Disentangling income and price effects in the demand for time online

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Abstract

The large negative impact of income on time spent online has been attributed to a negative own-price effect created by variation in the opportunity cost of time across internet users. Nonetheless, the coefficient on income could also be capturing a negative income effect: High-income users could reduce time spent online to consume, for example, leisure activities of higher quality. This paper estimates a demand function for time online using a time-use survey containing information on household income and individual labor earnings. In accordance with the negative income effect hypothesis, income still exerts a large negative impact after earnings are controlled for, whereas the response to earnings is negative only in certain ranges of the earnings distribution.

JEL codes: J22; L86

Keywords: Internet usage; Shadow value of time; Spanish Time Use Survey; Type II Tobit model.

1 INTRODUCTION

The analyses of internet usage in the U.S. conducted by Goolsbee and Klenow (2006) and Goldfarb and Prince (2008) revealed that, conditional on having internet at home, low-income internet users spend more time online than comparable high-income users. For Europe, the same pattern has been reported by Pantea and Martens (2013), which led these authors to wonder whether the "digital divide" had been reversed. In the same vein, Orviska and Hudson (2009) found a negative effect of income on the probability of using certain internet applications. After evaluating four possible interpretations of this seemingly general pattern, Goldfarb and Prince (2008) concluded that the most likely explanation lay in the different opportunity cost of time: As, 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-wage 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 wages. Yet, Pantea and Martens (2013) have cast some doubt on this interpretation finding that the effect of income on time spent online is virtually the same whether people are working or not.

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 this is not clear *a priori*. The most obvious possibility is that high-income internet users demand more leisure and spend, as a result, more time online.[1] In this case, and given that the observed total effect is negative, the positive income effect would be overcome by the negative price effect. On the other hand, and following Becker's (1965) view of the household as a factory combining non-market time and market-purchased goods in order to produce utility-

[1] This possibility is implicitly controlled for when leisure time is included among the explanatory variables.

generating commodities, it is also conceivable that, as income increases, individuals opt to reduce their time spent online and consume, instead, leisure activities of higher quality, i.e. of higher expenditures on goods consumed in conjunction with leisure time. In this case, part of the inverse empirical association between income and time spent online would be driven by time online being an inferior leisure activity.

An additional caveat is that the income variable utilized in the micro-data studies of internet usage mentioned previously is household income, which was the only measure of income available in the selected surveys. Household income, however, is an error-ridden proxy for the survey respondent's wage rate, for certain household income components such as asset income or the partner's wage are not perfectly related to the respondent's wage. As is well known, the presence of measurement error in an explanatory variable tends to attenuate its estimated coefficient and to inadequately control for its confounding effect on the well-measured variables.

In this paper, we aim at estimating a model for the demand of time online that permits a clearer identification of income and price effects. Identifying the extent of these responses is a matter of non-trivial importance 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 (due, for example, to changes in the level of family benefits), and of variations in the opportunity cost of time that leave income almost unaffected (caused, for example, by predicted life-cycle variations in wages). This same belief underlay the study by Goel et al. (2006) assessing income and price-of-access elasticities for the prevalence of internet subscribers/users in OECD economies.

The remainder of the paper is organized as follows. Section 2 discusses the data and the methods employed. The collection by the same survey of information on internet adoption and usage and of information on household and individual income is relatively rare, but it did occur in Spain for 2002-2003. Section 3 presents the results. Finally, Section 4 offers a conclusion.

2 DATA AND METHODS

As in Goldfarb and Prince (2008), the internet adoption/usage decision is modeled here 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):

$$\Pr_i\left(\text{adopt}\right) = \Pr\left(\gamma_1 S_i + \alpha_1 W_i + X_{1i}\beta_1 + \varepsilon_{1i} \geq 0\right) = \Phi\left(\gamma_1 S_i + \alpha_1 W_i + X_{1i}\beta_1\right) \quad (1)$$

$$I^*\left(S_i, W_i, X_{2i}\right) = \gamma_2 S_i + \alpha_2 W_i + X_{2i}\beta_2 + \lambda \frac{\hat{\phi}_i}{\Phi_i} + \varepsilon_{2i} \quad (2)$$

where, I_i^* is individual i's time spent online for personal reasons; S_i, household income; W_i, a measure of i's wage rate; X_{1i}, a vector of controls including i's leisure time as well as an intercept; X_{2i}, a sub-vector of X_{1i}; $\frac{\hat{\phi}_i}{\Phi_i}$, the estimated inverse Mills ratio of the first-stage regression (1); and ε_{1i} and ε_{2i}, individual-specific error terms with ε_{1i} ~ Normal(0, 1). We depart from Goldfarb and Prince (2008) by including among the regressors a measure of the individual wage rate in addition to total household income.[2] The resulting specification of I^*

[2] The use of the wage rate to valuing the opportunity cost of time has been criticized as being overly simplistic, as it can only be equated to the opportunity cost of time when workers freely choose their market work time and there is no disutility of labor. However, this is the only viable approach given the available survey. Feather and Shaw (2000) derived the opportunity cost of time in the presence of fixed work time. Among others, Small et al.

resembles Mincer's (1963) specification of the labor market supply function for married women. In this way, 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 an inferior activity. Since the only cost of marginal internet usage is the foregone value of time, the parameter α_2 is capturing the own-price effect on the demand for I^*. As explained, for example, in Deaton and Muellbauer (1980, p. 91), α_2 decomposes into a substitution effect (s_{I^*W}) and an income effect, the latter created by the variation in the consumer's real wealth when W changes:

$$\alpha_2 = s_{I^*W} - \frac{\partial I^*}{\partial S} I^*. \tag{3}$$

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.

