electronic ***International Journal of Time Use Research***
2014, Vol. 11, No. 1, 13-42 *dx.doi.org/10.13085/eIJTUR.11.1.13-42*

Has the digital divide been reversed? – Evidence from five EU countries

Smaranda Pantea and Bertin Martens

Smaranda Pantea (for correspondence)
Information Society Unit
Institute for Prospective Technological Studies (IPTS)
European Commission
Edificio Expo, C/Inca Garcilaso, 3
41092 Seville, Spain
e-mail: Smaranda.Pantea@ec.europa.eu

Bertin Martens
Information Society Unit
Institute for Prospective Technological Studies (IPTS)
European Commission
Edificio Expo, C/Inca Garcilaso, 3
41092 Seville, Spain
e-mail: Bertin.Martens@ec.europa.eu

Abstract

This paper examines whether there is a digital divide in the use of the internet in general and of specific websites (leisure, improving human capital and obtaining goods and services). It uses a unique dataset which covers the entire clickstream of almost 20,000 internet users in the five largest EU economies during 2011. Our main finding is that, for those who have access to the Internet, the income-based digital divide in internet use at home has been reversed. Low-income internet users spend more time on the internet at home than high-income users on all types of websites. There is some evidence of an education-based digital divide in the use of human capital and goods & services websites. Tertiary education has a negative effect on time spent on leisure websites and a positive effect on time spent on human capital and goods & services websites. Using quantile regressions, we find that the negative effect of income and the positive effect of education for human capital and goods & services websites hold for the entire conditional distribution of these online activities. Moreover, these effects are stronger for more intensive internet users. We discuss several possible explanations for these results.

JEL-Codes: L86, D12, D13

Keywords: Internet use, time allocation, leisure

The IPTS is one of the Joint Research Centers (JRC) of the European Commission. The views and opinions expressed in this paper are the authors' and do not necessarily reflect those of the JRC or the European Commission. Previous versions of this paper where presented at Applied Economics Meeting 2013, ZEW Conference on the Economics of Information and Communication Technologies 2013, NBER Summer Workshop on Economics of IT and Digitization, EARIE 2013, Jornadas de Economia Industrial 2013. The authors are grateful to discussants and participants in these conferences for helpful comments. They also thank Marc Bogdanowicz, Russell Cooper, Pierre Montaigner and Bernarda Zamora for detailed comments and suggestions. Errors and omissions remain the responsibility of the authors.

1 Introduction

There is considerable policy concern about the digital divide between people with different socio-economic characteristics, especially different income and education levels. The digital divide in access to internet has been extensively documented. However, less is known about the digital divide in internet use for people who have access to the internet, especially in Europe, and where it exists it is based mainly on survey data (Demoussis and Giannakopolous, 2006; Orviska and Hudson, 2009; Montagnier and Wirthmann, 2011).

This paper contributes to this area by studying the digital divide in internet use in the five largest countries in the EU. More precisely, it studies how, for those who have access to the Internet, income and education affect internet use at home in general and the use of specific websites (leisure, improving human capital and obtaining goods and services). It uses a unique dataset that covers the entire clickstream on the home computers of almost 20,000 internet users in the five largest EU economies during the year 2011. It builds on Goldfarb and Prince (2008) who study the role of income and education levels in internet use patterns in the US. We extend this study in several ways. First, we study the determinants of time spent online in the five largest EU economies using data on internet users' online behaviour (their entire clickstream), which is more objective and precise than survey data. Second, we study the determinants of time spent on three specific types of websites: (a) human capital improvement, such as career, education and health-related sites, (b) obtaining goods and services and (c) leisure. Third, we study whether the effects of income and education differ with intensity of internet use and employment status.

The main finding is that, for those who have access to internet, the income-based digital divide in internet use has been reversed: low income internet users spend more time online at home than high income internet users on all types of websites considered. However, we find evidence that there may be an education-related digital divide for specific internet uses such as websites related to human capital and to obtaining goods and services. Our robustness tests show that these results hold true for a variety of demographic subgroups: internet users in each of the five countries, internet users in one person households and internet users with different intensity of internet use. However, we find that the magnitudes of the effects differ by the intensity of use: the effect of income on time spent online is stronger for more intensive than for less intensive users, and the effect of education on time spent on human capital on human capital and goods and services websites is stronger for more intensive users than for less intensive users of these websites. We also find that access to internet outside home and employment status and occupation do not affect the effect of income on internet use. These results are surprising in the view of opportunity cost of time hypothesis.

The paper is organised as it follows. Section 2 reviews the related literature. Section 3 describes the data used and presents some preliminary evidence on the relationship between time spent online and income and other demographic characteristics. Section 4 describes the empirical methodology. Section 5 discusses the results of the estimation and Section 6 offers conclusions.

2 Related literature

Our study is mostly related to studies that examine internet use measured as time spent online and its welfare effects (Goolsbee and Klenow, 2006; Goldfarb and Prince, 2008; Brynjolfsson and Oh, 2012). In these studies, in line with Becker (1965), consumer utility depends on his consumption, which requires income obtained partly through labour, and on his leisure. Individuals choose the time spent on online leisure, offline leisure and work in order to maximise their utility subject to budget and time constraints (the sum of the amounts of time spent daily on each of these activities cannot be higher than 24 hours). Internet pricing consists of fixed cost of subscription and zero use fees. Then, conditional on internet adoption, the marginal cost of internet use is given only by the opportunity cost of time, which is determined by the income that the internet user could earn on the labour market. Therefore, the opportunity cost of spending time online is higher for high income earners than for low income ones. If both low and high income users benefit equally from internet, than given the higher opportunity costs for high income users, they will spend less time on internet.

Goolsbee and Klenow (2006), Goldfarb and Prince (2008) and Brynjolfsson and Oh (2012) test empirically this hypothesis on a sample of US internet users. All these studies find that, conditional on internet access, income has a negative effect on time spent online. Most of these studies suggest that higher opportunity costs of spending time online of the high income internet users explain this negative relationship. However, Goldfarb and Prince (2008) notices that there are several alternative explanations which are consistent with this negative relationship: (1) the opportunity cost hypothesis explained above (2) internet is more useful to low-income people, because they have different preferences or because they do not have better offline alternatives (3) low income earners have more leisure time, which leads them to spend more time online even if they have the same opportunity costs as high income people (4) cost of adoption of internet is an important cost barrier for low income individuals, but not for higher income and therefore only low income earners which place a higher value on internet will adopt internet, but most of high income people will adopt internet (including those who do not place a high value on it). It is important to mention these explanations do not exclude each other. The authors find that the selection and the amount of leisure time are not driving their results, but they find some evidence of differences in usefulness of internet for different income groups.

We explore more in detail the opportunity cost hypothesis and the differences in usefulness of internet for different income groups[1].

There are several studies that examine the use of the internet for specific purposes such as: e-commerce, job search, entertainment etc. (Demoussis and Giannakopolous, 2006; Goldfarb and Prince, 2008; Orviska and Hudson, 2009; Montagnier and Wirthmann, 2011; Pérez-Hernández and Sánchez-Mangas, 2011). Due to differences in data sources and in the dependent and explanatory variables they are not directly comparable. However, they show some common patterns. The most relevant for our study is that income, education, and other demographic characteristics have different effects on participation in different online activities. Goldfarb and Prince (2008) find that for US internet users, income and university/college education is negatively associated with using internet for activities related to leisure (chat, online games) and e-health, but positively associated with using it for activities related to buying (research purchases and ecommerce). Pérez-Hernández and Sánchez-Mangas (2011) found similar effects of education on online shopping for Spain. Demoussis and Giannakopoulos (2006) and Montagnier and Wirthmann (2011) find that education and household income are important determinants of the frequency of internet use in Europe. Although we draw on these studies, we differ from them in that our study does not examine the determinants of using internet for a specific purpose or with a certain frequency, but of the time spent on different online activities.

In conclusion, there is a very heterogeneous empirical literature related to the internet use, including a few studies on the relationship between income and/or education and internet use. However, most of these empirical studies are based on US survey data and most of them do not take into account several aspects of this relationship documented in other strands of literature (different types of online activities, intensity of use, and differences across different demographic groups). In this paper, we study different aspects of the effect of income and education on internet use using objective clickstream data from five largest EU countries.

3 Data description

The data used in this paper have been collected by Nielsen NetRatings through voluntary online consumer panels. The dataset contains information on all web pages clicked on from their home computers by 25,000 internet users in the five largest EU economies (France, Germany, Italy, Spain and United Kingdom) during the entire year 2011.

