. Therefore, the digital divide continues to be a target to combat at this time of greater shift towards digital. This is more clearly represented in the Sustainable Development Goals of the United Nations (UN), which considers innovation, education, and equality as fundamental to ensure sustained and sustainable economic growth in the long term (United Nations, 2015).

This is why, this paper studies in detail the impact of economic shocks on the evolution of ICT spending in the context of Spanish households. And extracts their relationship with the household profiles available to us to detect synergies or digital divides. The digital divide is the main reason for not being able to progress in society and its relationship with the inability to access ICT facilities (Perez-Amaral et al., 2021).

The exposed gaps motivated us to set the following research question: "What are the What is the influence of the pandemic COVID-19 on household spending to digitalize and what types of individuals are more likely to do so? Based on this, our research goal was to identify the impacts of ICT spending in relation to socioeconomic variables.

Thus, a first evaluation of ICT household spending using data on ICT expenditure and from the Spanish household survey. Furthermore, we present the use of digital services during the pandemic considering the individual relationship in an Online environment. The present paper also discusses the sociodemographic variables that can explain the ICT expenditure in a pandemic such as COVID-19 and analyze the impact on the most important measures of inequality: income and gender.

expenditure in ICT through the last fourteen years, building a study method and it is something that has hardly been done in this country.

The following chapter of the paper presents the main theoretical background on which we formulated research hypotheses. Then we outline the research design and describe the data and data analysis methods used in our study. Next, we present the study results and relate them to the stated hypothesis. The last section discusses the results, putting them in the context of related work, and concludes the paper by outlining limitations, future research directions, and practical implications of our research.

2. Theoretical Background

The COVID-19 pandemic has disrupted consumer activity and business operations of enterprises and had a strong impact on the digital transformation of enterprises and households (Guthrie et al., 2021). Due to the lockdown policy, also known as "stay-at-home orders," people have not been permitted to leave the house apart from getting daily exercise, going grocery shopping, and making "essential" trips. Thus, to do their shopping while avoiding possible COVID-19 infection, consumers started to purchase items online. As a result, the pandemic compelled customers to make the usage of the internet a habit in their daily routine.

Electronic commerce increased during COVID-19

The academic literature provides evidence about the important role of online retail in health-related and economic crises in the past (Li et al., 2020; Guthrie et al., 2021), specifically Guthrie et al., 2021 classified this impact into three groups with references: SARS outbreak (Forster and Tang, 2005), terrorist attacks (Predmore et al., 2007), and economic recession (Sarmento et al., 2019). Even though consumer behavior during the pandemic and post-COVID-19 has been analyzed and is under further analysis (Barnes, 2020; Guthrie et al., 2021; Park et al., 2022; Appolloni et al., 2023), there is evidence that electronic commerce (e-commerce) increased during COVID-19 (Levante, 2020; Halan, 2020) describes an increase not only in the number of customers shopping online but also in the number of first-time users for of e-commerce. Wang et al. (2022) enlarge the OECD, (2020a) categories of consumer behavior on which the pandemic has acted as a catalyst and found that there are six categories in response to the pandemic: health-related behaviors, abnormal buying behaviors, technology-related behaviors, information-related behaviors, leisure-related behaviors, and prosocial behaviors. Finally, Sheth (2020) distinguishes eight immediate consumer responses, such as hoarding behavior, embracing digital technologies, the discovery of new talent (for example cooking) and pent-up demand, and suggests that some of the shopping behaviors might turn into a habit (Pantano et al, 2020).

International organizations, industry reports, and consumer surveys have also shown an accelerated trend toward e-commerce during COVID-19 (Nielsen, 2020). A survey by UNCTAD (2020) found that the pandemic has resulted in sales growth of e-commerce

websites. The survey found that around 64 percent of third-party marketplaces have witnessed an increase in their sales during the period of March and July 2020. The Monitor Deloitte report (Pasamon, 2020) shows an e-commerce increase from 28% of the total sales on March 2nd to 59% on March 9th and 74% on March 29th.

ICT device infrastructure

The Lockdown announcement during the COVID-19 pandemic came as a shock to the people who were not prepared in terms of possession of required resources. The number of persons required to work from home for attending office work or attending the school/college/university classes would need in overall terms more ICT instruments and more internet data.

The analysis of IT facilities and ICT devices that homes required during the COVID-19 lockdown has received relatively little scholarly attention. On the other hand, multilateral organizations show that the required IT facilities for households during lockdown have been increased, following the OECD report (OECD,2020b) Telefónica, Spain, reports nearly 40% more bandwidth, with mobile traffic growth of 50% and 25% in voice and data, respectively. One critical element of the ICT infrastructure is Internet exchange points (IXPs), which are bulk traffic exchange crossroads where multiple networks connect (to exchange traffic). IXPs report record net increases of up to 60% in total bandwidth handled per country from December to March 2020.