Data to estimate (1)-(2) are from the Spanish Time Use Survey (STUS) 2002-2003, a full-scale time use survey conducted in Spain. As is now standard around the world, the time use information in the STUS was collected by the time diary method.[3] Each person aged 10

(2005), Aguiar and Hurst (2007), and Phaneuf (2011) estimated the opportunity cost of time from decision margins other than the labor/leisure.

[3] The STUS development and design followed the guidelines established by Eurostat in 2000 though published in 2004, see Eurostat (2004) and Spanish Statistical Office (2004). To avoid seasonal distortion in the use of time, the survey was conducted over the course of one year, distributing the whole survey size evenly between October 2002 and September 2003. The average number of activity episodes per day (21.5), the very low prevalence of diaries with fewer than 7 activity episodes (0.1 percent), and the low presence of diaries missing two or

years or older in the interviewed households was asked to list the main activity in each 10-minute interval of a complete 24-hours cycle (the diary day). These activities were then classified by the survey agency into standardized Eurostat activity codes (listed in Annex VI of Eurostat, 2004). STUS respondents were also requested to record the use of internet when doing the activity (except for working time), an information which was then codified by the agency into a series of indicator variables, one indicator for each 10-minute interval. In principle, this information would make it possible to construct a very accurate measure of I^*. In practice, the use of internet is underreported: The proportion of 10-minute intervals spent on online household management, communication by computer, and reading news online, in which the internet use indicator equals "No" is 38.9 percent; the other type of measurement error, that the indicator takes on value "Yes" in the course of activities in which one would not expect that internet were being used (e.g., sleep, personal hygiene and dressing, and practicing sports) is virtually non-existent. As to the potential consequences of this underreporting in I^*, it is well-known that if its extent were unrelated to the true I^* and to the other variables of the model, it would just inflate the variance of ε_2 and bias in the negative direction the coefficient on the intercept. But if the underreporting increased with I^* (as the cross-diarists correlation, 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 indicator is "No" suggests), all estimated coefficients of equation (2) would be biased toward zero (Bound et al., 2001, p. 3715-3716). Previewing our results, the underreporting of I^* is not so large that precludes distinguishing the main patterns in the data.

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more basic activities (0.5 percent) indicate diary data of good quality (Juster, 1985; Robinson, 1985; Fisher et al. 2012).

As in Goldfarb and Prince (2008), our main measure of I^* is time spent online for personal reasons irrespective of location, expressed here in minutes per day. More specifically, this measure will sum 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 internet use indicator equals “Yes”. With the help of an additional variable that records the diarist’s location on the course of the dairy day, I will alternatively define usage as minutes spent online from home. As to the definition of the leisure measure included among the controls, this will gather all time spent during the diary day on social life and entertainment, sports and outdoor activities, hobbies and games, and mass media, which are activities that we cannot pay somebody else to do for us and that are not biological needs (Sevilla et al., 2012).

Besides information on the use of time, the STUS 2002-2003 collected several other characteristics of households and household members. Respondents who were working at the time of the survey were asked to report their net average monthly earnings using a sequence of brackets (listed in Table 1 below). Information on net average monthly household income (also in brackets) and on internet adoption (*[Is your household equipped with] internet connection?*) was provided by the household’s reference person. I shall use the answer to the question on adoption to construct a household internet adoption indicator. Variables S and W will be represented by sets of dummy variables whose cardinality is given by the number of answer alternatives in the corresponding survey question.[4,5]

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[4] The lowest two household income categories were aggregated together due to the low prevalence in our subsample of observations with household income below 500 euros per month.

[5] Although the STUS collected accurate information on the amount of hours worked during the week before the diary day, I do not utilize the hourly wage as the empirical counterpart of

Our main sample will include observations of persons aged 16-74, in accordance with the Eurostat standards in relation to information society indicators. I also discarded persons reporting fewer than 7 activity episodes on the diary day, missing two or more of the four basic activities defined in Fisher et al. (2012), declaring not having internet at home but positive time online from home, or presenting missing or inconsistent data in some other variable used in the study. All this leaves us with 38,305 individuals, residing in 18,206 households. Of these, 10,948 live in the 4568 households with internet connection. As explained in the next paragraph, the sample is further restricted for some specifications to employed men aged 23-59, which yields a sample size of 10,350 individuals residing in 9527 households. Of these, 3609 live in the 3313 households with internet connection. Table 1 presents characteristics of both samples. In the full sample, the adoption rate is 28.6 percent, a figure increasing to 30.3 percent when observations are 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 the Spanish Statistical Office but lacking information on individual labor earnings) is 31.2 percent. Among adopters, the average respondent uses the internet 15.2 minutes per day for personal reasons, the weighted mean being 16.6 minutes per day, i.e. 1.9 hours per week. The population average calculated from the ICT-H is 5.4 hours per week.[6] There are three reasons why the difference between these two estimates may be exceeding the extent of

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W because, as monthly earnings are measured imprecisely, the resulting hourly wage would be measured with error.