The data only covers internet use at home. However, it is important to notice that internet access took place largely at home in 2011 (OECD, 2012). Therefore, while our results are not

[1] We cannot explore the selection hypothesis (4) and (3) because our sample consists entirely of active internet users the dataset and it does not contain information on total leisure time of internet users. However, we control for total leisure through proxy variables such as users' occupation, household size, marital status and presence of children.

informative about internet use from all places of access, they are informative about the most important way of accessing it.

The data covers only individuals who are active internet users. Acording to Nielsen, the sample of internet users is representative of the online population in these countries in terms of gender and age[2].

For each click it contains information on the URL, the time and date the website is accessed and time spent on the website. The data on the online activity is collected through a piece of software that internet users in the online panel voluntarily install on their PC. The data collection procedure uses information in the computer about which webpage is in focus (the page to which the keyboard and mouse activity is directed to). This helps correct for errors in measurement of the time spent on websites due to minimizing tabs, tabbed browsing and periods of inactivity. The websites visited are classified into subcategories and categories based on the content of the websites using a methodology developed by Nielsen. The dataset also contains information on basic social and economic characteristics of each user[3] (age, gender, marital/cohabitating status, presence of children in the household, size of household, household income range, highest educational level attained, and occupation) gathered through a questionnaire when the user installs the Nielsen software.

The sample used in the empirical analysis excludes records with missing information on the website category and on the demographic characteristics of the internet user, records of internet users younger than 16 or older than 74[4] and of self-employed internet users[5] and outliers[6]. The sample remaining after excluding these observations is still large covering close to 18680 users, which represent close to 80% of the initial user sample and more than 700 million clicks in each country, which represent more than 70% of the initial clickstream sample.

The dataset classifies each website in 15 categories and 85 subcategories. We group these categories and subcategories based on how each activity contributes to consumer utility, in line with Becker (1965) and Gronau (1977): leisure (contributes directly to the utility), human capital websites, such as career, health and education (contributes to the utility through future in-

---

[2] Nielsen provides incentives to participate and to remain in the panel in the form of vouchers and points which can be redeemed from their reward website or used in online games and sweepstakes(prize drawing), which might bias our sample towards people who are more likely to value these activities. As a robustness check we repeated the estimations excluding time spent on online games and gambling websites to make sure that our results are not driven by time spent on these websites. These estimations are not reported here.

[3] There are households where more than one user is registered with Nielsen. In these households the meter prompts the internet user to log in; however the match between user profile and his online activity is likely to be imperfect. To ensure that our results are not affected by this problem, we estimated our model also on the sample of one person households and the results were similar to those for the whole sample.

[4] We will focus on this age group to ensure comparability with Eurostat for Information Society Indicators and previous empirical studies.

[5] We do not know how much of their time online is work and how much is leisure. The main results are not affected by this exclusion.

[6] We exclude internet users who spend an implausible large or small amount of time online (internet users in the highest and the lowest 1% of average weekly time spent online). The main results are not affected by this exclusion.

come which can be spent of future consumption) and goods & services websites (contributes to the utility as an input in the production of the final goods/services consumed). Leisure activities include websites classified by Nielsen as Entertainment, Family and Lifestyle (except subcategory Health, Nutrition and Fitness), News & Information, Member Communities and Targeted Member Communities from Portals & Communities Internet Services. Human capital websites include websites classified by Nielsen as related to Education& Careers, Corporate[7], Health, Nutrition and Safety. Goods & services websites included websites related to obtaining goods and services, such as, Home & Fashion, Ecommerce, Travel, Government & Non-profit, Finance, Search Engines, General Portals & Search (subcategories General Portals and Search from Search Engines, Portals & Communities category), Special Occasions, Automotive, Computers & Electronics.

Table 1 presents summary statistics on the main variables used in this study for the sample used in the empirical analysis. The table shows that the average person spends 5 hours per week online: close to 3 hours and half on leisure websites, more than one hour on goods & services websites and around 8 minutes per week on websites related to work, education and health. The most popular leisure websites are, in order, social networks, online games, videos/movies and adult websites, the most popular goods & services websites are general portals and search and e-commerce websites and the most popular human capital websites are career websites.

Table 1
Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Time on all websites (minutes/week)	306.02	320.30	1.78	1973.38
Time on leisure websites (minutes/week)	214.05	270.18	0.02	1838.78
Time on human capital websites (minutes/week)	8.79	18.53	0	556.86
Time on goods & services websites ((minutes/week)	83.18	93.62	0.04	1479.06
Clicks on all websites (per week)	697.15	889.64	1.37	11161.60
Clicks on leisure websites (per week)	482.83	758.66	0.08	11028.79
Clicks on human capital websites (per week)	20.01	51.60	0	2630.19
Clicks on goods & services websites (per week)	194.31	242.47	0.17	3562.83
Female	0.51	0.50	0	1
Single	0.25	0.43	0	1
Age (years)	41.68	13.57	16	74
Children in the household	0.31	0.46	0	1
Household size 1-2	0.52	0.50	0	1
Household size 3-4	0.41	0.49	0	1
Household size >5	0.08	0.27	0	1

[7] We assume that people searched this category mainly for finding information about job vacancies. However, classifying it as a residual category or as goods & services website does not change the results.

Table 1 (Cont.)

Variable	Mean	Std. Dev.	Min	Max
Income ≤18000	0.21	0.41	0	1
Income 18-27000	0.23	0.42	0	1
Income 27-36001	0.17	0.38	0	1
Income 36-54000	0.22	0.42	0	1
Income 54-72000	0.10	0.30	0	1
Income >72000	0.06	0.23	0	1
Below secondary education	0.26	0.44	0	1
Secondary education	0.26	0.44	0	1
Tertiary education	0.48	0.50	0	1
Employed	0.66	0.47	0	1
Clerical/administrative	0.17	0.37	0	1
Craftsman/craftswoman	0.01	0.11	0	1
Education	0.04	0.20	0	1
Executive/managerial	0.09	0.29	0	1
Military	0.01	0.09	0	1
Operator/labourer	0.07	0.25	0	1
Other	0.06	0.24	0	1
Professional	0.04	0.20	0	1
Sales	0.04	0.19	0	1
Service	0.07	0.25	0	1
Technical	0.06	0.24	0	1
Unemployed	0.09	0.29	0	1
Student	0.09	0.29	0	1
Retired	0.10	0.29	0	1
Homemaker/carer	0.07	0.25	0	1

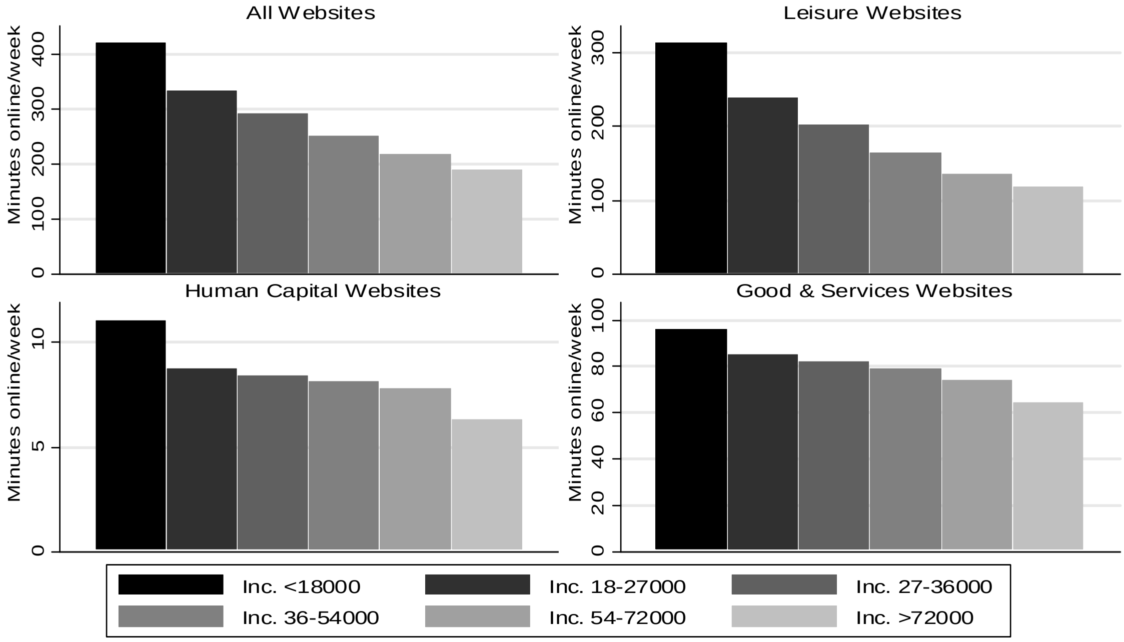
Source: Nielsen Clickstream data 2011, own calculations.

