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Internet Use and the U-shaped relationship between Age and Well-being

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Abstract

Extant research shows that the relationship between age and well-being is U-shaped. This paper investigates the effects of Internet use on subjective well-being over the life cycle. We argue that Internet use moderates the U-shaped relationship, affecting its turning point and slopes. We use the Eurobarometer annual surveys for the years 2010 to 2013, which provide rich information for close to 100,000 individuals in all European countries. The econometric analysis exploits exogenous variation in broadband Internet take-up across European countries, and presents 2SLS estimations for a recursive bivariate ordered probit model. The results provide support for our main hypothesis. Active Internet users have a different well-being pattern over the life cycle compared to other individuals. Specifically, we find that Internet users experience: (1) a more stable level and less pronounced decrease in life satisfaction in their younger adult life; and (2) an earlier and stronger recovery after the turning point of the U-shape.

Key words: Internet use; subjective well-being; life satisfaction; Eurobarometer

JEL codes: O33; I31; D31

1. Introduction

The literature on subjective well-being has pointed out a variety of factors that explain differences in happiness conditions reported by individuals (Frey and Stutzer, 2002; Senik, 2005; Clark et al., 2008; Dolan et al., 2008; Kahneman and Deaton, 2010; MacKerron, 2012). A new strand of research has recently extended this literature and started to investigate what effects Internet may have on individuals' well-being.

The introduction of the Internet variable in the study of subjective well-being is warranted. Digital technologies are pervasive, and nowadays most individuals use the Internet to carry out a variety of daily tasks, such as communication with friends and family, shopping and e-commerce, financial transactions and online banking, search information and access data at work. It is thus natural to ask whether these new ways of conducting daily activities are changing the costs and benefits related to them, and thus what impact Internet use will eventually have on subjective well-being (Castellacci and Tveito, 2018).

A small number of studies have recently presented first empirical investigations of this question. Some of these works have analyzed the overall relationship between Internet adoption and life satisfaction using survey data for several countries, and pointed out an overall positive correlation between the two variables for large samples of individuals (Kavetsos and Koutrompis, 2011; Graham and Nikolova, 2013; Penard et al., 2013; Ganju et al., 2016). Other papers have made use of country-specific surveys to investigate more specific hypotheses, such as Internet effects related to material aspirations and social comparisons (Lohmann, 2015; Sabatini and Sarracino, 2016), and those related to the use of social media and communication patterns (McDool et al., 2016; Rotondi et al., 2016; Sabatini and Sarracino, 2017).

Overall, the main endeavor of this recent strand of research has been to uncover a general relationship between Internet use and well-being for large samples of individuals, but there has until now been more limited effort to investigate the extent to which this relationship varies for different groups of individuals. Specifically, it is reasonable to postulate that individuals of different ages use the Internet to a different extent and for different purposes. The effects of online digital technologies on well-being may indeed vary substantially with age.

This is the point that we seek to investigate in the present paper. The work presents an empirical analysis of the relationships between Internet use intensity and subjective well-being, and its specific objective is study how this relationship varies over the life cycle. The investigation of this question is closely related to extant research on the U-shaped relationship between age and well-being

(Blanchflower and Oswald, 2004; 2008; Schwandt, 2016). According to this literature, subjective well-being over the life cycle is characterized by a remarkable empirical regularity, with a progressive decline in life satisfaction until late adult life, followed by a steady recovery and growth in subsequent years. In the present study, we draw insights from research on Internet and well-being, on the one hand, and literature on age and well-being, on the other, to investigate the following specific question: how does Internet use affect the U-shaped relationship between age and well-being? The argument that we develop in the paper is that Internet use *moderates* the U-shape of life, potentially affecting the location of its turning point (midlife crisis), and/or its slopes (i.e. the pace at which well-being declines and grows over the life cycle).

To investigate this hypothesis, we make use of the Eurobarometer survey, a large survey that covers several thousand individuals in all European countries. We use the four annual surveys that refer to the years 2010, 2011, 2012 and 2013, which provide a pooled cross-sectional dataset for close to 100,000 individuals. Our identification strategy exploits cross-country differences in broadband take-up among European nations as a source of exogenous variation that affects individuals' Internet use intensity. Our instrumental variable – lagged fixed broadband take-up – measures *peer effects* in Internet adoption, based on the idea that the intensity of Internet use of each individual will partly depend on the overall level of diffusion of broadband Internet in the country (Goolsbee and Klenow, 2002; Agarwal et al., 2009; Penard et al., 2013). The econometric analysis estimates a 2SLS recursive bivariate ordered probit model, which simultaneously estimates a treatment and an outcome equation using the CMP procedure developed by Roodman (2011).

The main general result of this analysis is that the effects of Internet use on subjective well-being are heterogeneous, varying significantly with age. The econometric results point out that active Internet users have a more stable level and less pronounced decrease in reported life satisfaction in their younger adult life; and that they also have an earlier and stronger recovery after the turning point of the U-shape, and steady growth throughout older adult life.

