DISENTANGLING INCOME AND PRICE EFFECTS IN THE DEMAND FOR TIME ONLINE

Jorge González Chapela

Centro Universitario de la Defensa de Zaragoza

Address: Academia General Militar, Ctra. de Huesca s/n, 50090 Zaragoza, Spain

Email: jorgegc@unizar.es – *Tel*: +34 976739834

Abstract

The large negative impact of income on time spent online observed among internet adopters, has been interpreted as an own-price effect created by the variation in the opportunity cost of time across income strata. However, the regression coefficient on income could also be capturing an income effect. This paper estimates a standard demand function for time online in Spain that includes a measure of the opportunity cost of time in addition to a measure of income. The effect of income barely changed when the opportunity cost of time was included. Results rather suggest that time spent online is an inferior leisure activity.

JEL codes: J22, L86

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1. INTRODUCTION

The studies of internet usage in the U.S. conducted by Goolsbee and Klenow (2006) and Goldfarb and Prince (2008) find that, conditional on having internet at home, low-income internet users spend more time online than high-income users. For Europe, the same pattern has been reported by Hadhri et al. (2012) and Pantea and Martens (2014), which led the latter to wonder whether the "digital divide" had been reversed. In the same vein, Orviska and Hudson (2009) report a negative effect of income on the probability of using several internet applications. After evaluating four possible interpretations of this seemingly general pattern, Goldfarb and Prince (2008) concluded that the most likely explanation lies in the different opportunity cost of time. Since conditional on adoption, the cost of additional internet usage amounts essentially to the foregone value of time, the cost of usage is higher for high-income users. Thus, according to this interpretation, the inverse relationship between income and time spent online observed among users would be the result of a negative own-price effect created by cross-people variation in the income they could earn in the labor market. But Pantea and Martens (2014) have cast doubt on this interpretation finding that the effect of income on time spent online among employed users (whose opportunity cost of time is more likely to be related to wages and hence income), is virtually the same as the effect observed among non-employed users.

Besides a price effect, the coefficient on the income variable included in the regression for time spent online could also be capturing an income effect, the direction of which is not clear *a priori*. Perhaps the most obvious possibility is that high-income users demanded more leisure and spent, as a result, more time online.[1] In this case, and given that the observed total effect of income is negative, the positive income effect would be overcome by the negative

[1] The inclusion of the quantity of leisure among the explanatory variables controls for this possibility.

price effect. On the other hand, consumers have preferences about the way their leisure time is spent. Americans, for example, prefer as a rule talking with friends to watching television (Juster 1985b), and socializing after work to using the computer at home (Kahneman et al. 2004). Hence, one would expect that, *ceteris paribus*, the demands for different leisure activities reacted differently to improvements in the standard of living, moving as a whole towards a more enjoyable composition of total leisure. Consequently, at least part of the inverse empirical association between income and time spent online could be the result of the latter being an inferior leisure activity.

The purpose of this paper is to estimate a standard model for the demand of time online that permits a clearer identification of income and price effects. Identifying the extent of these margins is important from both a substantive and a policy viewpoint, for it is an essential precondition for predicting the effect on time spent online of variations in income that leave the opportunity cost of time unchanged (e.g., changes in the level of family benefits), and of variations in the opportunity cost of time that leave income almost unaffected (e.g., predicted life-cycle variations in wages). The study by Goel et al. (2006) assessing income and price-of-access elasticities for internet subscription/usage in OECD economies is underlaid with the same belief.

Section 2 discusses the data and the methods used. The collection by the same survey of information on internet adoption and usage and of information on household and individual income is rare, but it did occur in Spain for 2002-2003. While the "factual use conditions" (Gerpott and Thomas 2014) of internet have changed dramatically since then (in Spain, for example, the proportion of households with broadband connection increased from 15 percent in 2004 to 69 percent in 2013: Eurostat 2005, 2013), the mechanisms investigated here seem as fundamental so as to be able to inform current debates about the digital divide. Another important caveat is that the 2002-2003 Spanish Time Use Survey did not ask about the factual use conditions of internet. Following Becker's (1965) view of the household as a factory combining non-market time and market-purchased goods to produce utility-generating commodities, it is conceivable that households endowed with more income had improved the quality of the technology to access the internet. Hence, if better access technology saved time online, the estimated income effect on the demand for time online would be biased in the negative direction, i.e. toward finding the hypothesized inferiority of time spent online. However, the evidence presented in Kolko (2010) indicates that a better access technology acts as an incentive to spend more time online (see also Lera-López et al. 2011), so that the estimated income effect would be biased in the positive direction. Section 3 presents the results. Time spent online is negatively associated with the opportunity cost of time, but the inclusion of the latter barely changes the effect of income. Section 4 provides some concluding observations.

2. DATA AND METHODS

As in Goldfarb and Prince (2008), I model the internet adoption/usage decision as a two-stage process. In the first stage, households decide whether to adopt the internet; in the second stage, household members decide how much time to spend online. The estimating equations for the adoption and usage decisions are assumed to follow a Type II Tobit model (Amemiya 1985):

$$\Pr(\text{adopt}) = \Pr(\gamma_1 S + \alpha_1 w + X_1\beta_1 + \varepsilon_1 \geq 0) = \Phi(\gamma_1 S + \alpha_1 w + X_1\beta_1) \tag{1}$$

$$I^* = \gamma_2 S + \alpha_2 w + X_2\beta_2 + \lambda \frac{\hat{\phi}}{\hat{\Phi}} + \varepsilon_2 \tag{2}$$

where, I^* is time spent online for personal reasons; S, total household income; w, a measure of the opportunity cost of time; X_1, a vector of controls; X_2, a sub-vector of X_1; $\hat{\phi}/\hat{\Phi}$, the estimated inverse Mills ratio of the first-stage regression (1); and ε_1 and ε_2, error terms with