The summary statistics of the demographic characteristics of the internet users also presented in Table 1 show that the sample used in the empirical analysis includes a large variety of internet users in terms of education, occupation, income and other demographic characteristics.

In Figure 1, we present some patterns that show how time spent online at home is linked to income. It shows that total time spent online and time spent on the specific online activities considered decreases with income. This relationship is strongest for all time spent online and for time spent on leisure websites, for the other two types of websites it is weaker. These patterns are consistent with the hypothesis that high income users have a higher opportunity cost of time and therefore spend less time on these online activities.

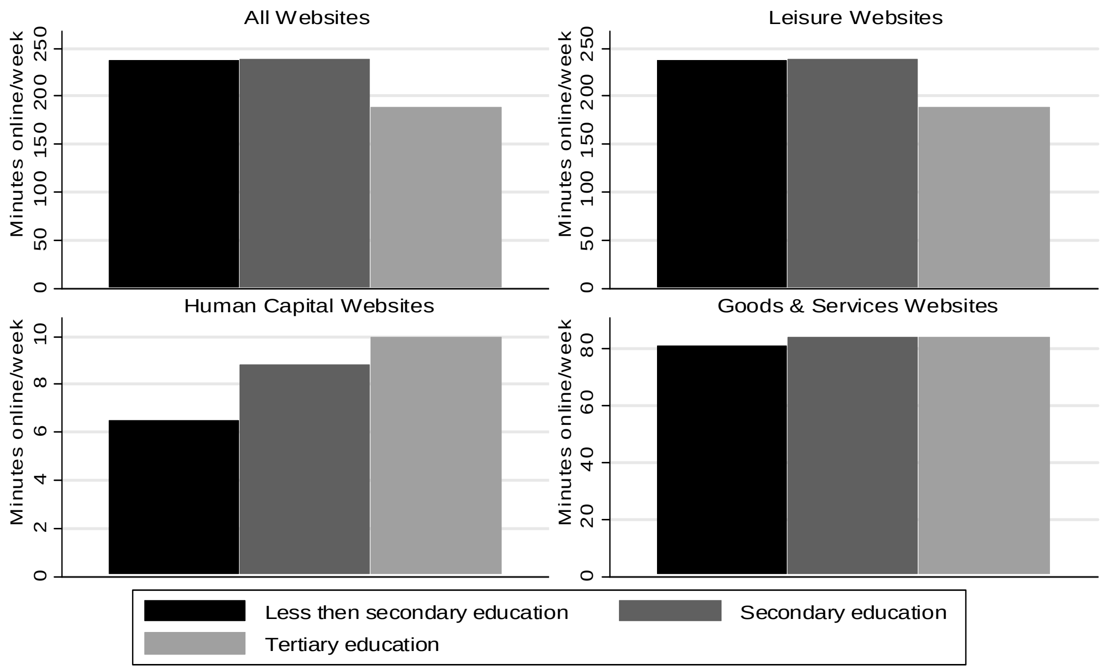
Figure 2 presents how average time spent online varies with educational attainment. Internet users with tertiary education spent less time online at home than users with lower educational attainment.

Figure 1
Time spent on different websites and household income



Source: Nielsen Clickstream data 2011, own illustrations.

Figure 2
Time spent on different websites and education



Source: Nielsen Clickstream data 2011, own illustrations.

This pattern might indicate higher opportunity cost of time for internet users with tertiary education. There is a clear positive relationship between human capital websites and time spent online, which suggests that there might be a digital divide in the ability to use these websites according to education levels. Finally, there is no relationship between time spent online on goods & services websites and education.

In summary, our descriptive analysis shows that there is a negative relationship between income and time spent online at home and mixed relationship between education and time spent online.

4 Methodology

Following Goldfarb and Prince (2008), we assume that time spent online is a function of total leisure time, total income, price of internet and other individual characteristics. We include controls for occupational and demographic characteristics related to life stage (being married/cohabitating and having children) to control for leisure time. Household income is our proxy for total money available. We also include several demographic characteristics which previous studies have shown to have an effect on time spent online. We estimate the following regression:

(1) $$TimeOnline_i = \alpha_0 + \beta_I{}' Income_i + \beta_E{}' Education_i + \beta_x{}' x_i + \varepsilon_i$$

$TimeOnline_i$ is the average time spent online per week on all or on a specified type of websites by internet user i. It is measured in minutes. Since we do not have a continuous income variable but only income groups, $Income_i$ is measured as a set of dummies for household income in a given interval. $Education_i$ are dummy variables that control for the highest educational attainment of the internet user. x_i are other social and economic characteristics of the internet user. Informed by previous empirical studies on the topic, we include the following characteristics of the internet user: gender, age, marital status, presence of children in the household, household size, occupation. The descriptive statistics for these variables are in Table 1. We also include country and region specific fixed effects.

The main variables of interest are *Income* and *Education*. The opportunity cost of time hypothesis[8], predicts that the opportunity cost of spending time online is higher for high income earners. Consequently, they will spend less time online overall and possibly also on different types of internet activities. Finding negative and significant coefficients on the income dummies ($Income_i$) will be interpreted as confirming this hypothesis. However, income may affect time spent online though preferences or access to internet outside home. We will examine these effects by estimating equation (1) on subsamples which differ with regard to these characteristics.

Education affects the ability of using internet for different purposes, the opportunity cost of time and also preferences. Previous studies showed that there is a strong relationship between

8 We assume fixed monthly internet subscription fees and consequently a zero marginal financial cost of internet use. Van Dijk (2012) found that more 80% of the internet access offers in the EU were unmetered.

education and digital skills[9]. If an online activity requires certain digital skills/abilities we would expect the coefficient of education to be positive. Thus, we would expect the coefficient of education to be positive for human capital and goods & services websites, which includes e-commerce and the use of different online services such as online banking or government web-sites, but not necessarily for most of leisure activities. Education may affect time spent online also through opportunity cost of spending time online. Controlling for income should account for this effect. In addition, high and low educated individuals may differ in their preferences regarding different online activities. However, in the empirical part we will examine aggregated groups of activities and a large number of detailed online activities, which would allow us to distinguish between these two possible explanations.

Trying to identify the relationship between income and times spent online using equation (1) could be problematic if income is not exogenous. In particular, there is a possibility that the intensive users of internet may have better ICT skills, which might be correlated with higher wages. This would result in reverse causality bias. This is not likely to be a problem for the data used in this study because the data on social and economic characteristics of the internet users, including income, was collected when the person installed the Nielsen meter on their computer and, thus, *before* the recording of their clickstream.

The sample used in this study consists of individuals who have access to internet at home and were active users of internet during the period studied. Therefore, we cannot examine the de-terminants of adoption of the internet or control for selection into subscription to internet. Moreover, the descriptive statistics presented in the previous section show that all users spent positive amounts of time on leisure and goods & services websites and 98.6% do so on human capital websites. Given that our dependent variable is not censored, or in the case of human capital websites it is be very little affected by censoring, we conclude that least squares estima-tion is the appropriate estimation method[10].

However, the error terms from estimating equation (1) for time spent on different types of web-sites might be correlated. Therefore, we estimate them as a system of seemingly unrelated re-gression (SUR) using a generalized least squares estimator. This method takes into account the possible correlation of error terms and yields more efficient results (Greene, 2002). As this es-timator is feasible only for linearly independent equations, we have to exclude one of the equa-tions. We use iterated seemingly unrelated regressions (ISUR) to ensure that estimates are in-variant to the equation excluded (Zellner, 1962). We use the fact that ISUR estimates are invar-iant to the equation excluded to obtain the coefficients for all equations. We do this by estimat-ing equation (1) for different groups of equations in which the dependent variables is time spent on different types of websites (or all websites).

[9] After learning by doing, formal education is the most important way in which individuals acquire digital skills (Eurostat Information Society Indicators, 2013).

[10] We have estimated the equation (1) using tobit for aggregated and detailed online activities and the marginal effects were very similar to the OLS results.

To test whether the effects of income and education are robust to the presence of outliers and whether they vary across the distribution of internet use we will use quantile regressions. In addition, we will carry out several other robustness checks which will be discussed in the results section. Most regressions are estimated on the pooled sample of the five countries described in Section 3[11].