On the whole, the contribution of this paper to the literature is twofold. First, we contribute to the recent strand of research on Internet and well-being by showing that the effects of Internet are widely heterogeneous among individuals of different ages, so that age-specific characteristics must be taken into account when analyzing benefits and risks that the Internet leads to. Second, we contribute to the literature on the U-shaped relationship between age and well-being by introducing a new conceptual dimension, the Internet, and by formally testing its moderation effects on the age-well-being relationship.

The paper is organized as follows: section 2 reviews the literature on Internet and subjective well-being; section 3 presents the data and empirical methods; section 4 presents the regression results; and section 5 summarizes and discusses the main findings.

2. Literature

A new strand of research has recently begun to investigate the effects of Internet use on life satisfaction and subjective well-being, carrying out econometric analyses of large survey datasets (see overview in Castellacci and Tveito, 2018). Two groups of studies contribute to this emerging literature. In the first group, papers typically make use of cross-country surveys (e.g. European Social Survey, Eurobarometer, Gallup World Poll) to provide estimates of the average correlation between Internet use and life satisfaction for a large sample of individuals in different countries.

Kavetsos and Koutrompis (2011) analyze the relationships between mobile phones, computers with Internet connection and life satisfaction using the Eurobarometer dataset for all European countries for the years 2005-2008. OLS estimates point out a positive correlation between computers with Internet connection and life satisfaction. Penard et al. (2013), using data from the European Value Survey for Luxembourg in 2008, study the effects of Internet use on life satisfaction. The 2SLS cross-sectional estimates reported in this paper do not find any significant effect when other relevant control variables are included in the regressions.

Graham and Nikolova (2013) carry out a cross-country study of the relationship between Internet access and life satisfaction, using data from the Gallup World Poll for a large number of world economies in the period 2009-2011. Ordered logit cross-sectional correlation coefficients reported in this paper are positive and significant, and they vary substantially across world regions. Ganju et al. (2016) also use data from the Gallup World Poll for the period 2006-2014, but aggregate them at the country-level. 2SLS estimates from panel regressions indicate that the effects of ICTs on life satisfaction are positive and significant.[1]

The second group of studies comprises papers that analyze large national household surveys, which often provide more specific variables to measure different types of online activities and Internet-

[1] Note however that the estimates in Ganju et al. (2016) cannot be directly compared to other papers in this literature because they are obtained from country-level data (rather than individual-level), and also because the explanatory variable is a composite indicator of Internet use and mobile phone subscriptions (rather than Internet use alone).

related use, and thus enable to test more elaborated hypotheses. As noted below, many of these studies point out negative (or moderating) effects that Internet use has on well-being through its interactions with income and relational factors.

Focusing first on the relational dimension, Franzen (2003) presents an early investigation of the idea that the use of Internet may decrease the time spent by individuals on face-to-face relational activities, which are known to be an important factor supporting well-being. The study focuses on Internet users in Switzerland, using the Random Panel Survey for this country for the years 1998 and 2001. Cross-sectional estimates in this study do not find however any significant correlation between Internet use and the size and extent of individuals' social activities.[2] More recently, Rotondi et al. (2016) study the effects of smartphone use, employing data from the Italian Multipurpose Survey on Households. 2SLS estimates point out a positive effect of smartphone use on life satisfaction, but they also show that this effect is weaker for those individuals that use the smartphone in combination with face-to-face social activities. Sabatini and Sarracino (2017) investigate the relationships between social media use, social capital and well-being, using the Italian Multipurpose Survey on Households. 2SLS and SEM results reported in this article point out a significant negative effect of social media use on subjective well-being. Further, McDool et al (2016) study the effects of social media use and children's well-being, using the Household Longitudinal Survey for the UK. The paper present a set of random effects ordered probit results, which consistently find negative effects of social media use for the sample of British children considered in this study.

Regarding income-related effects, Lohmann (2015) analyzes the hypothesis that Internet has negative effects on well-being by raising individuals' material aspirations. The work uses data from various sources, and specifically the German Socio-Economic Panel, the EU-SILC survey and the World Value Survey. OLS and ordered probit cross-sectional estimates reported in this paper indicate a positive and significant correlation between Internet use and life satisfaction, but also corroborate the hypothesis that Internet raises material aspirations and so weakens the positive effect of income on subjective well-being.[3] Finally, Sabatini and Sarracino (2016) investigate a similar mechanism using the Italian Multipurpose Survey on Households. The study finds in particular that use of social media

[2] Bruni and Stanca (2008) previously analyzed a similar idea focusing on the effects of time spent watching TV on time spent on face-to-face social interactions.

[3] This finding is largely in line with Bruni and Stanca's (2008) previous study of the effects of TV watching on material aspirations.

spurs social comparisons and raises income aspirations, thus moderating income-related effects on subjective well-being.

In short, this recent strand of research points out a variety of different results regarding the impact of Internet use on subjective well-being, some emphasizing positive effects and others suggesting negative impacts. A common characteristic of this literature is that nearly all papers seek to uncover a general relationship between Internet use and well-being for the whole sample of individuals in the dataset, but they do not investigate the extent to which this relationship may vary for different groups of individuals. In other words, extant research has until now had limited interest in the study of the heterogeneity of effects of Internet.