ε_1 ~ Normal(0, 1).[2] The main departure from Goldfarb and Prince (2008) is the inclusion among the regressors of a measure of the opportunity cost of time in addition to total household income, yielding a specification of I^* that resembles Mincer's (1963) labor supply function of married women. The parameter γ_2 represents a pure income effect on the demand for I^*. If I^* is normal, then $\gamma_2 > 0$, whereas $\gamma_2 < 0$ if I^* is inferior. Since the cost of marginal internet usage is essentially the foregone value of time, the parameter α_2 is

[2] The Type II Tobit model is a model for sample selection, that is, it assumes I^* is observed if and only if the household has adopted the internet. In practice, however, I^* could be observed even if the household has not adopted, and I^* could be zero even if the household has adopted. In the study sample, for instance, 0.4 percent of individuals living in households without internet connection did spend time online (these observations were excluded from the second stage), whereas 82.0 percent of individuals living in households with internet connection did not use internet on the observation day (this proportion was zero in Goldfarb and Prince 2008 because their survey asked for usual weekly hours spent online and they took the midpoint of each response interval). Nevertheless, models for corner solutions present shortcomings too. The Type I (or standard) Tobit model assumes that the partial effects of an explanatory variable on the adoption and usage decisions are of the same sign, which does not seem reasonable for this application. I also discarded two-part models and the Exponential Type II Tobit model discussed in Wooldridge (2010, p. 697) because these models' first-stage regression would represent the decision about using internet on the observation day, which is quite different from the decision about adopting internet. Since the equation for I^* in the Type II Tobit model is linear in parameters, it could seem that it does not suit well the data given the high proportion of observations with $I^* = 0$. However, there are reasons to recommend a linear specification for modelling the allocation of time (e.g., see Stewart 2013).

capturing an own-price effect on the demand for I^*. As explained in Deaton and Muellbauer (1980, p. 91), α_2 decomposes into a substitution effect and a traditional income effect created by the variation of real income when a price changes. If I^* is normal, then $\alpha_2 < 0$, but if I^* is inferior α_2 could even be positive. To allow identification of γ_2 and α_2 on more than functional form, the reduced-form adoption equation must include at least one variable correlated with adoption but not with usage.

The data to estimate (1) and (2) come from the 2002-2003 Spanish Time Use Survey (STUS), a full-scale survey conducted by the Spanish Statistical Office (INE). As is now standard around the world, the STUS gathered time-use information by the time diary method. Specifically, all household members aged 10 years and older were asked to list their main activity in each 10-minute interval of the previous 24-hour day (beginning at 6 am).[3] Those activities were then classified by the survey agency into standardized codes (listed in Annex VI of Eurostat 2004). Importantly, the STUS also collected information on the use of internet when doing each activity (except for working time), which was then codified by the agency into a series of dummy variables, one dummy for each 10-minute interval. While this information would make it possible to construct a very accurate measure of I^*, in practice the use of internet was underreported. The proportion of 10-minute intervals spent on online household management, communication by computer, and reading news online in which the internet use dummy was “No” is 38.9 percent; the other type of error, that the dummy was

[3] To avoid seasonal distortions, the STUS size was distributed evenly between October 2002 and September 2003. The mean number of activity episodes per day (21.5), the very low prevalence of diaries with fewer than 7 episodes (0.1 percent), and the low presence of diaries missing two or more basic activities (0.5 percent) all indicate the data is of good quality (Juster 1985a; Robinson 1985; Fisher et al. 2012).

"Yes" in the course of activities in which one would not expect that internet were being used (e.g., sleep, personal hygiene and dressing, or practicing sports), is virtually non-existent. The cross-diarists correlation of 0.64 between the number of 10-minute intervals spent on the three online activities listed above, and the number of those intervals in which the internet use dummy was "No", strongly suggests that the extent of underreporting is increasing in I^*. Hence, the estimated coefficients of equation (2) could be biased toward zero (Bound et al. 2001, p. 3715-3716), although, previewing the results, the underreporting was not so large that precludes distinguishing the main patterns in the data.

As in Goldfarb and Prince (2008), I^* represents time spent online for personal reasons irrespective of location, expressed here in minutes per day. More specifically, I^* sums together all time spent on the three online activities listed in the previous paragraph, all time spent obtaining information by computer, and all 10-minute intervals devoted to other non-working activities in which the diarist declared to be using internet. With the help of an additional variable that recorded the diarist's location in each 10-minute slot, I alternatively defined usage as minutes spent online from home. Besides the time diary, the STUS also collected a wide range of labor market and socio-demographic information by means of additional questionnaires. Thus, for example, the household's reference person was asked: *[Is your household equipped with] internet connection?* The response to this question was used to construct a household internet adoption indicator.

In accordance with the standards of Eurostat in relation to information society indicators, the study sample is made up of persons aged 16-74. I discarded individuals reporting fewer than 7 episodes in the observation day, who missed two or more of the four basic activities defined in Fisher et al. (2012), who declared not having internet at home but reported having spent time online from home, or who presented missing or inconsistent data in any other variable used in this study. This left us with 38,305 individuals (and as many time diaries) residing in 18,206 households, of whom 10,948 lived in 4,568 households with internet connection. However, for some specifications the sample was further restricted to employed men aged 23-59. This yielded a sample size of 9,681 individuals residing in 8,943 households, of whom 3,384 lived in 3,119 households with internet connection. Table 1 presents characteristics of these samples.

Among persons aged 16-74, the adoption rate was 28.6 percent, a figure increasing to 30.3 percent when observations were weighted with the survey weights. The corresponding population estimate calculated from the 2003 wave of the Spanish Household Survey of ICT Equipment and Usage (ICT-H, also conducted by INE but lacking information on individual earnings) was 31.2 percent. Among adopters, the average respondent used the internet 15.2 minutes per day for personal reasons. Of these, the largest part (13.8 minutes) pertained to communication and information by computer, which is considered generally computer use for leisure. The corresponding weighted mean was 16.6 minutes per day, i.e. 1.9 hours per week. The population average calculated from the ICT-H was 5.4 hours per week.[4] There are three reasons why the difference between these two estimates may be exceeding the extent of underreporting in the STUS. First, the ICT-H estimate includes time spent online for both personal and work-related reasons, from any location. Second, time-use information in the ICT-H was collected by means of stylized questions (*how long have you used the internet in the last week/three months?*), a method which commonly yields higher estimates than the time diary (e.g., see Juster et al. 2003). Third, in an unknown proportion of households the ICT-H questionnaire was asked of the household member more knowledgeable about household equipment and internet access, which might have selected the sample in terms of time spent online.