The scholarly literature shows that the adoption of new ICTs (i.e. Internet of Things, Robotics & Drones, Augmented Reality/Virtual Reality, Artificial Intelligence, and 3D printing) are increasing rapidly against traditional technologies (i.e., Internet, hardware, software, and telecommunications networks) that remain important for the growth of economic indicators (Erman, et al. 2022). Aligned with the previous analysis (Rojko et al., 2022) found that ICT spending declined more severely during the pandemic crisis than in the previous economic downturn (2008 Financial Crisis) and that new ICTs showed more visible resilience to crisis impacts, also all of them changing shares of traditional and new ICTs.

Digital inequality

Information and communication technologies (ICTs) influence income distribution directly and indirectly. A diverse pattern of decreases and increases in income inequality has emerged in parallel with increasing fixed and mobile connectivity. ICTs rarely are a single cause but interact with other technological, economic, and political forces to shape the extent of income inequality (Bauer, 2018). The analysis also suggests that ICTs have consequences on income distribution that cannot be effectively addressed with policies designed to close digital divides.

Digital inequality applies to the least well-equipped households who have suffered higher reductions in Internet speeds for the increased network bandwidth usage at the global level which was accelerated during the pandemic. In addition, households with insufficient technological equipment for each member have suffered as well higher constraints in their potential to perform online activities at home. (Stantcheva, 2022). The digital divide has also hampered low-income households in other ways, such as via reduced possibilities for online learning (Ong, 2020), as well as fewer opportunities to maintain a social life online, and adverse consequences for mental health (Beaunoyer et al.,2020). The pandemic has widened the digital divide. Financially constrained households were most in need of investment in adequate and up-to-date equipment and network services. (Stantcheva, 2022).

Perez-Amaral et al. (2021) analyze the digital gaps in Spain for the period 2007-2019, with a panel of 97,859 individual consumers, identifying digital gaps that persist over time, such as those related to age, education, and income.

3. Empirical Analysis

3.1. Data

The data have been collected from a survey conducted by the National Statistics Institute (INE). Data from the Household Budget Survey (HBS) until 2020 (INE, 2020) and the Survey on the Equipment and Use of Information and Communication Technologies in Households until 2022 (INE, 2022) have been used for this analysis. These surveys are carried out annually and constitute a panel of data since 2006 and 2002 respectively.

The HBS collects information on the different expenditures of Spanish households on all types of products, divided by the ECOICOP system, which collects expenditures on food, transport, housing, etc. under different headings. This paper focuses on ICT expenditure. It collects general characteristics of the households interviewed, their socio-demographic variables: household members, income, marital status, employment status, sex, age, etc., as well as the amounts spent on ICT. Also, the amounts spent on products and the number of products purchased. For its part, the Survey on the Equipment and Use of Information and Communication Technologies in Households collects information on the ICT equipment of Spanish households with persons over 10 years of age, with special attention to those aged between 16 and 74.

Both surveys, which are carried out by INE, are representative of Spanish society, as well as having an appropriate distribution of individuals in terms of gender, age, place of residence, etc. It should be emphasized that in both surveys, although they are panel surveys, the same individuals are not retained throughout the survey, with individuals repeating only two t-periods in the HBS and four annual periods in the Telecommunications Survey.

The main statistics of the variables used in this study are shown in Table 1, which will help to understand the future model, the size of the variables, and the observations included.

VARIABLE		MEAN	STD. DEV.	MIN	MAX	OBS
TOTEX	OVERALL	31526.09	18983.7	0	357980.3	N = 243038
	BETWEEN		17620.56	1044244	268878.2	n = 121519
	WITHIN		7063839	-117719.6	180771.8	T = 2
ICTEX	OVERALL	262.1705	502.5743	0	20790	N = 243038

	BETWEEN		394881	0	10395	n = 121519
	WITHIN		310.8868	-10132.83	10657.17	T = 2
MALE	OVERALL	.7086834	.45437	0	1	N = 243038
	BETWEEN		.4416764	0	1	n = 121519
	WITHIN		.1066528	.2086834	1.208683	T = 2
AGE	OVERALL	54.88679	14.92756	17	85	N = 243038
	BETWEEN		14.82836	17.5	85	n = 121519
	WITHIN		1.718363	23.88679	85.88679	T = 2
AGE²	OVERALL	3235391	1694971	289	7225	N = 243038
	BETWEEN		1684196	306.5	7225	n = 121519
	WITHIN		190.8448	-112609	6583391	T = 2
INCO	OVERALL	5.752915	2.837604	1	10	N = 243038
	BETWEEN		2.708982	1	10	n = 121519
	WITHIN		.8446567	1.252915	10.25292	T = 2
SR	OVERALL	.1738905	.3790161	0	1	N = 243038
	BETWEEN		.3555873	0	1	n = 121519
	WITHIN		.1311921	-.3261095	.6738905	T = 2
DENS	OVERALL	2.156161	.8602824	1	3	N = 243038
	BETWEEN		.857574	1	3	n = 121519
	WITHIN		.0682325	1.156161	3.156161	T = 2
TAMU	OVERALL	3.239547	1.627658	1	5	N = 243038
	BETWEEN		1.62716	1	5	n = 121519
	WITHIN		.0403911	2.739547	3.739547	T = 2

Table 1. Main Statistics

The dependent variable of this study, "ICT expenditure", a continuous quantitative variable, expresses citizens' expenditure on telecommunications in continuous terms. It is explained, after a selection study of the independent variables, by the variables: gender, age, income, education, size of the municipality of residence, population density, and having a second residence.