In this paper, we seek to study heterogeneous effects of Internet with respect to age. A few previous studies on this topic provide mixed evidence. Research focusing on Internet use at young ages (and particularly on the use of social media and video games) point out both positive and negative effects (Jackson et al., 2008; McDool et al., 2016; Castellacci and Tveito, 2018). On the other hand, research focusing on older adults indicates that Internet use has positive effects on well-being since it facilitates social contacts and communication, and it decreases isolation and depression (Chen and Persson, 2002; Ford and Ford, 2009; Lelkes, 2013).

In order to provide a more systematic understanding of Internet effects for individuals of different age groups, we turn to the literature on the U-shaped relationship between age and well-being. Blanchflower and Oswald (2004; 2008) point out the existence of a U-shape relationship between age and life satisfaction, a remarkable regularity that holds for a large number of countries worldwide. According to these studies, the turning point of the U-shape – i.e. the year at which individuals face a so-called midlife crisis – is between 35 and 65 years (depending on countries, sample, and model specifications).[4]

This literature has advanced two possible explanations of such U-shaped relationship. One is related to social comparisons. Individuals that live longer compare themselves to those less fortunate people who got sick and died before them. This leads on average to an increased valuation of life at older ages. A second explanation is related to adaptation mechanisms. As time goes by, individuals become progressively better at living the present, adapt to life's circumstances, and tend to be less frustrated and more patient when they face "unmet aspirations" (Schwandt, 2016).

[4] Blanchflower and Oswald (2004; 2008)' seminal papers have recently fostered a vivid debate. Some studies argue that the U-shape is a methodological artefact that can be explained by cohort effects, and/or by the use of inappropriate control variables (Glenn, 2009; Blanchflower and Oswald, 2009; Hellevik, 2017). Further, Frijters and Beatton (2012) point out that the U-shape may be affected by the omission of fixed effects in pooled cross-country regressions.

Drawing inspirations from this literature, we like to study the effects of Internet use on the U-shaped relationship between age and well-being. Specifically, we argue that Internet use moderates the effects of age on well-being. These moderation effects mean that the use of Internet may arguably affect the turning point of the U-shape (i.e. the time at which the midlife crisis sets in on average), and/or the slopes of the U-shaped curve (i.e. the speed at which the midlife crisis is met, and the subsequent recovery phase for older adults).

We posit that three possible mechanisms would explain such moderation effects. First, Internet leads to substantial time saving effects for individual users. It is reasonable to argue that these time-saving effects are stronger for middle-aged people, both in their working life and in their social life (e.g. the use of e-commerce can have substantial time saving effects in family life). If so, Internet reduces stress and time constraints that often characterize this phase of life.

Second, Internet greatly facilitates access to data and information. Again, these benefits may be stronger for individuals in their working life, and/or for older adults (e.g. using online security, health and other public services may provide substantial benefits for older people). Hence, the use of Internet may reduce the insecurity that often characterizes this phase of life, and it facilitates access to information that can support the management of family responsibilities (caring) that are often strongest for middle-aged and older adults.

Third, Internet provides a variety of new powerful virtual communication tools. According to previous research, the use of these tools (e.g. social media) are often negative for children and younger people, and positive for older adults, since the latter are typically more stable and less subject to loss of social capital, or social comparison effects, that are studied in the literature.[5] Thus, the effects of Internet (social media technologies) may possibly decrease further the progressive loss of well-being at younger ages, and strengthen the recovery phase after the midlife crisis.

3. Data and methods

The empirical analysis makes use of the Eurobarometer survey, a large survey that covers several thousand individuals in all European countries. We use the four annual surveys that refer to the years

[5] Further, it is also reasonable to argue that preferences shift after mid-life from career goals to family relationships. Since ICTs provide a powerful tool for distance communication, this will arguably be an important factor of well-being during late adult life (Deaton, 2013: 41).

2010, 2011, 2012 and 2013[6], which provide a pooled cross-sectional dataset for around 100,000 individuals. The reason we focus on these four survey waves is that these provide harmonized data for the main variables of interest, so that we can analyze variables that have the exact same formulation in the Eurobarometer questionnaire. Table 1 presents a list of the variables we use in the empirical analysis, and some descriptive statistics for the whole dataset.

< Table 1 here >

The econometric analysis seeks to investigate the effect of Internet use on life satisfaction for individuals of different age groups. An important issue that has to be taken into account is that the main explanatory variable of interest, Internet use intensity, is arguably not an exogenous and randomly assigned variable, but it is in turn dependent on a set of personal characteristics that define individuals' willingness and capability to use the Internet. Some of these personal characteristics may be unobserved, and they may in principle affect both the treatment variable Internet use and the outcome variable life satisfaction.