[4] Time spent online in the ICT-H was recorded in intervals. I computed midpoints except for the more than 50 hours per week interval, in which a value of 65 hours was assumed.

The net monthly income of each household was recorded in one of 8 intervals of uneven width. While replacing S in (1) and (2) with these dummies complicates the interpretation of the income responses, this approach seems the most plausible. Hsiao and Mountain (1985) approximated the marginal distribution of (annual) household income by a lognormal distribution, using it to evaluate the conditional means or to compute the covariance between income and other explanatory variables. However, the hypothesis that the distribution of household income in our sample is lognormal was rejected.[5] Alternatively, the midpoint of an income interval could be used to proxy for the unobserved S, but estimators computed from midpoints are generally biased (Haitovsky 1973), and Beaumont's (2005) corrections are not workable when intervals are of uneven width. For these reasons, dummy variables are used in place of the latent S. Due to the very low prevalence among adopters of households with income below 500 euros (see Table 1), the lowest two income categories were aggregated together.

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[5] Let μ and σ^2 denote, respectively, the mean and variance that characterize the marginal distribution of the logarithm of net monthly household income. The interval regression estimates of μ and σ^2 were 7.2762 and 0.3983. I tested the appropriateness of the lognormal assumption using a chi-squared goodness-of-fit test. The test statistic was 855.2. The critical value at 10% significance level with 5 df is 9.2. Clearly, the null hypothesis that the distribution of household income in our sample is lognormal cannot be accepted. The largest contributor to the criterion was the lowest income class. Following Hsiao and Mountain (1985), I proceeded by removing observations in that class and approximating the remaining observations' income distribution by a lognormal curve. After adjusting a truncated interval regression and redoing the test, the result was again a rejection of the null. I repeated the process eliminating each time the lowest/highest surviving income class that contributed the most to the criterion. But the null was rejected until I run out of degrees of freedom.

As is common, I inferred the opportunity cost of time from the hourly wage rate (Heckman 1974).[6] Specifically, w is measured as the prediction of the log of average hourly earnings from standard wage regressions run separately for male and female workers. Average hourly earnings (W^*) were calculated as net average monthly earnings divided by usual weekly hours of work times 4.3.[7] I do not use the log of W^* as the empirical counterpart to w because, since earnings were recorded in intervals, the resulting wage measure would contain error. (I suspect errors may be mean reverting, whereby the estimated α_2 could be attenuated, inflated, or even incorrectly signed: Bound et al. 2001, p. 3713.) Instead, and as in Biddle and Hamermesh (1990, p. 937), the log of W^* was regressed on a set of common

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[6] The use of the labor/leisure tradeoff to valuing the opportunity cost of time has been criticized as being overly simplistic, as it can only be properly equated to the opportunity cost of time of workers who freely choose their hours of work. However, this is the only viable approach given the available survey. Feather and Shaw (2000) derive the opportunity cost of time in the presence of fixed work time. Among others, Small et al. (2005), Aguiar and Hurst (2007), and Phaneuf (2011) estimate the opportunity cost of time from decision margins other than the labor/leisure.

[7] Monthly earnings are in intervals. I take the midpoint of each interval except when individuals claimed less than 500 euros (in which case I assign them the minimum monthly wage) or claimed 3,000 euros or more (in which case I assign them 4,564 euros, which is the mean of a Pareto curve fitted to the upper end of the earnings distribution: Ligon 1994). The information on working hours is obtained from the weekly work schedule collected by the STUS unless the worker considered the surveyed week to be unusual, in which case their hours derive from a direct question (*How many hours do you work per week?*), asked of those whose employment contract specified the number of working hours.

demographic variables,[8] obtaining the prediction ($\hat{w}$) for the entire sample of workers and non-workers. Then, $\hat{w}$ was included in (1) and (2) as the empirical counterpart to w. Besides accounting for the errors-in-variables problem, this procedure avoids the sample selection issue created by using data only on workers to estimate equations (1) and (2).

The controls included in X_2 are standard: educational category, marital status, age, sex, whether the respondent is foreigner, city size category, number of children in the household, leisure time on the observation day (measured in hours), and an intercept. The leisure measure gathers time spent on social life and entertainment, sports and outdoor activities, hobbies and games, and mass media, i.e. activities that we cannot pay somebody else to do for us and that are not biological needs (Sevilla et al. 2012). Additionally, X_1 includes a dummy for the presence of a teenager in the household, the number of cell phones owned by the household members (which I view as a proxy for optimism toward technology), and whether the household owns the home (owners may be more likely to bear technology installation costs). Among employed men aged 23-59, X_2 controls further for the respondent's occupation, whereas X_1 also contains whether the respondent brings work home and whether the respondent telecommutes, which are likely to increase the need for connection but not necessarily personal internet usage.

3. RESULTS

For comparison purposes, columns (1) and (2) of Table 2 present results obtained using a specification similar to Goldfarb and Prince (2008, Table 2). Results with the wage rate

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[8] The set of regressors includes educational categories, age and its square, marital status, being a foreigner, city size category, region, and an inverse Mills ratio term accounting for potential selectivity bias into employment. The estimation output is shown in Table A.1 of the appendix.

included among the explanatory variables are shown in columns (3) and (4). In interpreting the results, it must be remembered that the dummy variables for household income are defined so that their coefficients represent differences with respect to the base category (below €1,000 per month, expressed in euros of 2002/2003). Since some households contributed more than one individual to the sample, standard errors are clustered at the household level, but those in columns (3) and (4) are additionally robust to the presence of generated regressors.[9] In columns (2) and (4), which show the reduced-form probit regressions for internet adoption, an adjustment factor that allows the marginal effect of continuous variables and an approximation to the marginal effect of discrete variables to be computed, is also presented. The marginal effect of a probit model is

$$\frac{\partial \Pr\left(\text{adopt=1}\middle| S, w, X_1\right)}{\partial X_{1k}} = \phi\left(\gamma_1 S + \alpha_1 w + X_1 \beta_1\right)\beta_{1k}, \tag{3}$$

where the adjustment factor $\phi\left(\gamma_1 S + \alpha_1 w + X_1 \beta_1\right)$ was estimated by plugging in the parameter estimates and then averaging across individuals.