Table 2 lists the abbreviations used to express the variables in some of the tables that will appear, and explains their composition and coding, finding binary, continuous, and multiple response, categorical variables.

Variable		Values
MALE	Male	Male = 1, otherwise = 0
AGE	Age	Age of all individuals

TOTEX	Total Expenditure	Logarithmic value of a continuous variable
ICTEX	Total Expenditure on ICT	Logarithmic value of a continuous variable
SR	Second Residence	Second Residence = 1, otherwise = 0
DENS	Density	Dispersed area = 1; Intermediate zone =2; Densely populated area = 3
TAMU	Municipalities	Municipality with less than 10,000 inhabitants = 1; Municipality with 10,000 or more and less than 20,000 inhabitants = 2; Municipality with 20,000 or more and less than 50,000 inhabitants = 3; Municipality with 50,000 or more and less than 100,000 inhabitants = 4; Municipality with 100,000 inhabitants or more = 5.
INCO	Income	Income deciles
FORM	Formation	Cannot read or write or attended school for less than 5 years.= 1; Have completed primary education = 2; Certificates of Primary, ESO, EGB = 3; Bachillerato, BUP, COU = 4; FPII and equivalents = 5, Degree of 240 ECTS = 6; Degree of more than 240 ECTS, Master's Degree = 7; University doctorate = 8.
INTD	Int Daily	Use Internet Everyday = 1, otherwise = 0
ECOM	E-Commerce	E-Commerce = 1, otherwise = 0
EGOV	E-Government	E-Government = 1, otherwise = 0
EHE	E-Health	E-Health = 1, otherwise = 0
EBANK	E-Banking	E-Bank = 1, otherwise = 0
ELE	E-Learn	E-Lear = 1, otherwise = 0
COM	Computer	Computer = 1, otherwise = 0

Table 2. Variables of Interest

Once the variables that are going to be relevant in the study have been defined, it is necessary to make a correlation matrix of the variables to be used, to observe their relationship with the dependent variable. The correlation matrix is shown in table

3.

	TOTEX	ICTEX	MALE	AGE	AGE²	INCO	SR	DENS	TAMU
TOTEX	1.0000								
ICTEX	0.2748	1.0000							
MALE	0.1371	0.0429	1.0000						
AGE	-0.1384	-0.1315	-0.0494	1.0000					
AGE²	-0.1648	-0.1409	-0.0619	0.9902	1.0000				
INCO	0.6072	0.2088	0.1775	-0.2150	-0.2403	1.0000			
SR	0.2894	0.0372	0.0512	0.1301	0.1153	0.1977	1.0000		
DENS	0.0883	0.0396	-0.0764	-0.0427	-0.0454	0.1290	0.0558	1.0000	
TAMU	0.0683	0.0398	-0.0760	-0.0331	-0.0355	0.0985	0.0651	0.8361	1.0000

Table 3. Correlation Matrix

The correlation matrix shows that for the dependent variable ICTEX, the age-related variables have a very strong inverse relationship, negatively influencing the propensity to spend, while the rest of the explanatory variables have a positive influence, highlighting the impact of the income variable. As can be seen in the table, there is no multicollinearity between the variables, except for the variable density and the size of the municipality, which are not used together, so we can guarantee the correct estimation of the model. The relationships between the variables and the final model are presented and examined in the results section of this paper.

3.2 Methodology

The first step in understanding what type of methodology to follow to carry out the data analysis is to understand the way the data is arranged, in this case panel data. Panel data models have two dimensions (Stock & Watson, 2011), the individuals and the time series, in this case annual. In order to ensure that all years of the survey can be used and to be able to see the development of individuals, it is necessary that individuals remain in the panel over time. If data are not available for all individuals over time, data are considered missing and the panel would be unbalanced (Baltagi & Baltagi, 2008).

This would be the case with this panel of data, but when we examine it, we are not working with an unbalanced panel, as one might assume because there are missing values, but instead the examination is carried out in only two periods. This means that with this panel of data we would not be studying individuals over 14 years, but over two periods,

and we would be able to use the Chow test (Hansen, 2021) to study whether structural changes have occurred in the panel and to analyse whether the relationships between variables change over time.

To start the study, we will create the explanatory variables that we will use to estimate the dependent variable, as well as the dependent variable. As we have a continuous dependent variable, we will start by transforming its results into logarithms to avoid extreme values, in this case, the variable will be treated with no logarithm transformation at the end, as this improves the estimates.

One of the first steps in the HBS is to remove the weighting factor from the continuous variables in the panel. Since the HBS aims to represent the total expenditure in Spain, the results are raised by different factors depending on how common the results are for that household, this factor hast to be removed to obtain realistic values (INE, 2020).

The proposed estimation, therefore, estimates a demand model based on the socio-demographic characteristics of individuals: their gender, age, income, education, and place of residence. This panel data is a short panel data, 2 periods, with a large number of observations 243038, which ensures that the sample does not pose a problem for estimation.