[6] ICT-H respondents are asked to report if their time spent online falls within a sequence of intervals. My 5.4 hours estimate was computed taking the midpoint of each interval with the exception of respondents claiming more than 50 hours per week, to whom a value of 65 hours was assigned.

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 (e.g., *how long have you used the internet in the last week/three months?*), a method which commonly produces higher estimates than the time diary (see, e.g., Juster et al., 2003, and references cited therein). Third, in some 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. Of the 15.2 minutes spent online per day on average, 13.8 pertain to communication and information by computer, so that the biggest part of I^* is made up of leisure.

Labor earnings are observed only if the person works. This fact can introduce a potential sample selection problem if we use data only on workers to estimate equations (1) and (2). To overcome this problem, I try two different strategies. First, I run interval regression models (one for males and other for females) for the interval-coded earnings data in order to predict a labor earnings category for non-workers in the age range 16-74. The vector of explanatory variables is here made up of educational categories, age and its quadratic,[7] a foreigner indicator, the group unemployment rate (groups are defined by region, trimester, sex, and age interval), and an intercept. Alternatively, I estimate equations (1)-(2) on the subsample of employed men aged 23-59. As 85.4 percent of these men work, sample selection issues seem less significant for this group.

Included in X_2 are: educational category, whether the respondent is currently married, age, whether the respondent is female, whether the respondent is foreigner, city size category, number of children in the household, leisure time on the diary day (measured in hours), and an intercept. Additionally, X_1 includes: whether a teenager lives in the household, number of

[7] Information on actual labor force experience is not available in the STUS 2002-2003.

cell phones owned by the household (which I view as a proxy for optimism toward technology), and whether the household owns the home (I guess owners are more likely to bear technology installation costs). In the subsample, 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.

Before proceeding with the results, an issue requires some discussion. The Type II Tobit model is a model for sample selection, that is, it assumes I^* is observed only when the household has adopted the internet. Our situation, however, is different, because individual time spent online can be observed even when the household has not adopted. It is also possible that $I^* = 0$ even if the household has adopted. In our main sample, for instance, 82.0 percent of respondents living in households with internet connection did not use internet on the diary day. (That proportion is zero in Goldfarb and Prince (2008) because their survey asked for usual weekly hours spent online and because the authors took the midpoint of each response interval.) As the equation for I^* in the Type II Tobit model is linear in parameters, it could not suit well the data when the proportion of observations with $I^* = 0$ is non-trivial. The reason why I have estimated a Type II Tobit model is because models for corner solution responses 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 have 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 respondent's decision about using internet on the diary day, which is quite different from the household's decision about adopting internet.

3 RESULTS

For comparison purposes, columns (1) and (2) of Table 2 show the estimation results of the Type II Tobit specification presented in the first two columns of Goldfarb and Prince (2008, Table 2), but now obtained on our full sample. Results with individual labor earnings included among the explanatory variables are presented in columns (3) and (4) of that table. The sets of dummy variables for household income and individual labor earnings have been defined so that their coefficients are measuring differences with respect to the corresponding base case: below €1000 per month in the case of household income and less than €500 per month for labor earnings, both expressed in euros of 2002/2003. In all columns of Table 2, and given that there are households contributing more than one diarist to the sample, standard errors, shown in parentheses, are clustered at the household level. In columns (2) and (4), which show the reduced-form probit regressions for the household internet adoption decision, 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

$$\frac{\partial \Pr\left(\text{adopt=1}\middle| S, W, X_1\right)}{\partial X_{1k}} = \phi\left(\gamma_1 S + \alpha_1 W + X_1 \beta_1\right) \beta_{1k}\,, \tag{4}$$

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

Particularly as regards to the quality of the data on I^* provided by the STUS 2002-2003, it is reassuring to find that the estimates in columns (1) and (2) are generally consistent with Goldfarb and Prince's results. The main exception to this is the effect of education on usage, which is positive (but small). Thus, although the estimated coefficients of equation (2) could be here attenuated and measured less precisely than they could, the underreporting of I^* does not seem so large that precludes distinguishing the main patterns in the data. Observing the effect of household income, we see, as expected, that the probability of internet adoption increases almost evenly in this variable, and that internet usage decreases as more income is available. This decrease, however, is not continuous, for it presents a flat region in the range €2000 - €4999.99.

Estimates experience little change when labor earnings are included among the regressors (see columns (3) and (4) of Table 2). Again, the main exception to this is the positive effect of education on internet usage, which becomes larger and statistically significant once earnings are controlled for. As to the household income indicators, their estimated coefficients decrease only slightly in both the adoption and usage equations. Hence, and given that we are now holding fixed the respondent's labor earnings category, which can be considered a proxy for the respondent's opportunity price of internet usage, the inverse relationship between household income and usage seems the result of time spent online being an inferior leisure activity. The estimated effect of labor earnings on time spent online presents, in general, negative sign, although usage does not decrease uniformly as labor earnings increase. Indeed, the reduction in usage of just 2 minutes estimated for a person earning at least €3000 per month in comparison with a similar person earning less than €500 does not attain statistical significance. Interestingly, keeping constant household income the probability of internet adoption tends to increase with the respondent's labor earnings.