To take this issue into account, we adopt a two-equation instrumental variable approach. The first step is a selection equation that investigates the factors explaining why some individuals have higher Internet use intensity than others, whereas the second equation studies the relationship between life satisfaction and Internet use (plus a set of control factors). The econometric model (baseline specification) is the following:

$$LS_{ict} = \alpha + \gamma INT_{ict} + \delta \mathbf{X}_{ict} + \eta_c + \theta_t + \varepsilon_{ict} \quad (1)$$

$$INT_{ict} = \lambda + \varrho \mathbf{X}_{ict} + \mu Z_{ict} + \sigma_{ict} \quad (2)$$

where LS stands for life satisfaction, INT is internet use intensity, and **X** is a vector of covariates (control variables).[7] The sub-indexes *i*, *c* and *t* indicate individuals, countries and years respectively. η_c is a set of country-specific effects, and θ_t is a set of time dummies. The variable Z in equation (2) is an

[6] The surveys used are Eurobarometer 74.2 (2010), Eurobarometer 76.3 (2011), Eurobarometer 78.1 (2012) and Eurobarometer 80.1 (2013).

[7] Life satisfaction is measured by asking respondents to indicate their level of satisfaction on a four-point scale ranging from not very satisfied to very satisfied. Respondents rate their internet use intensity on a seven-point scale that goes from 1 "No access" to 7 "(Almost) everyday".

exogenous instrumental variable that is correlated with INT but not correlated with the error term of the outcome equation.

An identification strategy for this model has to consider two aspects. The first one is to formulate a comprehensive specification of equation (2), and in particular include in the vector **X** all variables that are known to affect Internet use intensity according to extant literature on the subject. We thus include the following factors previously pointed out in studies of the determinants of Internet adoption and use: age, gender, occupation type, education level, civil status, and geographical location (urban vs. rural area), along with a set of country-specific effects and time dummies. This is a comprehensive set of variables that are supposedly able to account for a substantial part of the variability of Internet use intensity (Gruber and Verboven, 2001; Kiiski and Pohjola, 2002; Chinn and Fairlie, 2006).

The second aspect of our identification strategy is to find an instrumental variable Z that provides exogenous variation correlated with the treatment variable Internet use intensity but uncorrelated with the error term of the outcome equation. We exploit cross-country differences in broadband take-up among European nations as a source of exogenous variation that affects individuals' Internet use intensity. Specifically, our instrumental variables are "peer effects" (Angrist and Pischke, 2009), based on the idea that the intensity of Internet use of each individual will not only depend on the set of personal characteristics noted above, but also on the overall level of diffusion of broadband Internet in the country.

The idea that peer effects affect Internet use intensity is in line with standard models of diffusion of ICTs (see e.g. Gruber and Verboven, 2001; Castellacci, 2010). These models argue that an individual is more likely to adopt and actively use new digital technologies if many other individuals have previously adopted and used the same technology. The reason is threefold: (1) *social learning*: adoption is easier if individuals can learn from other peers about the potential of the new technology; (2) *social pressure*: if most other peers are using a new digital technology (e.g. for communication purposes), it is hard for an individual not to use the same digital tool; (3) *network externalities*: since adoption and use costs depend on the size of users' network, the larger the number of peers using a digital technology the cheaper this will be for a given user (Goolsbee and Klenow, 2002; Agarwal et al., 2009; Penard et al., 2013). Since the new technology in question analyzed in this paper is the Internet, we argue that relevant peer effects for Internet adoption and use are not defined by localized spillover effects (e.g. at municipal or regional level), but they are rather related to a set of national factors that define the overall level of digitalization and Internet use in each country. In other words, we postulate that Internet use intensity of each individual i is affected by the overall level of broadband take-up in the country in which *i* lives. In fact, as shown by Troulos and Maglaris (2011), country-level factors such as national policies represent the main level of analysis to explain differences in broadband infrastructures and take-up in Europe, and these national differences are more important than differences across municipalities and regions within each country.

Based on these arguments, we initially considered four instrumental variables. Two of them measure the national diffusion of fixed (wired) broadband Internet: (1) fixed broadband take-up (subscriptions/100 people); (2) Percentage of households having a fixed broadband connection. The other two instruments measure the diffusion of wireless (mobile) broadband Internet (Clarke, 2014): (3) Percentage of individuals accessing the Internet through a mobile phone via UMTS (3G); (4) Wireless mobile broadband subscriptions. We take lagged values of these variables (one year before each survey period) in order to ensure that they predate the outcome variable and they are thus uncorrelated with common country-year shocks (Angrist and Pischke, 2009: 192-197). As explained in the next section, after testing the validity of these instruments, we eventually focused on the first instrumental variable – fixed broadband take-up (subscriptions/100 people) – and neglected the other three.

The key assumption of this identification strategy is that these country-year-specific instrumental variables affect individual life satisfaction only through their impact on Internet use intensity, and that they are therefore uncorrelated with any possible unobserved determinant of life satisfaction. This is a reasonable assumption, since for each individual *i* in our dataset, the extent of the diffusion of broadband Internet in the country in which *i* lives is determined by a set of country-level dimensions that cannot be affected by each individual (and particularly so since our country-level instrument *predates* the individual-level outcome variable).