When using a panel data format, the best models that reflect this temporal character are the fixed effects model and the random effects model. It can always be treated as an aggregate data model using cross-sections, but its problem is that it does not consider the time factor in the estimation and loses all the interest that panel data brings (Wooldridge, 2010). The following subsections explain the estimation models used.

3.2.1. Aggregated Model

The model is represented in equation (1), the independent variables are represented by X_{ji}, the error term v_i, the constant value is β_0, and the regression coefficients β_j. In estimating the pooled model, it is assumed that individuals are heterogeneous among themselves, they are equal over time, and assuming this temporal equality does not take into account panel data (Wooldridge, 2010).

$$TEI_i = \beta_0 + \beta_j X_{ji} + v_i \quad (1)$$

Fixed-Effects Model

The assumptions of the Fixed Effects Model are:

- The covariance between individuals and the explanatory variables is different from 0.
- They are estimated with the Between estimators and the within-groups fixed effects estimator itself.
- Between estimators use the mean of a variable over time, are unbiased, but inefficient.
- The within-groups fixed effect estimator provides efficient estimates.

The model is represented as follows:

$$(y_j - \bar{y}_i) = (x_j - \bar{x}_i)\beta + e_j - \bar{e}_i \quad (2)$$

The fixed effects model eliminates unobserved heterogeneity, although it eliminates constant values over time, which can be a problem when working with binary variables. The model proposes a test to compare it with the aggregate model, this test has as its null hypothesis the homogeneity of individuals over time, thus allowing a choice between the two models (Wooldridge, 2010). The fixed effects model does not examine t-stable variables well, so if there are many t-stable variables in the model, random effects should be used.

Random effects model

The main assumption of this model is that there is no relationship between the unobserved heterogeneity of the sample and the explanatory variables, which provides an efficient estimator that considers the time effect (Wooldridge, 2010). However, if the unobserved heterogeneity is correlated with the explanatory variables, fixed effects would be more appropriate.

$$\left(y_j - \theta\bar{y}_i\right) = \mu(1-\theta) + \left(x_j - \theta\bar{x}_i\right)\beta + v_j(1-\theta) \quad (3)$$

After the random effects estimation, the Breusch and Pagan test (Breusch & Pagan, 1980) must be performed. This test distinguishes between the aggregate and random models with the same null hypothesis of homogeneity of individuals.

Once the superiority of the fixed and random effects models over the aggregate model is confirmed, the Hausman test (Hausman, 1978) is used to decide which of the two models to use. This test examines whether unobserved heterogeneity is correlated with the explanatory variables. The null hypothesis is that the estimators are equal, which would imply that the random effects model would be a better estimator, but if the estimators are different then it is the fixed effects that are consistent and not the random effects.

The results section develops this whole process of finding the best model that reflects the above, commenting only on the best-fitting model.

The main problems with this panel data have already been discussed, namely that it is not possible to analyse the evolution of individuals over the whole period analysed. In order to approximate this, and to study relevant periods of demand, such as the 2008 crisis and the Covid-19 pandemic, and how individuals responded to these moments of stress, further studies will be carried out.

- A graphical analysis of the evolution of ICT expenditure in relation to the evolution of total expenditure and in relation to socio-demographic variables, analysing the differences between individuals and whether the expenditure we invest in ICT is now a larger part of total expenditure. This analysis will be carried out annually and monthly.

- Once the analysis is complete, we will study the implementation of some activities in the Covid-19 pandemic that are carried out online, to study their implementation and their ability to build user loyalty. This will be complemented by a study of ICT expenditure in the periods available closest to the pandemic, to find out the characteristics of individuals that most influence recent and annual expenditure.

4. Results and discussion

By applying the procedures established in the methodology to the HBS, a model capable of adequately estimating the propensity of Spanish individuals to spend on ICT has been developed. During this process, various ways of estimating the regression model were rejected, opting for the fixed effects model as opposed to the random effects model and the aggregate model.

When the null hypotheses of the Breusch and Pagan (1980) test and the test offered by the fixed effects model were rejected, the aggregate model was discarded because individuals were found to be heterogeneous over time and therefore the time factor had to be considered. The Hausman test (Hausman, 1978), with a p-value equal to 0, indicates that the fixed effects model should be used because it is consistent and the unobserved heterogeneity is related to the explanatory variables. These models and the contrasts would be presented below in Table 4.

	ICT Expenditure		
	Aggregate Model	**Fix-Effects**	**Random-Effects**
MALE	11.96*** (2.237)	21.215** (8.398)	13.040*** (2.408)
AGE	-2.474*** (.072)	-.403 (5.542)	-2.470*** (.079)
FORM	23.497*** (1.605)	-.044 (5.542)	24.139*** (1.149)
INCO	29.608*** (.401)	11.886*** (1.058)	28.754 (.426)
Constant	159.677*** (5.951)	200.99*** (36.05)	161.985*** (6.458)
n	243038	243038	243038
Groups	-	121519	121519
R^2-Within	.0534	.001	.001
R^2-Between	-	.076	.087
R^2-Within	-	.046	.053
Prob > F	0.000	.000	.000
Hausman	-	.000	.000
Chow	-	.000	-

Table 4. Panel Data Model

As can be seen, some of the proposed explanatory variables were dropped. The spatial variables, municipality size and population density would not be significant in the panel data model.