Nonetheless, these results must be interpreted with caution. As explained in the previous section, for non-workers the labor earnings interval was predicted from an interval earnings regression run separately on male and female workers. The evidence, however, suggests that the samples of workers are non-representative of the underlying populations of men and women aged 16-74, whereby the estimator of the interval earnings regression might be inconsistent. To reach this conclusion, I ran reduced-form probits for working in the market (one probit for men and other for women), using all observations of workers and non-workers. Besides the explanatory variables considered in the interval earnings regression, I included an indicator of chronic health problems and, in the case of women, the number of young children in the household, as additional predictors for being working. From these probits, I obtained for each worker the estimated inverse Mills ratio, which was then plugged in the corresponding interval earnings regression. Under the null of no sample selection, the coefficient on the inverse Mills ratio should be zero (see Wooldridge, Forthcoming, for the justification of this test).[8] But in the case of both male and female workers, the *p*-value of the test (0.00) is well below standard significance levels.

Hence, I have re-estimated the models in Table 2 on the subsample of employed men aged 23-59. Since, by construction, all respondents in this group are employed, their earnings interval is observed, and thus there is no need to predict it. Table 3 presents the results. Looking first at columns (1) and (2), which do not control for individual labor earnings, parameter estimates are consistent generally with those in Table 2, although they are now measured less precisely. Therefore, the patterns of internet adoption and usage among prime-age male workers do not appear to differ much from the behavior observed in the whole sample. Workers with at least a high school diploma devote some 6 minutes more per day to internet than comparable workers who did not graduate from high school. As to the effect of household income, we find, again, that the probability of internet adoption increases evenly in this variable, and that internet usage tends to decrease as more income is available. This decrease, however, is not uniform, but presents reversions in the ranges €1000 - €1499.99 and €3000 - €4999.99. It is surprising that the estimated household income effects in the usage equation are smaller in most cases than those shown in Table 2, even though household income seems *a priori* a better proxy for a worker's price of internet usage than for a non-worker. When labor earnings are controlled for, (columns (3) and (4) of Table 3), time spent

[8] While the inclusion of the inverse Mills ratio term in the second-stage interval earnings regression serves as a test of sample selection, it does not correct for sample selection.

online for personal reasons tends to decrease with household income, and now the effect becomes somewhat larger. As in the whole sample, the inverse relationship between internet usage and household income seems the result of a negative income effect on the demand for time spent online. Regarding the effect of labor earnings, usage, again, does not decrease uniformly as labor earnings increase, although most workers earning at least €500 per month spend less time online than a comparable worker with a pay of less than €500. The difference, however, is measured imprecisely and does not attain statistical significance.

These results appear to be robust to a variety of alternative specifications. The model in expressions (1) and (2) was 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 2002-2003 interviewed all persons of 10 years or older living in the surveyed households. Thus, 73.1 percent of the households in the full sample contribute more than one diarist to the sample. (This proportion is much smaller in the subsample: only 7.8 percent.) As different households may have different attitudes toward the internet, and these attitudes may, in turn, 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 diarist per household and re-run the models in Table 2. Results are presented in Table 5. The effect of education on internet usage becomes not statistically different from zero. The other estimates do not change much, though they are less precisely measured.

In accordance with previous studies, the preceding results indicate that subsidizing home internet access has a favorable impact on household adoption rates. But our main results also suggest that money transfers to families that leave unaltered internet users' opportunity cost of time will reduce internet usage among adopters. What do higher income adopters do with the extra time not spent online? Although investigating this issue is beyond the scope of the paper, the charts assembled in Figure 1 suggest that part of the extra time could be spent on alternative offline leisure activities. Most of these activities will have to be of higher quality, as virtually no goods are consumed in conjunction with time online.

4 CONCLUSIONS

The size of the negative partial effect of income on the demand for time online observed among Spanish internet users barely changes when a measure of the individual wage rate is included among the regressors. This result indicates that the variation in the opportunity cost of time across income groups is not driving that effect, which seems, rather, the consequence of time spent online being an inferior leisure activity. Using the labor/leisure margin of decision to approximate the opportunity cost of internet usage, we also find that the own-price effect in the demand for time online is negative only in certain ranges of the wage distribution, and that the effect of education on internet usage is mixed: While education exerts a positive effect on usage among employed men of prime age, it has almost no impact when the group of all persons aged 16-74 is considered.

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REFERENCES

Aguiar, Mark, and Erik Hurst. 2007. Life-cycle prices and production. *The American Economic Review* 97(5):1533-1559.

Amemiya, T. 1985. *Advanced Econometrics*. Cambridge, MA: Harvard University Press.

Becker, Gary S. 1965. A theory of the allocation of time. *The Economic Journal* 75:493-517.

Bound, John, Charles Brown, and Nancy Mathiowetz. 2001. Measurement error in survey data. In *Handbook of Econometrics, Vol. 5*, ed. J.J. Heckman and E. Leamer. Amsterdam: Elsevier Science B.V.

Deaton, Angus, and John Muellbauer. 1980. *Economics and consumer behavior*. Cambridge University Press, reprinted 1999.

Eurostat. 2004. *Guidelines on harmonized European time use surveys*. Luxembourg: Office for Official Publications of the European Communities.

Feather, Peter M., and W. Douglass Shaw. 2000. The demand for leisure time in the presence of constrained work hours. *Economic Inquiry* 38(4):651-661.

Fisher, Kimberly, Jonathan Gershuny, Evrim Altintas, and Anne H. Gauthier. 2012. *Multinational Time Use Study. User's Guide and Documentation. Version 5 – updated*. University of Oxford.