Figure 1 shows the cross-country distribution of the four instrumental variables and their evolution during the time span considered in this paper. Cross-country differences in broadband Internet in Europe are substantial. The EU's Digital Agenda, introduced in May 2010, formulates a set of objectives that national Member States should achieve to increase their degree of digitalization, and that will supposedly have substantial socio-economic benefits for European citizens (Gruber et al., 2014). However, National Broadband Plans that have subsequently been developed by Member States to implement the Digital Agenda have been quite different among European nations (EC, 2014), and policy targets have been met at different speeds. These cross-country differences are substantial on both the supply- and the demand-side. On the one hand, the supply of broadband infrastructures is affected by national regulation and competition policies that define entry costs and investment rates of telecommunication firms (Cambini and Jiang, 2009).[8] On the other hand, demand-side factors are also characterized by marked cross-country differences, linked for instance to different rates of diffusion of e- public services, as well as institutional differences in national education systems and public investments in e-skills (EC, 2014). These supply- and demand-side factors, however, are all related to country-level policies and patterns, which can reasonably be considered to be exogenous for each individual user of the Internet.[9]

After clarifying our identification strategy, it is important to point out the methods we will use to estimate the effects of Internet use for individuals of different age groups, and in particular to test moderation effects of Internet on the U-shaped relationship between age and well-being. As noted in the previous section, these moderation effects mean that we expect the use of Internet to affect (1) the turning point of the U-shape (i.e. the time at which the midlife crisis sets in on average), and/or (2) the slope of the U-shaped curve (i.e. the speed at which the midlife crisis is met, and the subsequent recovery phase for older adults). We test these hypotheses by inserting two interaction terms in the regressions: one is an interaction between age and Internet use, and the other is an interaction between age-squared and Internet use. The latter term is the one of our interest, using which we can test the two distinct moderation effects noted above (for further details on how to test moderation effects of U-shaped relationships, see Haans et al., 2016: 1187).

We estimate equations (1) and (2) through a 2SLS estimator. The next section will report results of two similar 2SLS models. The first is a 2SLS linear model, which ignores the fact that the outcome variable is categorical, and which we report as a benchmark. The second and preferred model is a 2SLS recursive bivariate ordered probit model, which simultaneously estimate the two equations adopting an ordered probit approach, given the categorical nature of both the outcome and treatment

[8] For instance, Serdarevic et al. (2016) show that the so-called *Ladder of Investment* regulatory model, based on unbundling and entry of new firms in the broadband provision market, is characterized by substantial differences and application modes in Central and Eastern EU countries compared to other economies in Western EU.

[9] Recent papers have adopted an identification strategy centered on supply-side factors, and in particular on the availability of broadband infrastructures, and its differences across municipalities and regions within a given country (Czernich et al., 2011; Bhuller et al., 2013; Bauernschuster et al., 2014; Falck et al., 2014; Rotondi et al., 2014; Akerman et al., 2015; Sabatini and Sarracino, 2017). The empirical approach in our paper differs from these previous works in two main respects. First, our treatment variable is Internet use *intensity*, rather than broadband Internet roll-out and diffusion rates as in most of these works. Secondly, our dataset provides information on individuals in all European countries (rather than individuals in different regions of the same country as in previous works), so it is reasonable to exploit variation in broadband Internet across countries, and neglect regional differences within each European nation for the reasons explained above.

variables (Monfardini and Radice, 2008; Sajaia, 2008).[10] We estimate this 2SLS recursive bivariate ordered probit model using the CMP procedure developed by Roodman (2011).

< Figure 1 here >

4. Results

4.1 First stage results and LATE analysis

We initially considered all four instrumental variables noted in the previous section, and used them to estimate equations (1) and (2). However, after testing the validity of these instruments, we concluded that only the first of these instrumental variables – fixed broadband take-up (subscriptions/100 people) – is reliable whereas the other three are less so (the appendix reports these validity tests). Hence, all results presented in this section are based on a 2SLS model that employs this instrumental variable.

Table 2 presents the results of the first stage estimations (equation 2), in which the dependent variable is the intensity of Internet use of each individual. The control variables take the sign as expected based on previous literature on the determinants of adoption and use of the Internet (e.g. Gruber and Verboven, 2001; Kiiski and Pohjola, 2002; Chinn and Fairlie, 2006). First, the table indicates that Internet use intensity decreases with age. Secondly, it is higher for people in the workforce that have higher education level and white-collar occupations. Unemployed workers do also have higher Internet use intensity than average, arguably because they have more time available to use the Internet for leisure and/or for job searching activities. Third, Internet use is on average higher for individuals that live in a large town as opposed a rural area or village. Fourth, it is stronger for people that have a good financial situation, and that regard their level in society to be higher than average compared to other citizens in the same country.

The bottom of table 2 also shows that the instrumental variable – lagged value of the country's fixed broadband take-up – is as expected positively and significantly related to Internet use intensity. As explained in the previous section, we interpret this finding as a country-specific "peer effect", i.e. based on the idea that an individual is more likely to adopt and actively use Internet if many other individuals

[10] The recursive bivariate probit is a seemingly unrelated regression model with correlated disturbances, in which the dependent variable of the first equation appears on the right-hand-side of the second equation. The model is estimated by MLE. Greene (2003, section 21.6.6, pp. 715-716) points out that in such a model the endogeneity of the RHS variable of the second equation can be neglected because this term does not affect the maximization of the log-likelihood (differently from what it would be the case in a linear recursive model not estimated by MLE).

in the same country have previously adopted and used it, due to social learning, social pressure and/or network externality effects (Goolsbee and Klenow, 2002; Agarwal et al., 2009; Penard et al., 2013).