It is worth noting that we have a model that includes 243038 observations, corresponding to 121519 individuals in 2 different periods. This model shows that the most important significant variables for estimating ICT expenditure are gender, where there is a gender gap which implies that men have a greater propensity to invest in technology than women, and income, which implies that household income also influences the expenditure that can be made on ICT, since it is logical that richer individuals can devote a greater part of their income to this type of expenditure, as they will cover other essential expenses earlier.

It is noticeable that the age and education variables are not significant in the fixed effects model but are significant in the aggregate and random effects model.

To investigate whether there is a structural change in ICT expenditure between the two periods, the Chow test is performed, which rejects the null hypothesis that the expenditure of individuals is the same between the two periods. It is important to note that this test is also performed on smaller parts of the panel, both in the 2008 crisis, in the Covid-19 crisis and in the change in the ICT measure suffered by this panel in 2016. Thus, there are differences in the spending propensities of individuals over time.

This study of expenditure can be complemented with other descriptive analytical tools that allow us to reflect the evolution of expenditure over time and, given the importance of income in estimating ICT expenditure, to examine whether there has been a greater propensity to spend over time, i.e., whether ICT expenditure has taken on a greater weight in total household expenditure.

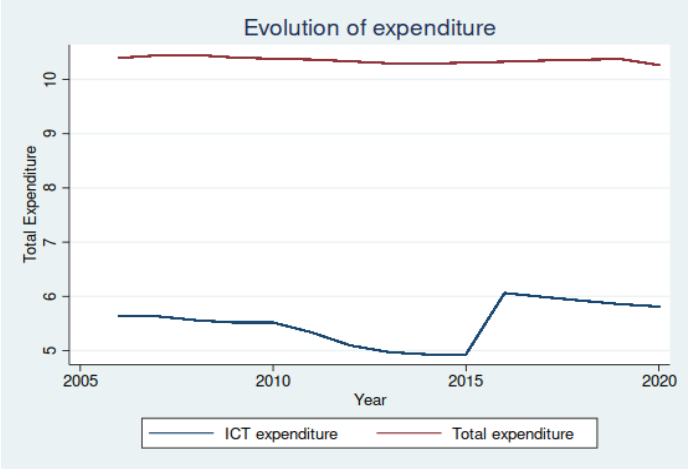

Figure 1. Evolution of ICT expenditure as a proportion of total expenditure.

Figure 1 shows the weight of ICT expenditure relative to total household expenditure from 2006 to 2020. This graph shows that the weight of ICT expenditure does not change much from 2006 to 2020, nor does total household expenditure differ significantly. It is not observed, at least at the annual level, that the 2008 crisis or Covid-19 represent an exceptional change in the telecommunications expenditure of Spanish households.

It is observed that there is a significant change from 2015 to 2016, with four times less invested in ICT in 2015 than in 2016. This change is due to a change in the survey's own measurements, optimising the way in which expenditure is estimated, as well as the items that make up this ICT expenditure, as this expenditure was under-represented in the previous items.

This change, considering how expenditure stabilizes over the next five years by reverting to previous expenditure measures, seems appropriate. However, it does not represent a change in the behaviour of households but simply indicates that new products are appearing in the calculation of ICT expenditure.

Given that there is no relevant change in the role of ICT expenditure in total expenditure, it would be worth looking at whether there are different patterns of IT consumption within individuals. For this purpose, ICT expenditure is plotted according to education level, income, age and gender. Figure 2 shows expenditure by gender. Only this graph will be

analysed here, as the other graphs show only a positive relationship between education or income and ICT expenditure, which is consistent with the values of the coefficients of the regressions shown above.

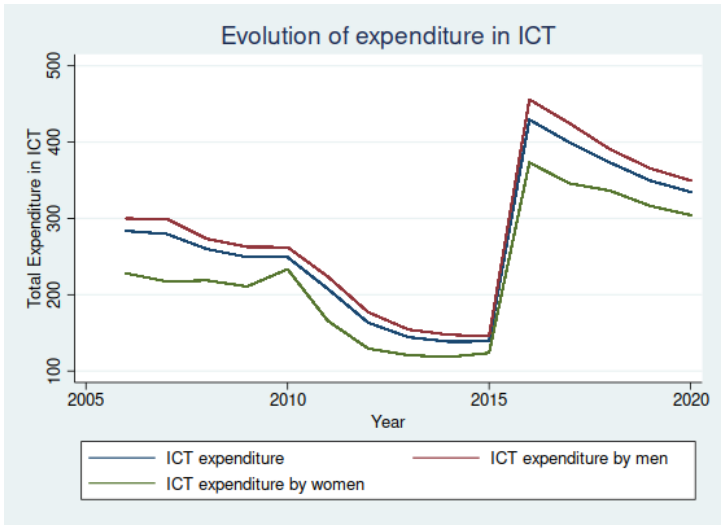

Figure 2. ICT expenditure by gender.