5 Results

Table 2 reports the results of the estimation of equation (1). The results for time spent on all websites (reported in the first column of Table 2) confirm that all income coefficients are negative and statistically significant. The household income group 0-18,000 Euros is taken as the reference group. Ceteris paribus, internet users in the second lowest household income group (18,000 - 27,000 Euros) spend on average 50 minutes per week less online at home than users in the lowest income group (less than 18,000); users in the highest income group (above 72.000) spend 2.5 hours per week less online at home. The differences between the coefficients of income intervals are statistically significant (see the bottom part Table 2).

Table 2
Baseline Model

	All websites	**Leisure websites**	**Human capital websites**	**Goods & services websites**
Income 18-27000	-50.48	-43.04	-1.62	-5.82
	[7.48]***	[6.44]***	[0.41]***	[2.13]***
Income 27-36001	-65.76	-59.91	-1.64	-4.20
	[7.95]***	[6.86]***	[0.47]***	[2.17]*
Income 36-54000	-99.47	-88.55	-2.14	-8.78
	[7.80]***	[6.53]***	[0.46]***	[2.33]***
Income 54-72000	-122.48	-107.49	-2.52	-12.47
	[9.33]***	[7.65]***	[0.58]***	[2.99]***
Income >72000	-148.03	-123.43	-3.80	-20.80
	[10.21]***	[8.41]***	[0.61]***	[3.23]***
Secondary educ.	17.71	6.34	2.33	9.03
	[7.29]**	[6.23]	[0.35]***	[2.01]***
Tertiary educ.	-1.85	-16.66	3.39	11.43
	[6.96]	[5.77]***	[0.35]***	[1.99]***

11 We found the same relationships between income and education and time spent online in all countries and therefore we decided to focus on the pooled sample.

Table 2 (Cont.)

	All websites	**Leisure websites**	**Human capital websites**	**Goods & services websites**
Female	-1.84	-8.48	2.77	3.87
	[4.88]	[4.17]**	[0.30]***	[1.40]***
Age	-1.18	-1.59	0.04	0.37
	[0.22]***	[0.19]***	[0.02]***	[0.07]***
Single	76.89	59.48	1.86	15.54
	[7.03]***	[6.09]***	[0.42]***	[1.97]***
Children	-7.75	-7.54	-0.95	0.74
	[6.53]	[5.40]	[0.40]**	[1.87]
Household size 3-4	-30.31	-22.37	-0.43	-7.51
	[7.08]***	[5.85]***	[0.42]	[2.14]***
Household size >5	-32.53	-22.10	-0.83	-9.60
	[10.31]***	[8.65]**	[0.63]	[3.20]***
Constant	360.09	311.18	6.25	42.66
	[51.48]***	[45.04]***	[5.98]	[14.63]***
N	18680	18680	18680	18680
R^2	0.10	0.10	0.03	0.05
F tests of differences in income coefficients (p values)				
$\beta_{Inc.\ 18\text{-}27000}=\beta_{Inc.\ 27\text{-}36000}$	0.03	0.00	0.94	0.47
$\beta_{Inc.\ 27\text{-}36000}=\beta_{Inc.\ 36\text{-}54000}$	0.00	0.00	0.21	0.02
$\beta_{Inc.\ 36\text{-}54000}=\beta_{Inc.\ 54\text{-}72000}$	0.00	0.00	0.46	0.11
$\beta_{Inc.\ 54\text{-}72000}=\beta_{Inc.\ >72000}$	0.00	0.02	0.04	0.01

Notes: ISUR estimates with bootstrapped standard errors in brackets. Dependent variables are average time spent per week on all and on a specific type of websites, measured in minutes. Other covariates: occupation, country and region fixed effects. *, ** and *** indicate significance at 10%, 5% and 1%. Source: Nielsen Clickstream data 2011, Own calculations.

The results suggest that time spent online at home decreases almost monotonically with the household income. These results are consistent with the opportunity cost hypothesis and with previous studies (Goolsbee and Klenow, 2006; Goldfarb and Prince, 2008; Brynjolfsson and Oh, 2012). They suggest that, among those who have access to internet at home, there is a reverse in the income-based digital divide in internet use: low-income users use internet more at home than high-income users. Columns 3, 4 and 5 in Table 2 show that this negative relationship between income and time spent online at home holds for each type of website considered. For leisure, the differences between the coefficients for the income intervals are statistically significant, suggesting a monotonically increasing negative income effect. This is consistent with the opportunity cost hypothesis, and with previous empirical studies on leisure online (Goolsbee and Klenow, 2006; Goldfarb and Prince, 2008; Brynjolfsson and Oh, 2012) and with studies on similar leisure activities such as TV watching (Frey et al., 2007). The tests for differences between income coefficients reported in the bottom part of Table 2 suggest that for internet users above the lowest income interval there is no relationship between time spent online on human capital and goods & services websites.

Education is negatively associated with time spent on leisure websites and a positively associated with time spent on human capital and goods & services websites. These results are in line with Goldfarb and Prince's (2008) findings that education has a negative effect on time spent on leisure, but a positive effect on e-commerce and research prior to purchases. The results for human capital and goods & services websites suggest that there might be a divide in terms of ability to use these types of websites.

The other variables included have the expected signs. Women spend less time on leisure websites, but more time on human capital and goods& services websites than men. Age has a mixed impact. The presence of children is associated with a negative, but mostly insignificant effect due to the high correlation with household size variables. Large household size is associated with less time spent online. Being single is associated with more time spent on all online activities. Overall, the results for the demographic characteristics are plausible and have the expected signs based on previous studies on internet use and time allocation.

These estimations are based on aggregated groups of activities. Aggregation of different types of websites that correspond to online activities may result in smoothing the effect of income and education. Therefore, we repeat the estimations at a more disaggregated level of categories of websites. These results are reported in Table 3.

Income is negatively associated with time spent on most leisure websites, except news websites. Education coefficients remain negative for entertainment and social networks, but turn positive and significant for more sophisticated leisure categories (news and internet services). Income is negatively associated with time spent on careers, education, corporate and health websites, while education is positively associated with time spent on these websites. Income coefficients vary significantly for different goods & services websites. They are negative and significant for e-commerce and general portal & search websites, but insignificant for government and non-profit websites and positive and significant for travel and online banking websites. The positive coefficients of income for the last two categories suggest that these categories of websites are used more by high income users than low income ones. The coefficients of education are always positive and significant for each of the goods & services categories. Overall, the results are in line with those obtained from more aggregated categories, but they differ for a few categories. They provide further evidence that education is positively associated with time spent on complex online activities.

We carry out several robustness tests. To address possible problems with the measurement of time spent online, we re-estimate equation (1) using average number of clicks per week as dependant variable. The results (reported in Table 9, in Appendix) confirm the results for time spent online. As indicated in footnote 3, the match between user profile and online activity may not be perfect in households with several individuals. Therefore, we re-estimate the baseline model on the sample of one person households, which are not affected by this problem.