Goel, Rajeev K., Edward T. Hsieh, Michael A. Nelson, and Rati Ram. 2006. Demand elasticities for internet services. *Applied Economics* 38:975-980.

Goldfarb, Avi, and Jeff Prince. 2008. Internet adoption and usage patterns are different: Implications for the digital divide. *Information Economics and Policy* 20:2-15.

Goolsbee, Austan, and Peter J. Klenow. 2006. Valuing consumer products by the time spent using them: An application to the Internet. *The American Economic Review* 96(2):108-113.

Juster, F. Thomas. 1985. The validity and quality of time use estimates obtained from recall diaries. In *Time, Goods, and Well-Being*, edited by F. Thomas Juster and Frank P. Stafford, pp.63-92. Institute for Social Research, University of Michigan.

Juster, F. Thomas, Hiromi Ono, and Frank P. Stafford. 2003. An assessment of alternative measures of time use. *Sociological Methodology* 33:19-54.

Mincer, Jacob. 1963. Market prices, opportunity costs, and income effects. In *Measurement in Economics: Studies in Mathematical Economics and Econometrics in Memory of Yehuda Grunfeld*, edited by C. Christ et al. Stanford, California: Stanford University Press.

Orviska, Marta, and John Hudson. 2009. Dividing or uniting Europe? Internet usage in the EU. *Information Economics and Policy* 21:279-290.

Pantea, Smaranda, and Bertin Martens. 2013. Has the digital divide been reversed? Evidence from five EU countries. Institute for Prospective Technological Studies, Digital Economy Working Paper 2013/06. Luxembourg: Publications Office of the European Union.

Phaneuf, Daniel J. 2011. Can consumption of convenience products reveal the opportunity cost of time? *Economics Letters* 113:92-95.

Robinson, John P. 1985. The validity and reliability of diaries versus alternative time use measures. In *Time, Goods, and Well-Being*, edited by F. Thomas Juster and Frank P. Stafford, pp.33-62. Institute for Social Research, University of Michigan.

Sevilla, Almudena, Jose I. Gimenez-Nadal, and Jonathan Gershuny. 2012. Leisure inequality in the United States: 1965-2003. *Demography* 49(3):939-964.

Small, Kenneth A., Clifford Winston, and Jia Yan. 2005. Uncovering the distribution of motorists' preferences for travel time and reliability. *Econometrica* 73(4):1367-1382.

Spanish Statistical Office. 2004. *Encuesta de Empleo del Tiempo 2002-2003 – Proyecto Metodológico y Resultados Nacionales*. Madrid, Spanish Statistical Office.

Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data*, second edition. Cambridge, MA: The MIT Press.

Wooldridge, Jeffrey M. Forthcoming. Quasi-Maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. *Journal of Econometrics*.

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

	Full sample (all respondents 16-74)					Subsample (employed men 23-59)				
Variable	Obs.	Mean	Std dev	Min	Max	Obs.	Mean	Std dev	Min	Max
Personal usage for adopters (min. per day)	10948	15.16	44.29	0	650	3609	15.99	42.40	0	530
Home usage for adopters (min. per day)	10948	14.95	44.03	0	650	3609	15.86	42.33	0	530
Age	38305	44.43	16.14	16	74	10350	40.90	9.87	23	59
Number of children in household	38305	0.62	0.89	0	8	10350	0.79	0.94	0	8
Leisure time (hrs. per day)	38305	4.80	2.95	0	20	10350	4.26	2.91	0	18.2
Number of cell phones in household	38305	1.68	1.30	0	16	10350	1.89	1.22	0	16
Variable (percentage)										
Internet adopted at home	38305	28.58				10350	34.87			
Household net monthly income < €1000	38305	25.53				10350	12.46			
€1000 - €1499.99	38305	24.69				10350	24.72			
€1500 - €1999.99	38305	18.39				10350	21.49			
€2000 - €2499.99	38305	12.67				10350	16.58			
€2500 - €2999.99	38305	7.83				10350	10.14			
€3000 - €4999.99	38305	9.08				10350	12.14			
≥ €5000	38305	1.82				10350	2.47			
Respondent's net monthly earnings <€500	19742	13.29				10350	4.57			
€500 - €999.99	19742	39.48				10350	34.76			
€1000 - €1249.99	19742	21.42				10350	27.47			
€1250 - €1499.99	19742	10.65				10350	13.57			
€1500 - €1999.99	19742	9.08				10350	11.13			
€2000 - €2499.99	19742	3.36				10350	4.69			
€2500 - €2999.99	19742	1.12				10350	1.65			
≥ €3000	19742	1.60				10350	2.15			
Less than high school graduate	38305	62.20				10350	51.38			
Exactly high school graduate	38305	17.19				10350	20.26			
More than high school graduate	38305	20.61				10350	28.36			
Married	38305	63.32				10350	70.73			
Female	38305	53.12				10350	0			
Foreigner	38305	2.74				10350	3.22			
In county seat	38305	37.3				10350	36.83			
In other city with > 100,000 people	38305	7.92				10350	8.06			
In other city with ≤ 100,000 people	38305	54.76				10350	55.11			
Manager						10350	9.10			
Technician/professional						10350	11.32			
Supporting technician/professional						10350	12.00			
Administrative worker						10350	5.11			
Service worker						10350	10.06			
Craftsman						10350	29.47			
Operator						10350	12.64			
Unskilled worker						10350	10.30			
Teen in the home	38305	27.46				10350	28.11			
Owner	38305	85.97				10350	85.00			
Brings work home						10350	5.13			
Telecommutes						10350	1.86			

Notes: Money variables are in euros of 2002/2003. Labor earnings pertain to the main job.