As to the quality of the internet usage information collected by the STUS, it is reassuring to find that the estimates in columns (1) and (2) agree generally with the patterns reported by Goldfarb and Prince (2008), the main exception being the effect of education on usage, which is positive (though small). As expected, the probability of internet adoption increases evenly with household income, and internet usage decreases as more income is available. (The decrease in usage is not continuous, for it presents a flat region in the range €2,000 - €4,999.99.) Thus, for example, an individual with household income in the range

[9] When $\hat{w}$ was statistically significant at or around 10 percent, all the standard errors were block-bootstrapped. The number of bootstrap replications was 1,499, as recommended by Davidson and MacKinnon (2000) for tests at level 0.01.

€2,000 - €2,499 is 0.194 more likely to have internet at home[10] and spends 4.7 minutes less online every day than a comparable individual with household income below €1,000.

The estimated effects of household income on both adoption and usage decrease only slightly when the predicted log of the hourly wage is included among the regressors. Thus, in comparison with the base category, an individual with household income in the range €2,000 - €2,499 is 0.184 more likely to have internet at home and spends 4.5 minutes less online every day. These estimates are precise and attain statistical significance at the 5 percent level or less. Since individuals' opportunity cost of time is now being held fixed, the inverse relationship between income and internet usage cannot be ascribed to a negative own-price effect. Rather, the results suggest that time spent online is an inferior leisure activity.

The wage rate is positively associated to the probability of adopting: holding household income fixed, a 1 percent increase in the hourly wage increases the probability by 0.003.[11] This estimate is precise and attains statistical significance at the 1 percent level. The same wage increase reduces time spent online by 0.6 percent on average, although this effect is imprecise. Interestingly, the positive effect of education on usage becomes larger after including the wage rate. Therefore, the omission of the latter imparts a downward bias on the importance of education in determining time spent online.

The wage rate may be a better measure of the opportunity cost of time for workers than for non-workers. Hence, I re-estimated equations (1) and (2) on the subsample of employed men aged 23-59. This group, moreover, can be considered as representative of the larger population of prime-age men, since 85.4 percent of them worked. The estimates, presented in Table 3, are consistent generally with those in Table 2, although they are

[10] This effect was computed with the finite-difference method.

[11] This effect was obtained as the product of the estimated coefficient associated to $\hat{w}$ times the adjustment factor divided by 100.

measured less precisely. When the wage rate is not included (columns (1) and (2)), the probability of internet adoption increases evenly in household income, and internet usage decreases as more income is available in the household. (Again, the decrease in usage is not uniform, but presents a reversion in the range €3,000 - €4,999.99.) Thus, a prime-age man with household income in the range €2,000 - €2,499 is 0.136 more likely to have internet at home and spends 6.4 minutes less online every day than a comparable individual with household income below €1,000. Including the wage rate (columns (3) and (4)) reduces these effects only slightly to 0.116 and 5.8, respectively. As to the effects of the wage rate itself, the results indicate that a 1 percent increase in the hourly wage increases the probability of adoption by 0.004 and reduces time spent online by 0.4 percent on average.[12] Again, the positive effect of education on usage becomes larger after including the wage rate.

Equations (1) and (2) were also re-estimated using time spent online from home as the empirical counterpart to I^*. As shown in Table 4, the main conclusions are preserved. The STUS interviewed all household members aged 10 years and older. Hence, 73.1 percent of the sample households contributed more than one individual to the sample. (This proportion is only 7.4 percent in the subsample of employed prime-age men.) Since different households can have different attitudes toward the internet, and these attitudes could be related to some of the explanatory variables, unobserved household heterogeneity could be playing some role in generating the results. To control for this possibility, I randomly selected one individual per

[12] Table A.2 in the appendix presents the results obtained with the log of W^* as the empirical counterpart to w. The wage effect on usage becomes positive ($\hat{\alpha}_2 = 2.5$, $S.E. = 1.7$), suggesting that time spent online is a Giffen good. Note, however, that $\hat{\alpha}_2$ might be incorrectly signed as a consequence of the presence of mean-reverting measurement error in W^* with large variance.

household and re-run the models in Table 2. Estimates, presented in Table 5, are consistent with the earlier results.

4. CONCLUSION

This paper has investigated the underlying mechanism behind the negative relationship between income and time spent online observed among internet adopters. In a variety of samples extracted from the time use survey conducted by the Spanish Statistical Office in 2002-2003, the size of the negative partial effect of income on the demand for time online barely changed when a measure of the hourly wage rate was included among the regressors. Hence, it appears that the negative effect of income on time spent online cannot be ascribed to the variation in the opportunity cost of time across income strata. Rather, it seems the result of time spent online being an inferior leisure activity. Consequently, money transfers to families that left unaltered the opportunity cost of time would reduce on average internet usage among adopters. On the other hand, the importance of education in determining time spent online was revised upwards when the wage rate was included among the regressors.