Table 3
Detailed website categories

	Leisure websites				Human capital websites			Goods & services websites				
	Entertain-ment & Lifestyle	News	Social networks	Internet services	Careers & education	Corporate	Health	Ecom-merce	Search & general portals	Travel	Online banking	Gov. & nonprofit
Income 18-27000	-16.42	0.49	-22.41	-4.71	-0.97	-0.51	-0.14	-4.20	-2.11	0.59	-0.06	-0.05
	[3.46]***	[0.79]	[4.07]***	[1.23]***	[0.28] ***	[0.26]*	[0.11]	[1.53]***	[0.73]***	[0.25]**	[0.41]	[0.20]
Income 27-36001	-20.46	-0.90	-32.37	-6.18	-0.93	-0.58	-0.14	-3.09	-2.66	1.09	0.39	0.08
	[3.59]***	[0.71]	[4.20]***	[1.32]***	[0.31] ***	[0.28]**	[0.10]	[1.53]**	[0.75]***	[0.28]***	[0.44]	[0.24]
Income 36-54000	-32.91	0.07	-46.10	-9.61	-1.30	-0.77	-0.08	-6.82	-4.32	1.19	1.10	0.08
	[3.38]***	[0.72]	[4.03]***	[1.30]***	[0.32] ***	[0.25]***	[0.11]	[1.57]***	[0.73]***	[0.25]***	[0.60]*	[0.23]
Income 54-72000	-42.68	-0.59	-50.69	-13.54	-2.00	-0.48	-0.04	-9.46	-5.41	1.12	1.31	-0.03
	[3.66]***	[0.88]	[4.67]***	[1.47]***	[0.40] ***	[0.39]	[0.13]	[1.87]***	[0.97]***	[0.33]***	[0.67]*	[0.24]
Income >72000	-52.80	-0.13	-52.24	-18.26	-2.45	-1.23	-0.12	-13.92	-8.22	1.41	0.35	-0.41
	[3.92]***	[1.24]	[5.36]***	[1.66]***	[0.45] ***	[0.31]***	[0.18]	[2.05]***	[1.00]***	[0.42]***	[0.76]	[0.28]
Secondary educ.	-1.69	3.36	0.76	3.92	1.18	0.90	0.25	3.54	2.21	1.30	1.28	0.70
	[3.26]	[0.63]***	[3.67]	[1.06]***	[0.22] ***	[0.25]***	[0.10]***	[1.36]***	[0.65]***	[0.22]***	[0.39]***	[0.14]***
Tertiary educ.	-12.47	4.89	-16.40	7.32	2.63	0.49	0.27	3.28	2.97	1.65	2.39	1.12
	[3.17]***	[0.64]***	[3.29]***	[1.09]***	[0.24] ***	[0.21]**	[0.09]***	[1.33]**	[0.63]***	[0.20]***	[0.47]***	[0.14]***
Constant	139.71	1.46	163.72	6.29	6.49	0.82	-1.06	20.72	14.92	2.20	2.51	2.30
	[34.77]***	[3.30]	[20.19]***	[6.59]	[5.59]	[1.16]	[0.20]***	[9.26]**	[3.36]***	[1.68]	[3.67]	[1.36]*
N	0.07	0.03	0.10	0.05	0.05	0.01	0.02	0.06	0.04	0.04	0.03	0.05
R^2	18680	18680	18680	18680	18680	18680	18680	18680	18680	18680	18680	18680

Notes: ISUR estimates with bootstrapped standard errors are in brackets. Dependent variable is average time spent per week on a specific category of websites, measured in minutes. Other covariates: other demographic characteristics and country and region fixed effects. *, ** and *** indicate significance at 10%, 5% and 1%. Source: Nielsen Clickstream data 2011, own calculations.

The results (reported in Table 10, in Appendix) are qualitatively similar to the baseline results. To examine whether the baseline results are driven by one country or a group of countries, we estimate equation (1) separately for each country. These results are reported in Table 11 to Table 14. The results indicate that in all countries there is a negative and significant relationship between time spent online and income and a positive relationship between education and time spent on human capital websites, although the magnitudes of the effects differ. Overall, these results confirm the baseline results.

Next, we use quantile regressions to examine whether our results for income and education are not driven by a few very intensive users (users that spend large amounts of time online). In addition, this method provides a more complete characterisation of the conditional distribution of time spent online by allowing the effect of income and education and other explanatory variable that to vary for different quantiles. The estimation results for the 10_{th}, 25_{th}, 50_{th}, 75_{th} and 90_{th} quantiles, for the four categories of websites, are reported in Table 4-Table 7.

Table 4
Quantile regressions – All websites

	Q10	Q25	Q50	Q75	Q90
Income 18-27000	-8.17	-26.95	-62.21	-86.49	-82.65
	[2.37]***	[5.39]***	[9.40]***	[14.25]***	[26.18]***
Income 27-36001	-11.63	-35.80	-70.40	-102.03	-135.86
	[2.42]***	[5.63]***	[8.66]***	[14.01]***	[26.68]***
Income 36-54000	-14.15	-44.39	-103.37	-141.80	-198.08
	[2.37]***	[4.93]***	[8.55]***	[13.96]***	[26.52]***
Income 54-72000	-15.93	-51.99	-118.13	-174.02	-260.99
	[2.55]***	[5.62]***	[9.59]***	[15.25]***	[29.25]***
Income >72000	-19.29	-63.28	-132.38	-206.48	-290.30
	[2.66]***	[5.66]***	[11.41]***	[16.43]***	[36.96]***
Secondary educ.	5.71	14.57	18.77	30.16	23.30
	[1.56]***	[3.39]***	[7.55]**	[13.02]**	[24.07]
Tertiary educ.	4.83	15.59	23.62	2.86	-48.10
	[1.47]***	[3.07]***	[7.08]***	[12.83]	[23.55]**
Constant	40.19	138.52	343.44	521.07	888.79
	[25.31]	[22.76]***	[68.57]***	[76.88]***	[185.45]***
N	18680	18680	18680	18680	18680
Pseudo R^2	0.02	0.04	0.06	0.08	0.10

Notes: Quantile regression estimates with bootstrapped standard errors in brackets.
Dependent variable is average time spent per week on all websites, measured in minutes.
Other covariates: other demographic characteristics, country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1%.
Source: Nielsen Clickstream data 2011, own calculations.

The online activity of the very intensive internet users is itself of interest because they account for a large part of online activity. For instance, the top 10% internet users in the distribution of the online activities studied account for 40% of time spent on leisure online, 36% of time spent on goods & services websites, and for more than 50% of total time spent on human capital websites.

Table 5
Quantile regressions – Leisure websites

	Q10	Q25	Q50	Q75	Q90
Income 18-27000	-4.68	-17.08	-50.55	-76.44	-103.85
	[1.41]***	[3.15]***	[6.79]***	[13.43]***	[26.08]***
Income 27-36001	-6.33	-23.20	-65.46	-106.45	-144.41
	[1.34]***	[3.05]***	[6.75]***	[12.51]***	[26.75]***
Income 36-54000	-7.37	-28.02	-81.86	-145.23	-211.52
	[1.28]***	[2.88]***	[6.21]***	[12.38]***	[25.47]***
Income 54-72000	-8.63	-32.99	-92.40	-166.67	-261.85
	[1.28]***	[3.11]***	[6.40]***	[13.62]***	[27.60]***
Income >72000	-9.81	-37.26	-101.24	-175.13	-280.67
	[1.32]***	[3.13]***	[6.83]***	[13.63]***	[31.24]***
Secondary educ.	2.32	4.25	15.72	11.92	-4.95
	[0.83]***	[1.97]**	[4.81]***	[9.68]	[25.37]
Tertiary educ.	1.99	5.97	9.33	-13.03	-70.66
	[0.70]***	[1.64]***	[4.11]**	[8.82]	[24.20]***
Constant	22.24	95.13	235.01	494.03	663.89
	[9.64]**	[15.50]***	[52.15]***	[47.92]***	[153.08]***
N	18680	18680	18680	18680	18680
Pseudo R^2	0.01	0.03	0.06	0.08	0.11

Notes: Quantile regression estimates with bootstrapped standard errors in brackets.
Dependent variable is average time spent per week on leisure websites, measured in minutes.
Other covariates: other demographic characteristics, country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1%.
Source: Nielsen Clickstream data 2011, own calculations.

The results show that the coefficients of income variables are significant across the entire conditional distribution of time spent online for all four activities considered. This confirms that our OLS results are not driven by a few very intensive internet users. We also tested and confirmed that these differences in the income coefficient for different quantiles are statistically significant. These results suggest that income has a greater effect for more intensive users. These results are consistent with the hypothesis of Nie and Hillygus (2002) that heavy use of internet crowds out other activities and light use does not. For overall time and leisure, education has a positive effect on the lower quantiles of these distributions but an insignificant and even negative effect on the higher quantiles of these distributions. For time spent on human capital and goods & services websites, education has a positive and significant effect across the entire distributions of these online activities and it has a greater effect for higher quantiles of these distributions, in line with OLS results.

Finally, we examine more in detail what drives the negative relation between time spent online and household income. Differences in access to internet at work, in opportunity cost of time and different usefulness of internet for users with different income levels could all lead to a negative relationship between time spent online and household income[12] (Goldfarb and Prince, 2008). Internet users who have access to internet at work may use it also for personal reasons and they may not need to use it as much at home as users without access to internet at work.