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

Independent variables	Heckman-usage defined as minutes online for personal reasons		Control for respondent's earnings	
	(1) Personal usage	(2) Home adoption	(3) Personal usage	(4) Home adoption
Household income €1000 - €1499.99	-2.15 (2.07)	0.329 (0.037)***	-1.93 (2.08)	0.318 (0.038)***
€1500 - €1999.99	-3.99 (2.06)*	0.466 (0.040)***	-3.63 (2.07)*	0.441 (0.041)***
€2000 - €2499.99	-5.10 (2.21)**	0.674 (0.045)***	-4.45 (2.25)**	0.641 (0.046)***
€2500 - €2999.99	-4.99 (2.43)**	0.771 (0.053)***	-4.44 (2.46)*	0.709 (0.054)***
€3000 - €4999.99	-5.13 (2.45)**	0.887 (0.052)***	-4.52 (2.49)*	0.792 (0.055)***
≥ €5000	-8.11 (3.08)***	1.054 (0.103)***	-8.09 (3.15)**	0.922 (0.108)***
Respondent's earnings €500 - €999.99			-5.48 (1.64)***	-0.055 (0.025)**
€1000 - €1249.99			-5.74 (1.99)***	-0.040 (0.033)
€1250 - €1499.99			-4.42 (2.05)**	0.168 (0.041)***
€1500 - €1999.99			-5.25 (2.11)**	0.227 (0.044)***
€2000 - €2499.99			-7.47 (2.46)***	0.181 (0.063)***
€2500 - €2999.99			-6.1 (3.11)**	0.358 (0.102)***
≥ €3000			-2.01 (3.17)	0.315 (0.096)***
Exactly high school graduate	1.66 (1.29)	0.435 (0.022)***	2.47 (1.29)*	0.419 (0.023)***
More than high school graduate	1.68 (1.25)	0.707 (0.022)***	2.68 (1.31)**	0.642 (0.024)***
Married	-5.00 (1.12)***	0.215 (0.025)***	-4.47 (1.11)***	0.202 (0.025)***
Age	-0.57 (0.04)***	-0.005 (0.001)***	-0.54 (0.04)***	-0.006 (0.001)***
Female	-8.98 (0.77)***	-0.020 (0.011)*	-9.38 (0.89)***	0.024 (0.014)*
Foreigner	10.77 (3.69)***	-0.264 (0.069)***	10.40 (3.69)***	-0.246 (0.069)***
In county seat	0.96 (0.99)	0.251 (0.026)***	1.05 (0.99)	0.245 (0.026)***
In other city with > 100,000 people	1.36 (1.56)	0.217 (0.045)***	1.46 (1.55)	0.213 (0.045)***
Number of children in household	-1.46 (0.46)***	-0.030 (0.016)*	-1.57 (0.46)***	-0.040 (0.016)**
Leisure time (hrs. per day)	3.14 (0.22)***	0.002 (0.003)	3.12 (0.22)***	0.003 (0.003)
Teen in the home		0.263 (0.032)***		0.255 (0.032)***
Owner		0.182 (0.038)***		0.186 (0.038)***
Number of cell phones in household		0.206 (0.014)***		0.210 (0.014)***
$\hat{\phi}/\hat{\Phi}$	-2.68 (1.99)		-2.11 (1.97)	
Intercept	37.19 (4.15)***	-1.914 (0.063)***	39.13 (4.11)***	-1.858 (0.065)***
R-Squared	0.118		0.119	
Log-Likelihood		-18,311.4		-18,250.1
Adjustment factor for marginal effects		0.268		0.267
Number of 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). Standard errors clustered at the household level are in parentheses. Non-workers' labor earnings have been predicted from an interval earnings regression run on workers only. Unreported categories: in columns (1) and (2), household income < €1000, less than high school graduate, and living in other city with ≤ 100,000 people; in columns (3) and (4), those in columns (1) and (2) plus respondent's earnings < €500. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