Our first stage estimates have a local average treatment effects (LATE) interpretation (Angrist and Pischke, 2009). They represent the effect of fixed broadband take-up on the sub-population of *compliers* in each country, i.e. individuals that intensify their Internet use when a larger number of individuals in that country have actively been using Internet in the previous two years.[11] Following the approach used in recent papers (Bhuller et al., 2013; Falck et al., 2014), we carry out an analysis of the characteristics of the complier group. In table 3, we report the estimated coefficients of the effect of the instrumental variable on Internet use intensity (first stage regressions) for different age sub-groups. The table shows that individuals that respond more actively to increases in fixed broadband infrastructures are older adults (55 + years old), followed by middle-aged and younger adults. In these age groups, individuals arguably use fixed broadband Internet as a professional tool in their working life, as well as for a variety of different uses related to their family and social life. On the other hand, the only age group for which the growth of national broadband Internet infrastructures did not have an effect on Internet use intensity is younger individuals (15-24 years old). A possible explanation of this finding is that younger people in our sample are those that in the period 2010-2013 increasingly begun to use wireless mobile broadband, which rapidly substituted the use of fixed broadband.

< Tables 2 and 3 here >

4.2 Second stage results

Table 4 presents the results of the second stage (equation 1), in which the dependent variable is the life satisfaction reported by each individual. We report results for both a 2SLS linear specification and a 2SLS bivariate ordered probit model, but the latter is the one of our interest, and which we will focus on in this section. We briefly discuss the results for the control variables first, before turning to the effect of the main variables of interest. The estimated results for the control variables are largely in line with extant research on the determinants of subjective well-being (Frey and Stutzer, 2002; Senik, 2005; Dolan et al., 2008; MacKerron, 2012). Table 4 indicates that the relationship between age and life satisfaction is U-shaped, with lowest reported subjective well-being for middle-aged individuals

[11] According to this interpretation, *always-takers* in our sample are individuals who would use Internet intensively anyway, even in the absence of strong country-specific peer effects; and *never-takers* are individuals who would not increase their Internet use even if broadband Internet diffused more rapidly in their country. *Defiers* are individuals who would reduce their internet use in response to increased broadband roll-out.

(estimated turning point at 53 years). We elaborate further on this result later in this section. Highly educated individuals report higher life satisfaction than less educated people. Regarding work-related control variables, white-collar workers report on average higher happiness levels than those in blue-collar occupations, and unemployed individuals much substantially lower satisfaction levels than employed people. Further, life satisfaction is higher for those individuals that have a good financial situation, and those that regard to be part of a higher society level than other citizens in their country. The first row in table 4 reports the estimation results for the main variable of interest: Internet use intensity. This has a positive effect on life satisfaction, which is statistically significant in our preferred 2SLS, the one estimated through Roodman's (2011) CMP recursive bivariate ordered probit. Marginal effects of the Internet use variable, not reported here, are positive and significant too.

Shifting the focus to the moderation effects of Internet use on the U-shaped relationship between age and well-being, we test these moderation effects by introducing two interaction terms in the regression model: (1) *Internet * age*; and (2) *Internet * age-squared*. The latter is the main interaction variable of our interest, providing a direct test of moderation effects of Internet use on the U-shape of life (see Haans et al., 2016). The last column of table 4 reports the full model specification that includes such interaction terms. The estimated coefficient of the variable *Internet * age-squared* is positive and significant, confirming our hypothesis that Internet use moderates the U-shaped relationship between age and well-being.[12]

< Tables 4 here >

As noted above, moderation effects can in principle take two distinct forms: (1) Internet use can affect the location of the turning point of the U-shape – i.e. changing the time at which, on average, individuals begin to experience a recovery period after midlife crisis; and/or (2) Internet use can change the curvature of the U-shape, making it flatter or steeper – i.e. changing the speed at which individuals fall into midlife crisis and recover thereafter. Tables 5 and 6 report the results of tests of these two moderation effects respectively.

Table 5 shows that the turning point moves towards the left as Internet use intensity increases (from around 52 to 48 years old), meaning that active Internet users, on average, begin a recovery period

[12] We also computed marginal effects of this interaction variable by comparing predicted probabilities for the two polar cases of Internet use (everyday vs. never) for different values of the age squared variable. In line with the estimated coefficient reported in table 4, the marginal effect of the interaction variable is positive and significant (+0,23, for life satisfaction = 4).

after the midlife crisis *earlier* than individuals who use Internet less actively. Further, table 6 reports the difference in the slope of the U-shape between active Internet users and no Internet users. We calculated this difference for four different years around the turning point, in order to test whether the curvature of the U-shape changes in the periods 5 to 10 years before and after the midlife crisis (following the method described in Haans et al., 2016: 1195). The slope differences reported in table 6 indicate that, for active Internet users, the U-shaped relationship becomes *flatter before* the turning point, and *steeper after* the turning point. This means that Internet use alleviates the decline in life satisfaction that characterizes young adults and middle-aged people until the midlife crisis; and that it strengthens the subsequent growth and recovery period for older adults.