APPENDIX

TABLE A.1—HECKMAN-CORRECTED HOURLY EARNINGS (W*) REGRESSIONS

Independent variables	Women aged 16-74		Men aged 16-74	
	(1)	(2)	(3)	(4)
	Log of W*	Employed	Lof of W*	Employed
High school graduate	.156 (.022)***	.389 (.025)***	.196 (.010)***	.078 (.028)***
University/college	.522 (.035)***	.778 (.030)***	.594 (.014)***	.218 (.037)***
Age	.026 (.010)***	.199 (.005)***	.023 (.007)***	.261 (.005)***
Age^2	-.0002 (.0001)*	-.003 (.000)***	-.0002 (.0001)**	-.003 (.000)***
Married	.071 (.020)***	-.381 (.026)***	.134 (.013)***	.343 (.032)***
Foreigner	-.258 (.040)***	-.078 (.063)	-.308 (.027)***	-.175 (.075)**
In county seat	.049 (.013)***	.049 (.023)**	.077 (.010)***	-.030 (.026)
In other city with > 100,000 people	.023 (.023)	-.063 (.040)	.053 (.017)***	.033 (.045)
Andalucía	.102 (.033)***	-.218 (.068)***	-.028 (.030)	-.360 (.075)***
Asturias	.003 (.043)	-.016 (.087)	.020 (.041)	-.407 (.094)***
Baleares	.193 (.047)***	.389 (.094)***	.026 (.039)	.004 (.109)
Canarias	.143 (.038)***	.033 (.081)	.022 (.035)	-.209 (.090)**
Cantabria	.147 (.044)***	.058 (.087)	.095 (.035)***	-.219 (.095)**
Castilla y León	.098 (.040)**	-.089 (.079)	-.061 (.034)*	-.167 (.086)*
Castilla-La Mancha	.124 (.042)***	-.044 (.083)	.002 (.036)	-.002 (.096)
Cataluña	.098 (.034)***	.331 (.069)***	.049 (.030)*	.033 (.077)
Comunidad Valenciana	.068 (.036)*	.133 (.076)*	-.004 (.032)	-.089 (.085)
Extremadura	.037 (.051)	-.152 (.093)	-.151 (.042)***	-.425 (.102)***
Galicia	.014 (.038)	.150 (.073)**	-.098 (.034)***	-.286 (.081)***
Comunidad de Madrid	.162 (.033)***	.162 (.073)**	.087 (.032)***	-.026 (.083)
Región de Murcia	.029 (.042)	.007 (.091)	-.072 (.036)**	-.185 (.097)*
Navarra	.166 (.039)***	.194 (.081)**	.199 (.034)***	.146 (.093)
País Vasco	.256 (.047)***	.067 (.091)	.208 (.044)***	-.228 (.101)**
La Rioja	.083 (.047)*	.148 (.095)	-.034 (.037)	.174 (.111)
Ceuta y Melilla	.279 (.059)***	-.185 (.092)**	.135 (.043)***	-.237 (.109)**
Having a chronic illness		-.288 (.030)***		-.658 (.031)***
No. of kids < 6		-.073 (.009)***		
$\hat{\phi}/\hat{\Phi}$	.037 (.068)		.018 (.045)	
Intercept	.716 (.235)***	-3.44 (.12)***	.889 (.143)***	-4.00 (.12)***
R-Squared	.203		.279	
Log-Likelihood		-10,243.7		-8,062.2
Adjustment for marginal effects		.288		.248
Observations	7,437	20,347	10,863	17,958

Notes: The estimation method is OLS in columns (1) and (3) and Probit in columns (2) and (4). Standard errors clustered at the household level are in parentheses. Unreported categories: less than high school graduate, living in other city with ≤ 100,000 people, Aragón. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Source: Spanish Time Use Survey, 2002-2003, INE.

TABLE A.2—INTERNET ADOPTION AND HECKMAN-CORRECTED USAGE (MINUTES PER DAY). EMPLOYED MEN AGED 23-59

Independent variables	Control for respondent's hourly wage	
	(1) Personal usage	(2) Home adoption
Household income €1,000 – €1,499.99	1.0 (4.1)	.098 (.059)*
€1,500 – €1,999.99	-4.9 (3.8)	.213 (.061)***
€2,000 – €2,499.99	-7.7 (3.9)**	.362 (.066)***
€2,500 – €2,999.99	-8.7 (4.1)**	.405 (.074)***
€3,000 – €4,999.99	-6.3 (4.2)	.484 (.078)***
≥ €5,000	-8.7 (5.2)*	.498 (.140)***
Log of W^*	2.5 (1.7)	.160 (.037)***
High school graduate	6.6 (2.2)***	.400 (.035)***
University/college	5.0 (2.9)*	.602 (.054)***
Married	-2.3 (2.4)	.208 (.043)***
Age	-.4 (.1)***	.000 (.002)
Foreigner	10.8 (6.8)	-.256 (.097)***
In county seat	1.8 (1.7)	.149 (.034)***
In other city with > 100,000 people	.6 (2.5)	.188 (.055)***
No. of children in household	-.0 (.9)	-.040 (.020)**
Leisure (hrs. per day)	2.9 (.3)***	.004 (.005)
Teen in the home		.201 (.039)***
Owner		.190 (.048)***
No. of cell phones in household		.189(.016)***
Brings work home		.220 (.080)***
Telecommutes		.146 (.136)
$\hat{\phi}/\hat{\Phi}$	1.4 (4.2)	
Intercept	16.7 (10.0)*	-1.931 (.121)***
R-Squared	.075	
Log-Likelihood		-5,118.0
Adjustment for marginal effects		.298
Observations	3,384	9,681

Notes: The estimation method is OLS in column (1) and Probit in column (2). All estimations include 8 occupation dummies. Money variables are in euros of 2002/2003. Standard errors clustered at the household level are in parentheses. Unreported categories: household income < €1,000, less than high school graduate, living in other city with ≤ 100,000 people. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Source: Spanish Time Use Survey, 2002-2003, INE.