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

Independent variables	Heckman-usage defined as minutes online for personal reasons		Control for respondent's earnings	
	(1) Personal usage	(2) Home adoption	(3) Personal usage	(4) Home adoption
Household income €1000 - €1499.99	2.87 (3.85)	0.148 (0.055)***	2.34 (4.06)	0.097 (0.060)
€1500 - €1999.99	-2.25 (3.58)	0.285 (0.056)***	-3.09 (3.78)	0.215 (0.062)***
€2000 - €2499.99	-3.93 (3.77)	0.459 (0.060)***	-4.68 (4.00)	0.376 (0.067)***
€2500 - €2999.99	-5.11 (3.94)	0.522 (0.068)***	-6.30 (4.19)	0.421 (0.075)***
€3000 - €4999.99	-2.12 (4.05)	0.614 (0.069)***	-3.92 (4.32)	0.476 (0.079)***
≥ €5000	-3.60 (5.01)	0.718 (0.126)***	-7.19 (5.08)	0.516 (0.145)***
Respondent's earnings €500 - €999.99			-7.31 (6.00)	0.063 (0.076)
€1000 - €1249.99			-6.60 (6.20)	0.106 (0.081)
€1250 - €1499.99			-3.94 (6.28)	0.218 (0.086)**
€1500 - €1999.99			-3.76 (6.27)	0.235 (0.090)***
€2000 - €2499.99			-5.73 (6.41)	0.253 (0.104)**
€2500 - €2999.99			-4.44 (6.79)	0.306 (0.141)**
≥ €3000			0.80 (6.97)	0.432 (0.144)***
Exactly high school graduate	5.78 (2.32)**	0.363 (0.038)***	5.26 (2.33)**	0.350 (0.038)***
More than high school graduate	5.94 (2.36)**	0.560 (0.040)***	5.22 (2.39)**	0.536 (0.040)***
Married	-1.57 (2.36)	0.243 (0.041)***	-1.90 (2.34)	0.221 (0.042)***
Age	-0.45 (0.09)***	0.001 (0.002)	-0.47 (0.09)***	-0.001 (0.002)
Foreigner	9.44 (6.18)	-0.246 (0.092)***	10.01 (6.23)	-0.225 (0.091)**
In county seat	1.70 (1.63)	0.169 (0.033)***	1.59 (1.63)	0.164 (0.033)***
In other city with > 100,000 people	1.74 (2.48)	0.205 (0.054)***	1.40 (2.47)	0.197 (0.054)***
Number of children in household	-0.05 (0.84)	-0.032 (0.019)*	-0.14 (0.86)	-0.043 (0.019)**
Leisure time (hrs. per day)	2.95 (0.33)***	0.005 (0.005)	2.94 (0.33)***	0.005 (0.005)
Teen in the home		0.183 (0.038)***		0.186 (0.038)***
Owner		0.205 (0.046)***		0.210 (0.046)***
Number of cell phones in household		0.184 (0.015)***		0.189 (0.016)***
Brings work home		0.214 (0.076)***		0.211 (0.076)***
Telecommutes		0.161 (0.126)		0.167 (0.127)
$\hat{\phi}/\hat{\Phi}$	2.57 (4.12)		1.93 (4.05)	
Intercept	14.64 (9.59)	-2.063 (0.096)***	23.83 (11.11)**	-2.031 (0.115)***
R-Squared	0.073		0.075	
Log-Likelihood		-5473.9		-5462.3
Adjustment factor for marginal effects		0.298		0.298
Number of observations	3609	10,350	3609	10,350

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. All regressions include occupation fixed effects. Unreported categories: in columns (1) and (2), household income < €1000, less than high school graduate, and living in other city with ≤ 100,000 people; in columns (3) and (4), those in columns (1) and (2) plus respondent's earnings < €500. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

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

Independent variables	All persons aged 16-74		Employed men aged 23-59	
	(1)	(2)	(3)	(4)
Household income €1000 - €1499.99	-2.31 (2.07)	-2.21 (2.08)	3.81 (3.77)	3.46 (3.98)
€1500 - €1999.99	-4.05 (2.05)**	-3.85 (2.07)*	-1.54 (3.49)	-2.34 (3.70)
€2000 - €2499.99	-5.08 (2.21)**	-4.62 (2.25)**	-3.50 (3.69)	-4.07 (3.92)
€2500 - €2999.99	-5.13 (2.42)**	-4.87 (2.45)**	-4.71 (3.84)	-5.75 (4.09)
€3000 - €4999.99	-4.91 (2.45)**	-4.57 (2.50)*	-1.23 (3.98)	-2.77 (4.26)
≥ €5000	-7.36 (3.09)**	-7.54 (3.17)**	-2.38 (4.99)	-5.44 (5.08)
Respondent's earnings €500 - €999.99		-5.08 (1.63)***		-6.42 (6.03)
€1000 - €1249.99		-5.09 (1.97)***		-6.10 (6.22)
€1250 - €1499.99		-3.40 (2.06)*		-3.43 (6.30)
€1500 - €1999.99		-4.35 (2.13)**		-2.66 (6.30)
€2000 - €2499.99		-7.01 (2.41)***		-5.63 (6.39)
€2500 - €2999.99		-4.51 (3.30)		-4.30 (6.80)
≥ €3000		-1.70 (3.18)		0.76 (7.00)
Exactly high school graduate	1.81 (1.29)	2.48 (1.29)*	5.56 (2.33)**	5.08 (2.33)**
More than high school graduate	1.82 (1.25)	2.53 (1.31)*	5.28 (2.35)**	4.63 (2.38)*
Married	-4.66 (1.12)***	-4.24 (1.11)***	-1.43 (2.36)	-1.75 (2.34)
Age	-0.56 (0.04)***	-0.53 (0.04)***	-0.46 (0.09)***	-0.48 (0.09)***
Female	-8.94 (0.77)***	-9.18 (0.89)***		
Foreigner	10.20 (3.55)***	9.94 (3.54)***	9.10 (6.04)	9.60 (6.09)
In county seat	1.05 (1.00)	1.11 (0.99)	1.73 (1.63)	1.65 (1.63)
In other city with > 100,000 people	1.54 (1.59)	1.59 (1.59)	2.49 (2.54)	2.18 (2.53)
Number of children in household	-1.34 (0.46)***	-1.46 (0.46)***	-0.07 (0.84)	-0.13 (0.87)
Leisure time (hrs. per day)	3.07 (0.21)***	3.05 (0.22)***	2.88 (0.33)***	2.87 (0.32)***
$\hat{\phi}/\hat{\Phi}$	-2.21 (1.99)	-1.79 (1.97)	1.85 (4.12)	1.24 (4.05)
Intercept	36.07 (4.13)***	38.14 (4.09)***	15.71 (9.59)	23.88 (11.09)**
R-Squared	0.114	0.115	0.072	0.074
Number of observations	10,948	10,948	3609	3609