As can be seen, the gender gap shown in the model is confirmed, with men spending more on ICT than women. This gap has a moment of narrowing after the 2008 crisis, but returns to previous values shortly after, but the difference in spending between men and women seems to have narrowed since 2006.

It should be noted that in annual terms the impact of the crises is not reflected either in total expenditure or in ICT expenditure. It seems worthwhile to look more closely at both periods to see if we can find greater differences, both in the share of ICT expenditure in total expenditure and in the study with a gender perspective.

Trends in ICT expenditure during the 2008 economic crisis

Figure 3 shows the previous studies, ICT expenditure as a share of total expenditure and ICT expenditure by men and women separately.

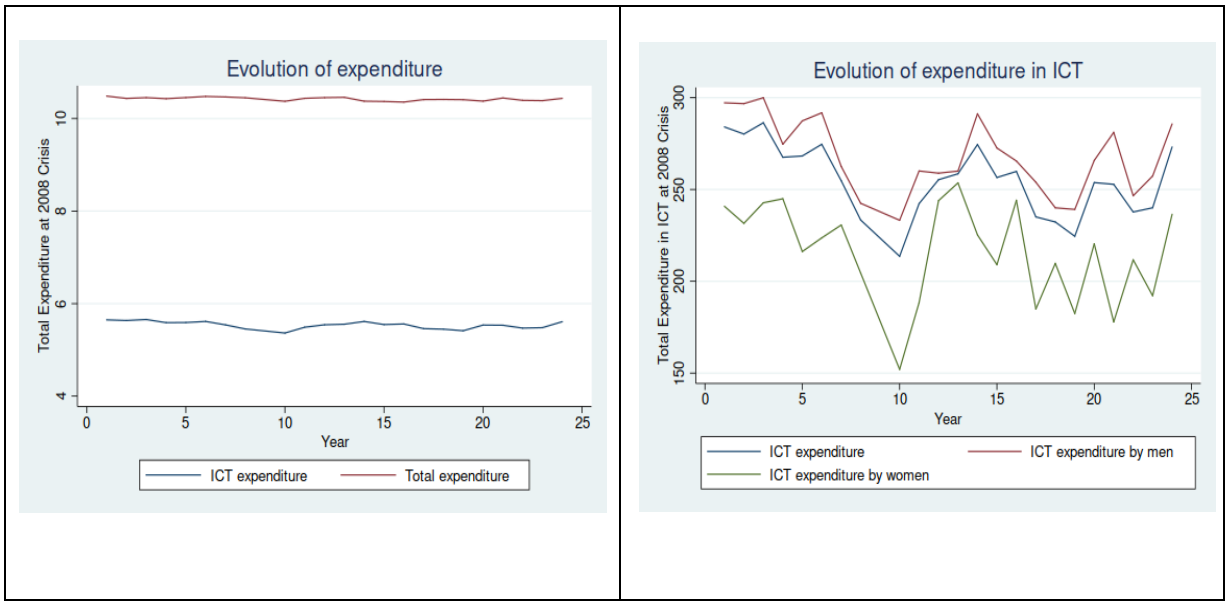

Figure 3. ICT expenditure during 2008 Crisis.

Looking at both figures, in October 2008, the month in which the financial crisis began, ICT expenditure fell as a share of total household expenditure. It is also important to note that in the first few months of the crisis, there was virtually no monthly variation in total expenditure.

On the other hand, the picture that looks only at ICT expenditure shows more interesting values. In October there is a sharp drop in ICT expenditure, much more pronounced for women than for men, and women are much more sensitive to ICT expenditure. Much steeper increases are followed by steeper decreases in a short period of time. Men, however, suffer from the crisis in a much milder way, but with a much more constant and continuous decline in spending. The aforementioned gender gap remains and it appears that men are much more consistent in their investment in technology.

Evolution of ICT expenditure during the Covid-19 crisis.

Having analysed 2008, it is necessary to observe whether these trends are observed 12 years later during the coronavirus crisis.