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TABLE 1—DESCRIPTIVE STATISTICS: 2002-2003 SPANISH TIME USE SURVEY

	Persons aged 16-74					Employed men aged 23-59				
Variable	Obs.	Mean	S.D.	Min	Max	Obs.	Mean	S.D.	Min	Max
Age	38305	44.4	16.1	16	74	9681	40.8	9.9	23	59
No. of children in household	38305	0.6	0.9	0	8	9681	0.8	0.9	0	8
Leisure (hrs. per day)	38305	4.8	3.0	0	20	9681	4.2	2.9	0	18.2
No. of cell phones in household	38305	1.7	1.3	0	16	9681	1.9	1.2	0	16
Observed average hourly wage[a]	18300	6.9	6.5	0.8	320	9681	6.9	5.5	0.9	163
Predicted average hourly wage	38305	6.6	1.8	2.7	14.9	9681	7.0	2.1	2.9	14.8
Variable (percentage)										
Internet adopted at home	38305	28.6				9681	35.0			
Net monthly household income < €500	38305	6.5				9681	0.9			
€500 - €999.99	38305	19.0				9681	11.0			
€1,000 – €1,499.99	38305	24.7				9681	24.9			
€1,500 – €1,999.99	38305	18.4				9681	21.7			
€2,000 – €2,499.99	38305	12.7				9681	16.8			
€2,500 – €2,999.99	38305	7.8				9681	10.2			
€3,000 – €4,999.99	38305	9.1				9681	12.1			
≥ €5,000	38305	1.8				9681	2.4			
Less than high school graduate	38305	62.2				9681	51.2			
High school graduate[b]	38305	23.5				9681	30.3			
University/college	38305	14.3				9681	18.5			
Married	38305	63.3				9681	70.8			
Female	38305	53.1				9681	0			
Foreigner	38305	2.7				9681	3.2			
In county seat	38305	37.3				9681	37.2			
In other city with > 100,000 people	38305	7.9				9681	8.2			
In other city with ≤ 100,000 people	38305	54.8				9681	54.6			
Manager						9681	8.4			
Technician/professional						9681	11.5			
Supporting technician/prof.						9681	11.7			
Clerical worker						9681	5.3			
Service worker[c]						9681	7.7			
Sales worker						9681	3.4			
Craftsman or related worker						9681	29.5			
Operator						9681	12.8			
Unskilled worker						9681	9.8			
Teen in the home	38305	27.5				9681	28.1			
Owner	38305	86.0				9681	84.9			
Brings work home						9681	5.0			
Telecommutes						9681	1.7			
Variable	Adopters aged 16-74					Adopters employed men 23-59				
Personal usage (min. per day)	10948	15.2	44.3	0	650	3384	16.2	42.5	0	530
Home usage (min. per day)	10948	14.9	44.0	0	650	3384	16.0	42.4	0	530
Age	10948	40.1	14.0	16	74	3384	41.6	9.6	23	59
No. of children in household	10948	0.7	0.9	0	8	3384	0.8	0.9	0	8
Leisure (hrs. per day)	10948	4.6	2.9	0	18.1	3384	4.3	2.9	0	18.2
Observed average hourly wage[a]	6407	8.2	6.9	0.8	320	3384	8.5	6.4	1.2	163
Predicted average hourly wage	10948	7.3	2.2	2.9	14.8	3384	8.0	2.3	3.3	14.8

Variable (percentage)				
Net monthly household income < €500	10948	1.0	3384	0.2
€500 - €999.99	10948	6.8	3384	4.6
€1,000 – €1,499.99	10948	18.1	3384	15.9
€1,500 – €1,999.99	10948	19.0	3384	19.2
€2,000 – €2,499.99	10948	18.6	3384	20.2
€2,500 – €2,999.99	10948	13.4	3384	14.2
€3,000 – €4,999.99	10948	18.7	3384	20.9
≥ €5,000	10948	4.4	3384	4.7
Less than high school graduate	10948	38.7	3384	31.2
High school graduate[b]	10948	32.3	3384	35.2
University/college	10948	28.9	3384	33.7
Married	10948	63.1	3384	74.7
Female	10948	51.2	3384	0
Foreigner	10948	1.8	3384	1.7
In county seat	10948	47.8	3384	46.1
In other city with > 100,000 people	10948	8.8	3384	8.8
In other city with ≤ 100,000 people	10948	43.4	3384	45.1
Manager			3384	11.6
Technician/professional			3384	22.0
Supporting technician/prof.			3384	17.9
Clerical worker			3384	6.1
Service worker[c]			3384	7.0
Sales worker			3384	3.7
Craftsman or related worker			3384	19.0
Operator			3384	9.0
Unskilled worker			3384	3.7

Notes: Money variables are in euros of 2002/2003. [a]: Workers only. [b]: Includes vocational training. [c]: Includes the military.

TABLE 2—INTERNET ADOPTION AND HECKMAN-CORRECTED USAGE (MINUTES PER DAY). PERSONS AGED 16-74

Independent variables	Heckman-usage: minutes online for personal reasons		Control for respondent's hourly wage	
	(1) Personal usage	(2) Home adoption	(3) Personal usage	(4) Home adoption
Household income €1,000 – €1,499.99	-2.0 (2.1)	.329 (.037)***	-1.9 (2.1)	.319 (.038)***
€1,500 – €1,999.99	-3.7 (2.1)*	.462 (.040)***	-3.6 (2.0)*	.442 (.041)***
€2,000 – €2,499.99	-4.7 (2.2)**	.665 (.045)***	-4.5 (2.2)**	.636 (.046)***
€2,500 – €2,999.99	-4.5 (2.4)*	.752 (.053)***	-4.2 (2.4)*	.724 (.055)***
€3,000 – €4,999.99	-4.5 (2.4)*	.854 (.053)***	-4.1 (2.5)*	.813 (.053)***
≥ €5,000	-7.3 (3.0)**	1.014 (.103)***	-6.9 (3.1)**	.961 (.105)***
Predicted log of hourly wage ($\hat{w}$)			-9.4 (5.9)	1.166 (.157)***
High school graduate	2.4 (1.2)**	.443 (.021)***	4.2 (1.4)***	.229 (.036)***
University/college	1.0 (1.4)	.822 (.026)***	6.4 (3.3)*	.174 (.093)*
Married	-5.0 (1.1)***	.221 (.025)***	-3.7 (1.3)***	.072 (.034)**
Age	-.6 (.0)***	-.005 (.001)***	-.5 (.1)***	-.013 (.001)***
Female	-9.0 (1.0)***	-.028 (.011)***	-9.6 (.9)***	.023 (.018)
Foreigner	10.8 (3.7)***	-.286 (.070)***	8.2 (4.0)**	.017 (.083)
In county seat	1.1 (1.0)	.239 (.026)***	1.8 (1.0)*	.153 (.030)***
In other city with > 100,000 people	1.4 (1.6)	.213 (.045)***	1.7 (1.5)	.171 (.047)***
No. of children in household	-1.4 (.5)***	-.033 (.016)**	-1.4 (.4)***	-.042 (.016)**
Leisure (hrs. per day)	3.1 (.2)***	.001 (.003)	3.1 (.2)***	.003 (.003)
Teen in the home		.262 (.032)***		.268 (.031)***
Owner		.186 (.038)***		.194 (.038)***
No. of cell phones in household		.208 (.014)***		.211 (.014)***
$\hat{\phi}/\hat{\Phi}$	-2.2 (2.0)		-2.0 (2.0)	
Intercept	36.1 (4.1)***	-1.881 (.063)***	47.1 (9.0)***	-3.291 (.202)***
R-Squared	.118		.118	
Log-Likelihood		-18,251.8		-18,172.8
Adjustment for marginal effects		.267		.266
Observations	10,948	38,305	10,948	38,305