Figure 2 shows this U-shaped relationship with our data, comparing the whole sample with the sub-sample of individuals that use Internet every day. The difference between the two curves is remarkable. Both U-shaped curves are quite close to each other and decline together for younger individuals (until approximately 25 years old). However, as individuals enter adult life, progressively assuming job and family responsibilities, the two curves begin to diverge substantially. Active Internet users maintain approximately the same level of life satisfaction until they are around 50 years old, and do not experience the sharp decline experienced by the rest of the sample. Further, after the turning point of the U-shape, active Internet users seem to experience a much more pronounced and rapid recovery from the midlife crisis, reporting steadily increasing levels of life satisfaction as time goes by. In the next section, we will discuss some possible reasons explaining these patterns, along with limitations and future extensions of this line of research.

< Table 5, table 6 and figure 2 here >

5. Conclusions

The paper has presented an empirical analysis of the effects of Internet use on subjective well-being, using a large pooled cross-section from the Eurobarometer surveys for the years 2010, 2011, 2012 and 2013. The econometric analysis has investigated the relationship between individuals' Internet use intensity and life satisfaction, and how this relationship varies with age. To take into account the possible selection bias related to individuals' Internet use choice, we have made use of an instrumental variable approach that exploits exogenous variation in broadband Internet take-up across European countries.

The results of 2SLS bivariate ordered probit estimations point out that Internet use moderates the U-shaped relationship between age and well-being. Active Internet users have a different life satisfaction pattern over the life cycle compared to other individuals in the sample. Specifically, we find that Internet users: (1) have a more stable level, and less pronounced decrease, in reported life satisfaction in their younger adult life; (2) have an earlier and stronger recovery after the turning point (midlife crisis), and steady growth throughout older adult life.

What could be the reasons explaining these moderation effects? As noted in the theory section above, three general characteristics of Internet use may explain these findings. One is that Internet leads to substantial time saving effects for individual users. It would be reasonable to think that these time-saving effects are more important channels of well-being for middle-aged people, enabling a more effective management of responsibilities linked to work and family life. The Internet may therefore contribute to reduce the stress and time constraints that are related to this phase of life, hence alleviating the decline in well-being that is typically observed in the passage from youth to adult life.
Second, another important characteristic of the Internet is that it greatly facilitates access to data and information. The benefits that this increased amount of information may lead to in terms of well-being may be stronger for adults during their working life, and for older adults. In particular, the use of Internet may facilitate access to information that can support the management of family responsibilities (e.g. caring) that are often strongest for middle-aged and older adults; and it may also reduce the insecurity that often characterizes the older adult phase of life (e.g. through online security services, health and other public services, that may provide substantial benefits for older people).
Finally, the Internet provides a variety of new powerful communication tools. It is reasonable to think that digital communication technologies, such as social media, may lead to stronger benefits for adults, rather than teenagers and younger individuals, since adult people are in general more stable and less subject to loss of social capital, or to social comparison effects that, according to extant literature, are often related to the use of these new communication tools.
Taken together, these three mechanisms may explain the main empirical result pointed out in this paper that Internet use alleviates the decline in life satisfaction in the years before the midlife crisis, and that it strengthens the growth and recovery period subsequent to it. In the present study, though, we have not been able to empirically investigate the relevance of these three explanations due to the lack of variables in our dataset that could specifically measure these time-saving, information access and communication-related effects of Internet use on well-being. This calls for further research

investigating how the effects of Internet on well-being vary with age, and employing more detailed variables and measures of different types of activities and services that people carry out through the Internet.

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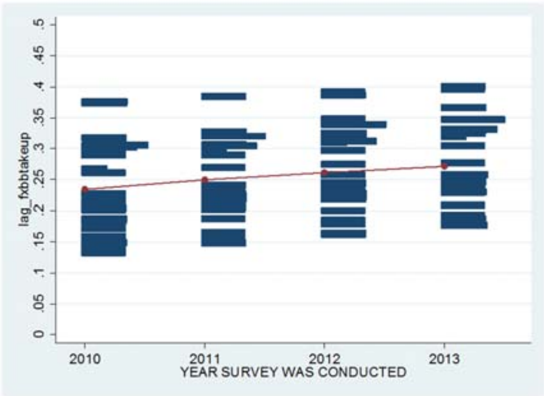
Table 1: Descriptive statistics