Table 6
Quantile regressions – Human capital websites

	Q10	Q25	Q50	Q75	Q90
Income 18-27000	-0.07	-0.30	-0.77	-1.74	-4.13
	[0.03]**	[0.07]***	[0.16]***	[0.42]***	[0.98]***
Income 27-36001	-0.10	-0.36	-0.81	-2.17	-4.04
	[0.03]***	[0.07]***	[0.18]***	[0.46]***	[1.31]***
Income 36-54000	-0.16	-0.47	-1.05	-2.59	-5.15
	[0.03]***	[0.08]***	[0.17]***	[0.43]***	[1.08]***
Income 54-72000	-0.16	-0.55	-1.49	-3.85	-8.03
	[0.03]***	[0.08]***	[0.19]***	[0.51]***	[1.26]***
Income >72000	-0.22	-0.72	-2.04	-4.70	-9.22
	[0.03]***	[0.08]***	[0.19]***	[0.57]***	[1.34***
Secondary educ.	0.11	0.30	0.89	2.15	4.06
	[0.02]***	[0.05]***	[0.11]***	[0.28]***	[0.78]***
Tertiary educ.	0.16	0.45	1.44	3.88	7.44
	[0.02]***	[0.05]***	[0.12]***	[0.31]***	[0.72]***
Constant	0.17	0.95	1.92	8.54	22.71
	[0.37]	[0.40]**	[0.90]**	[4.97]*	[30.78]
N	18680	18680	18680	18680	18680
Pseudo R^2	0.01	0.01	0.03	0.04	0.05

Notes: Quantile regression estimates with bootstrapped standard errors in brackets.
Dependent variable is average time spent per week on human capital websites, measured in minutes.
Other covariates: other demographic characteristics, country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1%.
Source: Nielsen Clickstream data 2011, own calculations.

Users who have access to internet at work are likely to be employed in skilled occupations which are associated with higher wages, which may lead to a spurious correlation between household income and time spent online. Internet users with higher income may have higher opportunity costs of time and therefore they spend less time online. Finally, Goldfarb and Prince (2008) suggest that internet could be more useful to lower income internet users because

[12] Another possible explanation is that high income internet users are more likely to have access to internet from portable devices, which are not covered by the Nielsen meter. However, OECD (2012) suggests that internet traffic from such devices accounted for 6.8% of internet traffic in UK, 4% in Spain and less than 3% in France of all internet traffic in these countries in August 2011. To the extent that these figures are representative of other months of the year and of other two countries, they suggest that the internet traffic on these devices represented only a small share of total internet activity and cannot by itself explain the large differences in time spent online by high and low income internet users.

they can obtain services which are not available/affordable to them offline or they have different preferences.

Table 7
Quantile regressions – Goods & services websites

	Q10	Q25	Q50	Q75	Q90
Income 18-27000	-0.27	-1.73	-3.36	-5.95	-12.96
	[0.58]	[1.23]	[1.74]*	[3.16]*	[7.04]*
Income 27-36001	-0.88	-1.92	-2.81	-1.86	-4.58
	[0.60]	[1.25]	[1.94]	[3.51]	[7.14]
Income 36-54000	-1.59	-4.59	-7.84	-11.19	-13.85
	[0.56]***	[1.14]***	[1.94]***	[3.68]***	[6.86]**
Income 54-72000	-1.69	-5.35	-10.06	-20.36	-27.13
	[0.65]***	[1.37]***	[2.26]***	[3.93]***	[9.18]***
Income >72000	-2.90	-9.73	-16.14	-25.07	-41.38
	[0.62]***	[1.56]***	[2.72]***	[4.65]***	[8.97]***
Secondary educ.	2.04	4.79	10.23	14.20	18.74
	[0.43]***	[0.90]***	[1.53]***	[3.31]***	[5.87]***
Tertiary educ.	2.37	6.46	13.36	17.46	26.35
	[0.44]***	[0.96]***	[1.45]***	[3.05]***	[5.34]***
Constant	5.76	29.10	35.78	74.95	147.79
	[4.34]	[10.55]***	[19.51]*	[23.23]***	[39.98]***
N	18680	18680	18680	18680	18680
Pseudo R^2	0.03	0.04	0.04	0.04	0.05

Notes: Quantile regression estimates with bootstrapped standard errors in brackets.
Dependent variable is average time spent per week on goods & services websites, measured in minutes.
Other covariates: other demographic characteristics, country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1%.
Source: Nielsen Clickstream data 2011, own calculations.

We examine whether access to internet at work drives the results by estimate equation (1) for individuals with different access to internet at work. Based on users' occupations we distinguish between: (1) users employed in occupations where they are likely to have access to internet at work, (2) individuals employed in occupations where they are not likely to have access to internet at work, (3) internet users who are homemakers, retired and unemployed, who are likely to have access to internet only from home[13]. We classified the occupational groups provided by Nielsen and reported in Table 1 into those likely to provide or not access to internet at work based on the OECD broad definition of ICT-skilled occupations (OECD, 2010) [14].

[13] It is important to mention, that all internet users may access internet from public libraries, internet cafes, etc. However, internet use from these places is not likely to account for a large part of their internet use and there is no reason while such use would vary systematically with household income.

[14] OECD definition is based on three digit ISCO 88 codes and occupations provide by Nielsen are similar to one digit ISCO 88 codes. Thus, we classified the occupational categories provided by Nielsen in occupations ICT skilled ones if they included an ICT skilled occupation. Thus, clerical/administrative, executive/managerial, professionals, education and technical were classified as occupations where users are likely to have access to

We examine whether the opportunity cost drives the results by comparing the results of estimating equations (1) separately for employed internet users, whose opportunity cost of time is most likely to be related to wages and hence income, and internet users who were not employed at the time of the survey (full-time students, retired, homemakers and unemployed internet users) whose opportunity cost of time is not related with the income they could earn in labour markets. In the latter estimations the coefficients of income indicate the differences in time spent online between students (or retired, homemaker or unemployed users) from households with different income levels.

Given that all tests are based on comparing the coefficients of income for different occupational groups we report all these regression in Table 8. These equations were estimated jointly using OLS. For expositional reasons we report here only the results for all time spent online.

The results show that income has a negative effect on overall time spent online for employed internet users with access to internet at work and without, for employed and not employed internet users, and for specific categories of not employed internet users: students, homemakers, unemployed or retired. Moreover, almost all differences in the coefficients of income between different occupational groups are not statistically significant, as reported in Table 16. This suggests that the income has a similar effect on time spent online for internet users in all these occupational groups.

More specifically, the across equation tests of the differences in coefficients indicate that we cannot reject the hypothesis that income has the same effect on time spent online by users employed in ICT skilled occupations (who likely have access to internet at work), those employed in non ICT skilled occupations (who likely do not have access to internet at work), students (who may have access to internet at university) and homemakers, retired and unemployed internet users (who likely only have internet access at home). The fact that income does not have statistically different effects on time spent online internet users with different access to internet outside home, suggest that access to internet outside home is not a main driver of our results.

The tests in the lower panel of this table indicate that the differences in the effects of income on time spent online for employed internet users and for not employed users (students, homemakers, retired and unemployed) are statistically insignificant.

computers at work and craftsman/craftswoman, military, operator/labourer, sales and services as occupations where users are not likely to have access to computers at work. Internet users who indicated their occupation as "other" were not included in any of these groups.

Table 8
Time spent online on all websites – Differences between occupational groups

Internet users' occupations	Employed in ICT skilled	Employed in non ICT skilled	Employed	Not employed	Students	Home-makers	Retired	Un-employed
Income 18-27000	-39.03	-41.43	-50.70	-45.02	11.17	-60.45	-45.93	-52.25
	[14.54]***	[15.78]***	[10.01]***	[12.79]***	[26.77]	[31.60]*	[24.23]*	[21.96]**
Income 27-36001	-52.19	-44.89	-55.20	-83.44	-85.41	-64.83	-61.77	-104.78
	[14.71]***	[17.24]***	[10.51]***	[13.63]***	[23.99]***	[36.04]*	[24.58]**	[29.13]***
Income 36-54000	-88.63	-98.28	-97.23	-101.41	-102.54	-179.56	-61.09	-41.60
	[14.05]***	[16.54]***	[9.92]***	[13.98]***	[24.01]***	[34.03]***	[24.95]**	[36.08]
Income 54-72000	-116.76	-113.81	-121.77	-118.78	-114.11	-164.76	-62.91	-77.05
	[15.41]***	[21.82]***	[11.35]***	[16.59]***	[27.73]***	[41.51]***	[30.07]**	[56.62]
Income >72000	-146.26	-207.39	-154.44	-121.86	-99.46	-160.61	-119.33	-27.95
	[15.97]***	[23.53]***	[12.25]***	[21.80]***	[34.66]***	[55.82]***	[33.38]***	[72.58]
Secondary educ.	-8.55	5.14	-1.94	37.17	39.74	31.74	38.14	11.58
	[13.66]	[14.50]	[9.31]	[11.69]***	[20.26]**	[30.28]	[21.24]*	[26.25]
Tertiary educ.	-35.88	-10.92	-22.71	18.28	39.94	-9.99	8.50	-13.83
	[12.51]***	[15.01]	[8.92]**	[10.72]*	[22.30]*	[29.01]	[17.36]	[24.31]
Constant	441.08	340.73	415.33	482.58	281.33	498.54	707.72	422.66
	[31.20]***	[43.12]***	[25.27]***	[36.17]***	[60.45]***	[107.10]***	[105.30]***	[59.59]***
N	7573	3604	12311	6369	1688	1227	1780	1674
R^2	0.09	0.10	0.09	0.10	0.19	0.15	0.12	0.09

Notes: OLS estimates with heteroskedasticity robust standard errors are in brackets. Dependent variable is average time spent per week, measured in minutes. Other covariates: other demographic characteristics and country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1%.
Source: Nielsen Clickstream data 2011, own calculations.