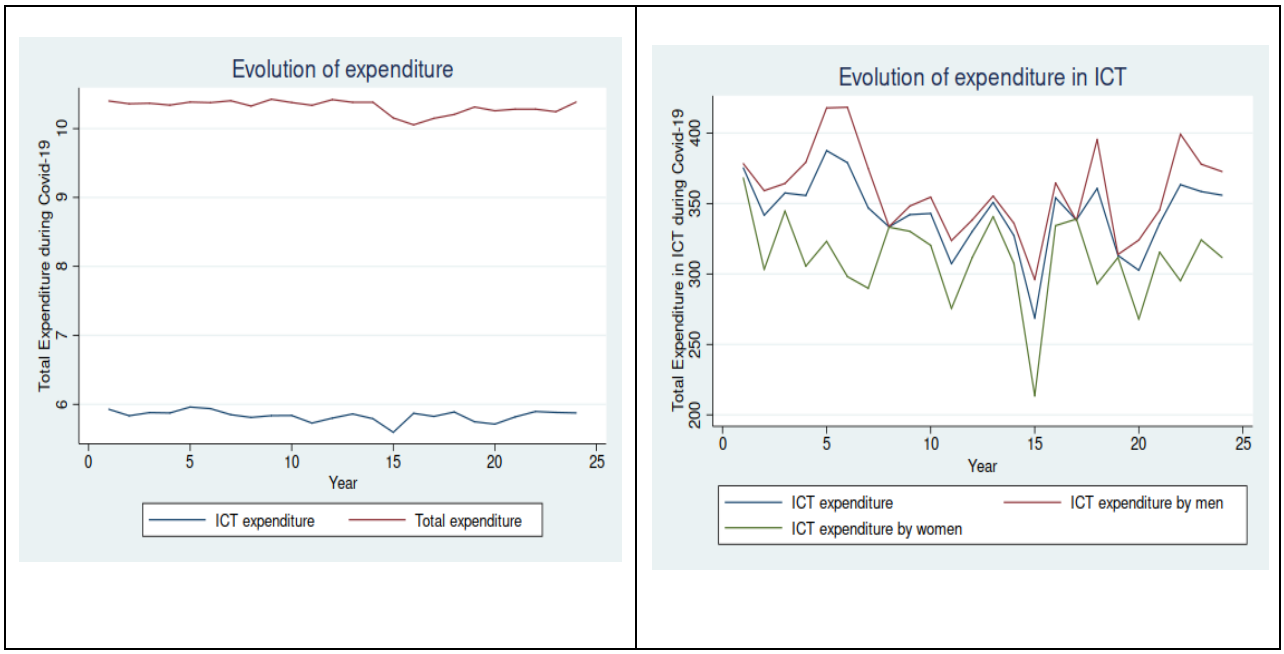

Figure 5. ICT expenditure during the Pandemic

At first glance it does not seem so, but the first graph in Figure 4, which compares ICT expenditure with total expenditure, shows that this crisis is reflected in these absolute values. In March 2020, there is a clear decline in both types of expenditure. A reduction that is more sustained over time for total expenditure than for ICT expenditure, which takes the whole year to return to pre-March levels.

As far as the gender gap is concerned, it is maintained until 2020, but 12 years later the gap is smaller, there are moments when men's and women's expenditure converge and women's ICT expenditure is more stable, with the abrupt changes in trend observed in 2008 coming to an end. However, as in 2008, the decline around the time of the crisis is much more pronounced for women.

These values observed during the pandemic are far from the discourses of increased adoption of digital skills or increased digitisation. These are common discourses when talking about the pandemic. Therefore, to close the block of results, as mentioned in the methodology, we will analyse the pattern of ICT spending from 2017 to 2020 with cross-sectional data, in Table 5, as well as the evolution of the adoption of some online services from 2019 to 2022, to study the impact of the pandemic not on spending but on the use of ICTs.

	ICT Expenditure			
	2017	**2018**	**2019**	**2020**
MALE	23.502** (9.575)	5.078 (8.988)	8.400 (9.227)	7.708 (13.130)
AGE	-6.462*** (.316)	-6.197*** (.297)	-5.441*** (.309)	-4.808*** (.445)
FORM	1.496 (3.092)	1.334 (2.913)	5.108* (2.971)	15.998*** (4.197)
INCO	40.702*** (1.759)	37.140*** (1.673)	32.722*** (1,721)	32.307*** (2.454)
DENS	-24.502*** (5.217)	-18.359*** (4.930)	-20.484*** (5.111)	-8.821 (7.226)
Constant	561.804*** (27.25)	542.198*** (25.662)	487.526*** (26.573)	374.382*** (38.217)
n	18216	17149	15862	7555
R-square	.074	.0760	.063	.066
F	.000	.000	.000	.000

Table 5. Cross Section Modelling of ICT Expenditure 2017 - 2020.

According to the cross-sectional models, the joint significance of the models and the R^2 are adequate, so they would be good models for estimating ICT expenditure for all the proposed years.

The variables that are significant in all years are age and income. Age has a negative effect on ICT expenditure, suggesting that there is a gap that keeps older people away from telecommunications investment, while the relationship between income and expenditure holds: the more money you have, the more you are willing to spend.

What is curious about these models, however, are the variables that become or cease to be significant as the time series progresses. Individuals' education becomes important for telecommunications expenditure as soon as the pandemic starts. This may be due to the need to invest in order to be able to work from home, or to continue their education after the end of face-to-face courses.

On the other hand, place of residence and gender are no longer significant, indicating a narrowing of the gender gap. However, the interpretation of the location variable is more complicated as it has a negative coefficient. According to the estimation, the less populated the municipality, the more individuals spend on ICT, but this no longer seems

to be the case, which would indicate that spending has increased in more densely populated areas or that it has decreased in cities.

To conclude this study, it is necessary to look not at expenditure but at ICT usage. This is reflected in Table 6. The first thing to notice in Table 6 is that Internet or computer use has not changed at all with the pandemic, but habits have changed.

Firstly, the number of users of all services has increased since 2020, implying a narrowing of the digital divide and the creation of new markets. However, it should be noted that not all have grown equally.