Notes: The estimation method is OLS in columns (1) and (3) and Probit in columns (2) and (4). Money variables are in euros of 2002/2003. The individual's hourly wage has been predicted from a standard wage regression run on workers only, but accounting for possible selectivity into employment. Standard errors clustered at the household level are in parentheses; those in columns (3) and (4) are additionally robust to generated regressors. Unreported categories: household income < €1,000, less than high school graduate, living in other city with ≤ 100,000 people. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Source: Spanish Time Use Survey, 2002-2003, INE.

TABLE 3—INTERNET ADOPTION AND HECKMAN-CORRECTED USAGE (MINUTES PER DAY). EMPLOYED MEN AGED 23-59

Independent variables	Heckman-usage: minutes online for personal reasons		Control for respondent's hourly wage	
	(1) Personal usage	(2) Home adoption	(3) Personal usage	(4) Home adoption
Household income €1,000 – €1,499.99	1.7 (4.1)	.146 (.058)**	1.9 (4.1)	.120 (.060)**
€1,500 – €1,999.99	-3.8 (3.8)	.275 (.059)***	-3.5 (3.8)	.234 (.061)***
€2,000 – €2,499.99	-6.4 (3.9)	.438 (.063)***	-5.8 (3.9)	.379 (.065)***
€2,500 – €2,999.99	-7.1 (4.1)*	.493 (.071)***	-6.5 (4.1)	.434 (.073)***
€3,000 – €4,999.99	-4.2 (4.2)	.601 (.072)***	-3.5 (4.2)	.523 (.074)***
≥ €5,000	-5.8 (5.2)	.664 (.132)***	-5.1 (5.1)	.570 (.137)***
Predicted log of hourly wage ($\hat{w}$)			-7.1 (8.7)	1.479 (.195)***
High school graduate	7.1 (2.2)***	.417 (.035)***	8.7 (2.5)***	.114 (.054)**
University/college	5.9 (2.9)**	.642 (.053)***	10.3 (5.7)*	-.238 (.127)*
Married	-1.9 (2.5)	.227 (.043)***	-.8 (2.6)	.036 (.049)
Age	-.4 (.1)***	.001 (.002)	-.4 (.1)***	-.008 (.002)***
Foreigner	10.2 (6.8)	-.284 (.097)***	7.9 (7.1)	.127 (.110)
In county seat	1.9 (1.7)	.157 (.034)***	2.4 (1.7)	.039 (.039)
In other city with > 100,000 people	.9 (2.5)	.200 (.055)***	1.3 (2.4)	.119 (.058)**
No. of children in household	.1 (.9)	-.031 (.020)	.1 (.9)	-.042 (.019)**
Leisure (hrs. per day)	3.0 (.3)***	.008 (.005)	3.0 (.3)***	.007 (.005)
Teen in the home		.196 (.039)***		.203 (.039)***
Owner		.188 (.048)***		.188 (.047)***
No. of cell phones in household		.184 (.016)***		.194 (.017)***
Brings work home		.219 (.080)***		.226 (.082)***
Telecommutes		.131 (.135)		.145 (.135)
$\hat{\phi}/\hat{\Phi}$	2.1 (4.2)		2.8 (4.1)	
Intercept	17.4 (9.9)*	-1.788 (.115)***	24.9 (15.8)	-3.564 (.261)***
R-Squared	.075		.075	
Log-Likelihood		-5,128.0		-5,094.4
Adjustment for marginal effects		.299		.297
Observations	3,384	9,681	3,384	9,681

Notes: The estimation method is OLS in columns (1) and (3) and Probit in columns (2) and (4). All estimations include 8 occupation dummies. Money variables are in euros of 2002/2003. The individual's hourly wage has been predicted from a standard wage regression run on workers only, but accounting for possible selectivity into employment. Standard errors clustered at the household level are in parentheses; those in column (4) are additionally robust to generated regressors. Unreported categories: household income < €1,000, less than high school graduate, living in other city with ≤ 100,000 people. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Source: Spanish Time Use Survey, 2002-2003, INE.