These results cast doubt on the opportunity cost of time hypothesis. They could be interpreted as lending support to the hypothesis that low income internet users benefit more from internet than high income internet users who may have better alternatives or different preferences as suggested by Goldfarb and Prince (2008). Our model does not allow us to distinguish between these possible explanations. A further research step would be to specify a model which allows doing this.

6 Conclusions

This paper contributes to the debate regarding digital divide in access and use of internet between individuals with different socio-economic characteristics. While there is a large amount of literature on the digital divide in access, less is known about the digital divide in use. The evidence that exists is based on survey data and focuses on US.

We build on Goldfarb and Prince (2008), who study the role of income and education levels on internet use patterns in the US, which we extend to study the determinants of three specific online activities: leisure, human capital improvement and obtaining goods and services. In addition, we study whether the relationship between income and education and time spent online differs by users' intensity of use and occupation.

Our main finding is that, for those who have access to internet, the income based digital divide in internet use has been reversed: low income internet users spend more time online overall and on websites related to leisure. Internet users in the lowest income group also spend more time on human capital and goods & services websites. However, we find evidence of an education-related digital divide in the use of human capital and goods & services websites. The robustness checks show that these results hold true for a variety of demographic groups: internet users in each of the five countries, internet users in one person households, internet users who are employed, unemployed and out of the labour force (unemployed, students, retired people and homemakers) and internet users with different intensity of internet use.

Overall, the results suggest that for those with access to internet, there is a reversal in the income-based digital divide and that currently the main digital divide in internet use is driven by education and that it concerns not the internet in general, but specific uses such as those related to career, education and health and obtaining goods and services. These are the online activities generally regarded as valuable by policy makers and that they seek to encourage by increasing access to internet. These results highlight the importance of education for enabling internet users to participate in these online activities.

Appendix

Table 9
Robustness checks – Clicks

Websites	All	Leisure	Human capital	Goods & services
Income 18-27000	-112.24	-95.87	-4.34	-12.04
	[20.97]***	[18.37]***	[1.26]***	[5.40]**
Income 27-36001	-139.19	-128.17	-4.41	-6.62
	[22.55]***	[19.99]***	[1.30]***	[5.63]
Income 36-54000	-222.31	-199.64	-5.32	-17.34
	[21.52]***	[18.65]***	[1.24]***	[5.94]***
Income 54-72000	-269.12	-234.43	-6.24	-28.44
	[26.32]***	[22.48]***	[1.64]***	[7.49]***
Income >72000	-349.42	-291.44	-9.88	-48.09
	[26.32]***	[22.79]***	[1.67]***	[7.94]***
Secondary educ.	53.70	24.57	5.85	23.28
	[20.66]***	[17.69]	[1.21]***	[5.51]***
Tertiary educ.	-17.41	-49.35	7.54	24.41
	[18.67]	[15.81]***	[0.94]***	[5.22]***
Constant	1003.54	837.99	25.73	139.82
	[170.65]***	[161.62]***	[18.51]	[36.09]***
N	18680	18680	18680	18680
R^2	0.08	0.08	0.02	0.03

Notes: ISUR estimates with bootstrapped standard errors are in brackets.
Dependent variable is the average number of clicks per week. Other covariates:
Other demographic characteristics and country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1
Source: Nielsen Clickstream data 2011, own calculations.

Table 10
Robustness checks – One person households

Websites	All	Leisure	Human capital	Goods & services
Income 18-27000	-24.42	-18.26	-1.90	-4.26
	[13.29]*	[11.87]	[0.75]**	[3.82]
Income 27-36001	-57.84	-51.12	-2.34	-4.38
	[15.88]***	[14.30]***	[0.84]***	[4.59]
Income 36-54000	-75.65	-71.01	-0.75	-3.89
	[16.03]***	[13.99]***	[1.08]	[4.66]
Income 54-72000	-97.17	-94.91	-1.37	-0.89
	[20.89]***	[17.74]***	[1.65]	[6.89]
Income >72000	-123.72	-106.89	-4.13	-12.70
	[24.31]***	[20.64]***	[1.35]***	[6.97]*
Secondary educ.	-63.29	-57.47	1.95	-7.78
	[17.39]***	[15.47]***	[1.06]*	[4.57]*
Tertiary educ.	-88.27	-87.52	1.76	-2.51
	[16.21]***	[14.36]***	[0.81]**	[4.61]
Constant	529.00	450.68	8.58	69.74
	[84.54]***	[74.43]***	[5.57]	[35.24]**
N	4671	4671	4671	4671
R^2	0.11	0.12	0.04	0.03

Notes: ISUR estimates with bootstrapped standard errors are in brackets
Dependent variable is the average time spent per week. Other covariates:
Other demographic characteristics and country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1
Source: Nielsen Clickstream data 2011, own calculations.

Table 11
Country specific results – Germany

Websites	**All**	**Leisure**	**Human capital**	**Goods & services**
Income 18-27000	-82.32	-60.13	-2.27	-19.93
	[17.52]***	[15.78]***	[0.89]**	[4.95]***
Income 27-36001	-79.88	-67.79	-2.31	-9.78
	[18.88]***	[16.67]***	[0.82]***	[6.02]
Income 36-54000	-130.72	-110.02	-2.80	-17.91
	[17.93]***	[15.78]***	[0.92]***	[5.84]***
Income 54-72000	-141.96	-128.78	-3.70	-9.47
	[21.13]***	[17.50]***	[1.10]***	[7.63]
Income >72000	-188.31	-153.64	-4.48	-30.19
	[23.61]***	[19.79]***	[1.44]***	[7.74]***
Secondary educ.	-20.76	-24.11	0.85	2.50
	[16.75]	[14.04]*	[0.57]	[5.23]
Tertiary educ.	-50.44	-49.35	2.16	-3.25
	[16.06]***	[13.49]***	[0.79]***	[5.11]
Constant	462.36	361.91	2.95	97.50
	[85.41]***	[72.28]***	[1.72]*	[25.73]***
N	3928	3928	3928	3928
R^2	0.10	0.11	0.04	0.04

Notes: ISUR estimates with bootstrapped standard errors are in brackets.
Dependent variable is the average time spent per week. Other covariates:
Other demographic characteristics and country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1.
Source: Nielsen Clickstream data 2011, own calculations.

Table 12
Country specific results – Spain

Websites	All	Leisure	Human capital	Goods & services
Income 18-27000	-38.56	-39.47	-0.33	1.24
	[14.28]***	[12.39]***	[0.81]	[3.76]
Income 27-36001	-36.95	-40.45	-0.55	4.06
	[14.94]**	[13.09]***	[1.04]	[3.97]
Income 36-54000	-73.94	-73.70	-1.98	1.74
	[15.52]***	[13.30]***	[0.89]**	[4.58]
Income 54-72000	-84.92	-79.16	-1.68	-4.08
	[21.25]***	[18.53]***	[1.64]	[5.53]
Income >72000	-130.32	-108.62	-4.13	-17.57
	[22.19]***	[18.81]***	[1.09]***	[5.76]***
Secondary educ.	69.09	51.42	3.91	13.77
	[16.41]***	[14.53]***	[0.79]***	[3.71]***
Tertiary educ.	40.51	19.95	4.86	15.71
	[13.99]***	[12.72]	[0.65]***	[3.33]***
Constant	227.01	200.71	4.69	21.62
	[71.48]***	[61.53]***	[6.39]	[15.01]
N	3767	3767	3767	3767
R^2	0.08	0.08	0.08	0.08

Notes: ISUR estimates with bootstrapped standard errors are in brackets.
Dependent variable is the average time spent per week. Other covariates:
Other demographic characteristics and country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1.
Source: Nielsen Clickstream data 2011, own calculations.