Notes: The estimation method is OLS in all columns. Standard errors clustered at the household level are in parentheses. In regressions (1) and (2), non-workers' labor earnings have been predicted from an interval earnings regression run on workers only. Regressions in columns (3) and (4) include occupation fixed effects. Unreported categories: in columns (1) and (3), household income < €1000, less than high school graduate, and living in other city with ≤ 100,000 people; in columns (2) and (4), those in columns (1) and (3) plus respondent's earnings < €500. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

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

Independent variables	Heckman-usage defined as minutes online for personal reasons		Control for respondent's earnings	
	(1) Personal usage	(2) Home adoption	(3) Personal usage	(4) Home adoption
Household income €1000 - €1499.99	-1.14 (2.96)	0.314 (0.035)***	-0.90 (3.02)	0.297 (0.036)***
€1500 - €1999.99	-3.78 (2.97)	0.479 (0.038)***	-3.37 (2.99)	0.442 (0.039)***
€2000 - €2499.99	-5.57 (3.12)*	0.683 (0.042)***	-4.84 (3.20)	0.636 (0.043)***
€2500 - €2999.99	-2.68 (3.47)	0.817 (0.049)***	-2.26 (3.51)	0.741 (0.051)***
€3000 - €4999.99	-5.03 (3.50)	0.945 (0.049)***	-4.56 (3.59)	0.846 (0.053)***
≥ €5000	-3.65 (4.61)	1.119 (0.093)***	-4.33 (4.61)	0.999 (0.101)***
Respondent's earnings €500 - €999.99			-4.61 (2.45)*	0.036 (0.040)
€1000 - €1249.99			-5.36 (2.87)*	0.054 (0.050)
€1250 - €1499.99			-4.06 (3.04)	0.237 (0.059)***
€1500 - €1999.99			-4.84 (3.23)	0.288 (0.065)***
€2000 - €2499.99			-8.04 (3.53)**	0.265 (0.090)***
€2500 - €2999.99			0.89 (5.21)	0.452 (0.155)***
≥ €3000			-1.49 (4.66)	0.257 (0.127)**
Exactly high school graduate	-0.34 (1.86)	0.474 (0.031)***	0.33 (1.82)	0.453 (0.031)***
More than high school graduate	-0.33 (1.81)	0.738 (0.029)***	0.57 (1.80)	0.668 (0.032)***
Married	-4.98 (1.57)***	0.182 (0.028)***	-4.59 (1.54)***	0.175 (0.028)***
Age	-0.56 (0.06)***	-0.006 (0.001)***	-0.53 (0.06)***	-0.007 (0.001)***
Female	-10.54 (1.22)***	-0.028 (0.023)	-10.93 (1.45)***	0.024 (0.026)
Foreigner	15.12 (5.60)***	-0.223 (0.073)***	14.88 (5.61)***	-0.199 (0.073)***
In county seat	2.28 (1.39)	0.190 (0.024)***	2.43 (1.39)*	0.185 (0.024)***
In other city with > 100,000 people	0.19 (2.22)	0.182 (0.042)***	0.34 (2.23)	0.179 (0.042)***
Number of children in household	-1.86 (0.62)***	-0.020 (0.015)	-1.92 (0.63)***	-0.029 (0.016)*
Leisure time (hrs. per day)	2.93 (0.31)***	-0.001 (0.004)	2.91 (0.31)***	0.001 (0.004)
Teen in the home		0.254 (0.030)***		0.258 (0.030)***
Owner		0.160 (0.034)***		0.167 (0.034)***
Number of cell phones in household		0.224 (0.011)***		0.228 (0.011)***
$\hat{\phi}/\hat{\Phi}$	-1.96 (2.69)		-1.52 (2.61)	
Intercept	38.53 (5.92)***	-1.847 (0.067)***	40.43 (5.93)***	-1.858 (0.072)***
R-Squared	0.111		0.113	
Log-Likelihood		-7944.2		-7922.2
Adjustment factor for marginal effects		0.243		0.243
Number of observations	4568	18,206	4568	18,206

Notes: The estimation method is OLS in columns (1) and (3) and Probit in columns (2) and (4). Standard errors, reported in parentheses, are robust to heteroskedasticity in columns (1) and (3). Non-workers' labor earnings have been predicted from an interval earnings regression run on workers only. Unreported categories: in columns (1) and (2), household income < €1000, less than high school graduate, and living in other city with ≤ 100,000 people; in columns (3) and (4), those in columns (1) and (2) plus respondent's earnings < €500. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

FIGURE 1—AVERAGE PROPORTION OF LEISURE SPENT ON DIFFERENT LEISURE ACTIVITIES, BY HOUSEHOLD INCOME

(a) All persons aged 16-74	(b) Employed men aged 23-59