TABLE 4—HECKMAN-CORRECTED INTERNET USAGE FROM HOME (MINUTES PER DAY)

Independent variables	Persons aged 16-74		Employed men aged 23-59	
	(1)	(2)	(3)	(4)
Household income €1,000 – €1,499.99	-2.2 (2.1)	-2.1 (2.1)	2.7 (4.0)	3.0 (4.0)
€1,500 – €1,999.99	-3.9 (2.0)*	-3.7 (2.0)*	-3.1 (3.7)	-2.7 (3.7)
€2,000 – €2,499.99	-4.8 (2.2)**	-4.6 (2.2)**	-5.9 (3.9)	-5.3 (3.8)
€2,500 – €2,999.99	-4.7 (2.4)**	-4.5 (2.4)*	-6.6 (4.0)	-6.0 (4.0)
€3,000 – €4,999.99	-4.4 (2.4)*	-4.1 (2.4)*	-3.3 (4.2)	-2.5 (4.1)
≥ €5,000	-6.8 (3.1)**	-6.4 (3.0)**	-4.3 (5.2)	-3.5 (5.1)
Predicted log of hourly wage ($\hat{w}$)		-7.8 (5.6)		-7.8 (8.7)
High school graduate	2.3 (1.2)**	3.8 (1.4)***	6.7 (2.2)***	8.4 (2.5)***
University/college	1.4 (1.4)	5.9 (3.0)*	5.3 (2.9)*	10.1 (5.7)*
Married	-4.6 (1.1)***	-3.6 (1.2)***	-1.7 (2.5)	-.5 (2.6)
Age	-.6 (.0)***	-.5 (.1)***	-.4 (.1)***	-.4 (.1)***
Female	-8.9 (.8)***	-9.4 (.9)***		
Foreigner	10.2 (3.6)***	8.1 (3.7)**	9.7 (6.6)	7.3 (6.9)
In county seat	1.2 (1.0)	1.7 (1.0)*	1.9 (1.7)	2.5 (1.7)
In other city with > 100,000 people	1.6 (1.6)	1.9 (1.6)	1.7 (2.5)	2.1 (2.5)
No. of children in household	-1.3 (.5)***	-1.3 (.5)***	.1 (.9)	.2 (.9)
Leisure (hrs. per day)	3.1 (.2)***	3.1 (.2)***	2.9 (.3)***	2.9 (.3)***
$\hat{\phi}/\hat{\Phi}$	-1.9 (2.0)	-1.7 (2.0)	1.4 (4.2)	2.1 (4.1)
Intercept	35.3 (4.1)***	44.4 (8.6)***	18.2 (9.9)*	26.4 (15.8)*
R-Squared	.114	.114	.073	.074
Observations	10,948	10,948	3,384	3,384

Notes: The estimation method is OLS in all columns. Money variables are in euros of 2002/2003. The individual's hourly wage has been predicted from a standard wage regression run on workers only, but accounting for possible selectivity into employment. Estimations (3) and (4) include 8 occupation dummies. Standard errors clustered at the household level are in parentheses. Unreported categories: household income < €1,000, less than high school graduate, living in other city with ≤ 100,000 people. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Source: Spanish Time Use Survey, 2002-2003, INE.

TABLE 5—INTERNET ADOPTION AND HECKMAN-CORRECTED USAGE (MINUTES PER DAY). ONE RANDOMLY SELECTED PERSON AGED 16-74 PER HOUSEHOLD

Independent variables	Heckman-usage: minutes online for personal reasons		Control for respondent's hourly wage	
	(1) Personal usage	(2) Home adoption	(3) Personal usage	(4) Home adoption
Household income €1,000 – €1,499.99	-1.5 (3.0)	.316 (.035)***	-1.3 (3.0)	.303 (.036)***
€1,500 – €1,999.99	-4.3 (3.1)	.475 (.038)***	-4.1 (3.1)	.456 (.039)***
€2,000 – €2,499.99	-5.0 (3.3)	.668 (.042)***	-4.6 (3.3)	.635 (.044)***
€2,500 – €2,999.99	-5.2 (3.7)	.791 (.049)***	-4.9 (3.6)	.764 (.051)***
€3,000 – €4,999.99	-6.0 (3.6)*	.883 (.050)***	-5.6 (3.6)	.839 (.053)***
≥ €5,000	-2.2 (4.8)	1.064 (.094)***	-1.7 (4.8)	1.013 (.096)***
Predicted log of hourly wage ($\hat{w}$)			-5.7 (7.9)	1.343 (.170)***
High school graduate	-.9 (1.7)	.456 (.028)***	.3 (2.0)	.210 (.044)***
University/college	.7 (2.0)	.860 (.033)***	4.0 (4.3)	.115 (.104)
Married	-5.6 (1.5)***	.198 (.028)***	-4.9 (1.7)***	.039 (.038)
Age	-.5 (.1)***	-.007 (.001)***	-.5 (.1)***	-.016 (.002)***
Female	-9.1 (1.2)***	-.063 (.023)***	-9.4 (1.4)***	.001 (.029)
Foreigner	11.5 (5.3)**	-.214 (.070)***	9.9 (5.5)*	.142 (.089)
In county seat	2.2 (1.4)	.182 (.024)***	2.6 (1.5)*	.083 (.029)***
In other city with > 100,000 people	-.4 (2.1)	.191 (.042)***	-.2 (2.1)	.145 (.045)***
No. of children in household	-1.2 (.6)**	-.023 (.016)	-1.2 (.6)*	-.035 (.015)**
Leisure (hrs. per day)	3.3 (.3)***	-.002 (.004)	3.3 (.3)***	.001 (.004)
Teen in the home		.243 (.030)***		.252 (.031)***
Owner		.161 (.034)***		.170 (.036)***
No. of cell phones in household		.223 (.011)***		.227 (.013)***
$\hat{\phi}/\hat{\Phi}$	-2.3 (2.8)		-1.9 (2.7)	
Intercept	34.1 (6.0)***	-1.786 (.067)***	40.5 (12.6)***	-3.431 (.224)***
R-Squared	.115		.115	
Log-Likelihood		-7,914.2		-7,867.8
Adjustment for marginal effects		.242		.241
Observations	4,568	18,206	4,568	18,206

Notes: The estimation method is OLS in columns (1) and (3) and Probit in columns (2) and (4). Money variables are in euros of 2002/2003. The individual's hourly wage has been predicted from a standard wage regression run on workers only, but accounting for possible selectivity into employment. Standard errors are in parentheses; those in columns (1) and (3) are robust to arbitrary heteroskedasticity and those in column (4) are robust to generated regressors. Unreported categories: household income < €1,000, less than high school graduate, living in other city with ≤ 100,000 people. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Source: Spanish Time Use Survey, 2002-2003, INE.