Table 13
Country specific results – France

Websites	All	Leisure	Human capital	Goods & services
Income 18-27000	-42.14	-28.69	-3.31	-10.14
	[17.93]**	[14.65]*	[1.40]**	[4.94]**
Income 27-36001	-67.94	-58.65	-2.81	-6.48
	[17.31]***	[13.93]***	[1.39]**	[5.28]
Income 36-54000	-95.86	-77.41	-4.00	-14.45
	[17.06]***	[13.43]***	[1.35]***	[5.05]***
Income 54-72000	-111.19	-89.80	-3.03	-18.37
	[16.95]***	[13.96]***	[1.73]*	[5.07]***
Income >72000	-128.99	-103.18	-4.36	-21.44
	[18.97]***	[14.93]***	[1.54]***	[5.84]***
Secondary educ.	17.52	9.82	2.21	5.49
	[14.23]	[11.58]	[1.09]**	[4.01]
Tertiary educ.	0.02	-11.54	2.30	9.26
	[10.27]	[8.34]	[0.72]***	[3.28]***
Constant	227.47	185.60	2.42	39.44
	[37.54]***	[28.41]***	[2.89]	[13.16]***
N	4028	4028	4028	4028
R^2	0.10	0.11	0.06	0.09

Notes: ISUR estimates with bootstrapped standard errors are in brackets.
Dependent variable is the average time spent per week. Other covariates:
Other demographic characteristics and country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1.
Source: Nielsen Clickstream data 2011, own calculations.

Table 14
Country specific results – Italy

Websites	All	Leisure	Human capital	Goods & services
Income 18-27000	-42.39	-35.54	-1.68	-5.16
	[16.44]***	[13.90]**	[0.72]**	[4.75]
Income 27-36001	-76.66	-66.81	-1.53	-8.31
	[16.07]***	[13.88]***	[0.80]*	[4.70]*
Income 36-54000	-112.74	-99.08	-1.72	-11.95
	[16.08]***	[13.19]***	[0.82]**	[5.00]**
Income 54-72000	-88.65	-83.66	-0.15	-4.84
	[20.65]***	[17.08]***	[1.36]	[6.25]
Income >72000	-131.47	-112.71	-1.49	-17.28
	[25.25]***	[20.11]***	[1.84]	[8.07]**
Secondary educ.	33.44	11.72	2.20	19.52
	[15.79]**	[13.91]	[0.57]***	[4.06]***
Tertiary educ.	30.33	5.10	3.91	21.31
	[18.26]*	[16.15]	[0.68]***	[4.61]***
Constant	400.89	340.94	7.93	52.02
	[73.97]***	[67.07]***	[4.28]*	[12.52]***
N	3535	3535	3535	3535
R^2	0.08	0.08	0.04	0.05

Notes: ISUR estimates with bootstrapped standard errors are in brackets.
Dependent variable is the average time spent per week. Other covariates:
Other demographic characteristics and country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1.
Source: Nielsen Clickstream data 2011, own calculations.

Table 15
Country specific results – United Kindom

Websites	All	Leisure	Human capital	Goods & services
Income 18-27000	-53.39	-50.22	-2.00	-1.17
	[20.21]***	[16.94]***	[1.32]	[5.31]
Income 27-36001	-76.98	-68.72	-2.82	-5.44
	[23.51]***	[20.38]***	[1.45]*	[6.69]
Income 36-54000	-98.28	-92.24	-1.14	-4.91
	[21.30]***	[17.75]***	[1.43]	[6.32]
Income 54-72000	-163.29	-138.83	-3.72	-20.74
	[24.93]***	[20.62]***	[1.51]**	[7.38]***
Income >72000	-145.82	-126.94	-4.52	-14.36
	[34.69]***	[28.89]***	[1.65]***	[10.63]
Secondary educ.	35.19	17.94	3.07	14.18
	[26.02]	[22.52]	[1.49]**	[7.35]*
Tertiary educ.	15.57	-8.80	3.89	20.48
	[24.25]	[21.21]	[1.36]***	[6.71]***
Constant	477.98	408.93	2.25	66.80
	[52.41]***	[43.97]***	[3.41]	[14.53]***
N	3422	3422	3422	3422
R^2	0.09	0.11	0.02	0.04

Notes: ISUR estimates with bootstrapped standard errors are in brackets.
Dependent variable is the average time spent per week. Other covariates:
Other demographic characteristics and country and region fixed effects.
*, ** and *** indicate significance at 10%, 5% and 1.
Source: Nielsen Clickstream data 2011, own calculations.

Table 16
T-tests of differences in coefficients across equations in Table 8 (p-values)

	Employed in ICT skilled occupations minus					
	Employed in non ICT skilled occupations	**Not employed**	**Student**	**Homemaker**	**Unemployed**	**Retired**
Income 18-27000	0.91	0.76	0.10	0.54	0.62	0.81
Income 27-36001	0.75	0.12	0.24	0.75	0.11	0.74
Income 36-54000	0.66	0.52	0.62	0.01	0.22	0.34
Income 54-72000	0.91	0.93	0.93	0.28	0.50	0.11
Income >72000	0.03	0.37	0.22	0.81	0.11	0.47
Secondary educ.	0.49	0.01	0.05	0.23	0.50	0.06
Tertiary educ.	0.20	0.00	0.00	0.41	0.42	0.04
				Employed minus		
		Not employed	**Student**	**Homemaker**	**Unemployed**	**Retired**
Income 18-27000		0.73	0.03	0.77	0.95	0.86
Income 27-36001		0.10	0.25	0.80	0.11	0.81
Income 36-54000		0.81	0.84	0.02	0.14	0.18
Income 54-72000		0.88	0.80	0.32	0.44	0.07
Income >72000		0.19	0.14	0.91	0.09	0.32
Secondary educ.		0.01	0.05	0.23	0.50	0.06
Tertiary educ.		0.00	0.00	0.41	0.42	0.04

Notes: P-values of the t-tests of differences in coefficients on income and education across equations for different occupational groups in Table 8. Source: Nielsen Clickstream data 2011, own calculations.

References

Brynjolfsson, E. and J. H. Oh (2012), The attention economy – Measuring the value of free goods on the internet, http://digitalcommunity.mit.edu/community/latest_research/blog/2012/09/19/measuring-the-attention-economy.

Becker, G. S. (1965), A theory of the allocation of time, in: *Economic Journal*, Vol. 75, No. 299, 493-517.

Buchinsky, M. (1998), Recent advances in quantile regression models – A practical guide for empirical research, in: *Journal of Human Resources*, Vol. 33, No. 1, 88 -126.

Demoussis, M. and N. Giannakopoulos (2006), Facets of the digital divide in Europe – Determination and extent of internet use, in: *Economics of Innovation and New Technology*, Vol. 15, No. 3, 235-246.

Eurostat (2010), Eurostat Information Society Indicators Database.

Frey, B. S., Benesch C., and A. Stutzer (2007), Does watching TV makes us happy?, in: *Journal of Economic Psychology*, Vol. 28, No. 3, 283-313.

Greene, W. H. (2002), Econometric Analysis, 5th ed., Prentice Hall, London.

Goldfarb, A. and J. Prince (2008), Internet adoption and usage patterns are different – Implications for the digital divide, in: *Information Economics and Policy*, Vol. 20, No. 1, 2-15.

Goolsbee, G and P. J. Klenow (2006), Valuing consumer products by the time spent using them – An application to the internet, in: *American Economic Review*, Vol. 96, No. 2, 108-113.

Gronau, R. (1977), Leisure, home production and work – The theory of the allocation of time revisited, in: *Journal of Political Economy*, Vol. 85, No. 6, 1099-1123.

Montagnier, P and A. Wirthmann (2011), Digital divide – From computer access to online activities – A micro data analysis, OECD Digital Economy Working Papers, No. 189.

Nie, N. D. and D. S. Hillygus (2002), The impact of internet use on sociability – Time-diary findings, in: *IT & Society*, Vol. 1, No. 1, 1-20.

OECD (2010), Information Technology Outlook, 2010, Paris.

OECD (2012), Internet Economy Outlook 2012, Paris.

Orviska, M. and J. Hudson, (2009), Dividing or uniting Europe? – Internet usage in the EU, in: *Information Economics and Policy*, Vol. 21, No. 4, 279-290.

Pérez-Hernández, J. and R. Sánchez-Mangas (2011), To have or not to have internet at home – Implications for online shopping, in: *Information Economics and Policy*, Vol. 23, No. 3, 213-226.

Van Dijk (2012), Broadband internet access costs, European Commission, Directorate General for Communications Networks, Content and Technology Report, Brussels.

Zellner, A. (1962), An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias, in: *Journal of the American Statistical Association*, Vol. 57, No. 298, 348-368.