		2019	2020	2021	2022
COMPUTER	0	27.95	32.80	29.53	29.67
	1	72.05	67.20	70.47	70.33
INTERNET DAILY	0	4.36	3.60	4.67	5.00
	1	95.64	96.4	95.33	95.00
e-COMMERCE	0	36.82	35.42	30.07	31.8
	1	63.18	64.58	69.93	68.2
e-LEARN	0	63.18	58.20	73.82	58.05
	1	36.82	41.80	26.18	41.95
e-HEALTH	0	35.42	23.88	48.92	21.87
	1	64.58	76.12	51.08	78.03
e-GOVERNMENT	0	38.54	36.87	32.11	44.96
	1	61.46	63.13	67.89	55.04
e-BANK	0	41.36	36.35	32.23	29.17
	1	58.61	63.65	67.77	70.83

Table 6. Evolution in the use of online services during Covid-19.

The market that has benefited the most is online banking, with 15% more of the Spanish population adopting and maintaining e-banking since 2019, reflecting an upward trend year-on-year, as well as the maintenance of new users. The other major beneficiary is e-health, with online health services now used by 80% of the population.

E-commerce and e-learning services have reached 5% more of the Spanish population, as has e-government, which has seen a sharp drop in users over the past year. This means that, in general, although the Covid-19 crisis seems to have meant a reduction in ICT spending in 2020, it has also meant an intensification in the use of ICT, and that digital

inequality must be explained not only in terms of spending, but also in terms of usage and equipment.

5. Conclusions

Based on the demand for online devices and services, this paper aims to explore digital inequality. In order to achieve a broad and diverse study, it takes into account the different gaps in access to and use of technologies and draws on multiple perspectives.

Access to ICTs ensures the proper development of individuals in society, giving them access to better jobs and education, and is ultimately a driver of social mobility. Therefore, although it may seem redundant, it is important to understand that individuals with higher incomes will invest part of their income in ICT-related products. This inequality in access to ICT has been demonstrated and reflected in our research throughout the 14 years of this study and continues to be reflected in the last 4 years of the cross-sectional study. Income support is, therefore, necessary to ensure that individuals have access to telecommunications products and services.

However, our work shows that it is not only a question of addressing this type of digital divide, but an access divide also resulting from the inability to access products. In the panel data analysis, we find another divide that affects all cohorts in our database. The gender gap increases from the fourteenth year of analysis and continues to the present day. Although it narrowed considerably after the pandemic, this may be due to the need to adapt to a fully digitalised society during the quarantine period and the rise of teleworking. It is important to raise awareness and adopt public policies that help to close the gender gap in ICT spending and help women, especially those with few resources, to access better working conditions and thus motivate an improvement in the labour market.

This is essential because of the importance of expenditure on ICT for digital literacy, having into account that education is increasing its importance at the time of estimate digital inequality. This seems to represent a gentrification of spending, and companies and the public sector need to encourage widespread access to higher-quality products that allow us to take advantage of the benefits of the digital market. This education gap, the usage gap, is shown in the modelling of the most recent cohorts, but it is not transversal to the whole panel.

Therefore, the public sector and companies, some because of their social work and others because of the need to implement their corporate social responsibility proposal, must get

involved in improving or implementing digital literacy in society and among their employees, with a particular focus on vulnerable groups.

Taking all this into account, we must also be aware of another conclusion: in order to analyse digital inequality, it is not enough to study it from the point of view of expenditure, but it is also essential to study it from the point of view of use and of owned equipment.

At the moment, it is not enough to consider only the products purchased as expenditure, expenditure can be reflected in different ways, expenditure on online services, expenditure on online services, expenditure on online services, expenditure on online services, all of which are also online expenditures and are not considered in this study.

This is another of the conclusions of our analysis: while ICT expenditure is stagnating or falling, the use of online services is growing exponentially year after year, which is a contradiction and implies the need to update the ways of measuring telecommunications expenditure.

It is also essential to analyse households' ICT equipment; not all households spend the same amount each year, so it is necessary to understand the resources currently available to households in order to understand whether that household suffers from digital inequality. This is one of the current limitations of this study.

These data provide us with following future lines of research:

- Although this is one of the first studies of its kind in Spain, it opens the way for more in-depth analyses in this area. One of the most interesting areas to explore is the gender gap in digital inequality and its relationship with women's lower propensity to spend on ICT. Such a study could become a reference for public policy analysis.

- To reflect digital inequality and its relationship with individual spending, it is necessary to consider spending on online content and services. These services offer improvements in the lives of individuals, and not including them means a loss of expenditure to be taken into account and a delay in the analysis. Especially at a time when, as our study shows, the use of these services is growing rapidly.

- Another point to be studied in the future, and an interesting conclusion from the analysis of recent years, is that individuals invest more in rural areas than in urban areas. This may be because they need equipment that is not needed in urban areas due to the immediacy of the availability of things. But this urban-rural comparison would be of particular interest specially to reflect the needs of individuals who need connectivity. Knowing their needs will help to support public and private policies to repopulate rural areas.

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