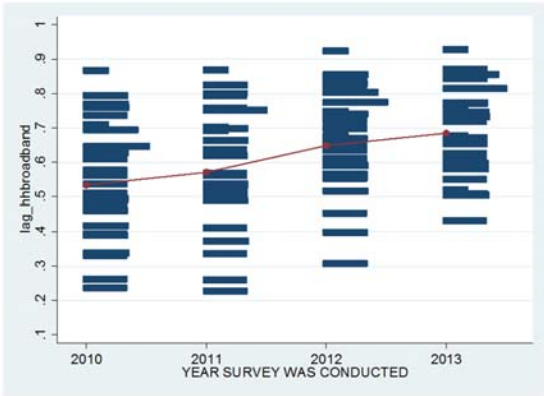
	Mean	St.dev.	Min	Max	Obs
Life satisfaction	2.84	0.82	1	4	98,681
Internet use	4.91	2.41	1	7	98,681
Age	50.60	16.66	15	98	98,681
Women	0.54	0.50	0	1	98,681
Unemployed	0.10	0.31	0	1	98,681
16-19 years of education	0.48	0.50	0	1	98,681
20+ years of education	0.33	0.47	0	1	98,681
Unmarried	0.14	0.35	0	1	98,681
Divorced	0.08	0.28	0	1	98,681
Widow	0.09	0.29	0	1	98,681
Other relationships	0.01	0.09	0	1	98,681
Financial situation good	0.60	0.49	0	1	98,681
Living in a rural area or village	0.36	0.48	0	1	98,681
Living in a large town	0.27	0.44	0	1	98,681
Society level above mid-point	0.47	0.50	0	1	98,681
White-collar	0.37	0.48	0	1	98,681
Blue-collar	0.15	0.36	0	1	98,681
Fixed broadband takeup	25.47	6.67	13.29	40.11	98,681

Figure 1: Cross-country distribution of fixed and mobile broadband

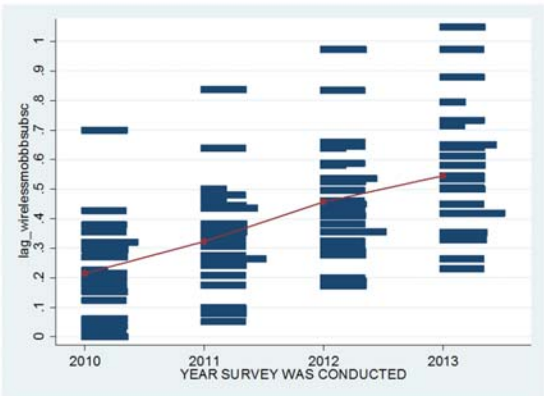
Fixed broadband take-up



Households with broadband connection



3G mobile phone broadband



Wireless mobile broadband subscriptions

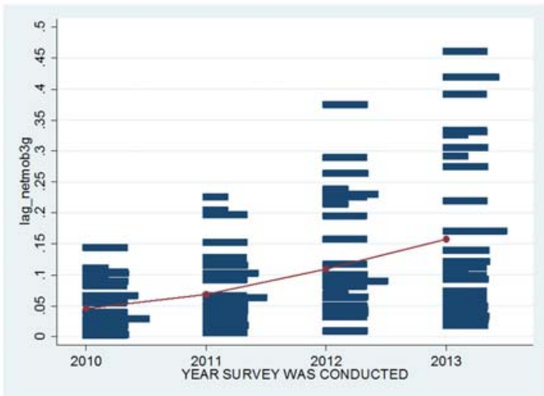


Table 2: First stage results. Dependent variable: internet use intensity.

	2SLS linear	**2SLS bioprobit**
Age	-0.0269***	-0.0329***
	(0.0021)	(0.0016)
Age squared	-0.0002***	-0.0000
	(0.0000)	(0.0000)
Women	-0.1110***	-0-0961***
	(0.0116)	(0.0085)
Unemployment	0.2339***	0.0631***
	(0.0262)	(0.0165)
16-19 years of education	0.9178***	0.4077***
	(0.0192)	(0.0115)
20+ years of education	1.499***	0.9125***
	(0.0210)	(0.0138)
Unmarried	-0.1290***	-0.1135***
	(0.0170)	(0.0137)
Divorced or separated	-0.0499**	-0.0708***
	(0.0234)	(0.0151)
Widowed	-0.3637***	-0.1678***
	(0.0227)	(0.0144)
Other relationships	-0.0079	-0.0030
	(0.0612)	(0.0527)
Financial situation	0.3562***	0.2081***
	(0.0137)	(0.0093)
Living in a rural area or village	-0.1931***	-0.1261***
	(0.0136)	(0.0096)
Living in a large town	0.1417***	0.1426***
	(0.0141)	(0.0109)
Society level above mid-point	0.3427***	0.2434***
	(0.0127)	(0.0091)
White-collar job	0.8859***	0.6183***
	(0.0193)	(0.0128)
Blue-collar job	0.2105***	0.0515***
	(0.0232)	(0.0141)
Fixed broadband take-up $_{t-1}$	0.0388***	0.0113*
	(0.0083)	(0.0064)
Observations	98,681	98,681

Heteroskedasticity-robust standard errors in parentheses. All regressions include time dummies and country fixed effects. * p<0.10; ** P<0.05; *** P<0.01.

Table 3: LATE results: compliers for different age groups.

	P[X=x]	Coefficient of fixed broadband take-up
Age groups		
Young (15-24)	0.0508	-0.0169
Younger adults (25-39)	0.2470	0.0073
Middle-aged (40-54)	0.2805	0.0009
Older adults (55+)	0.4217	0.0104

Table 4: Second stage results. Dependent variable: life satisfaction.

	2SLS linear	2SLS linear	2SLS bioprobit	2SLS bioprobit
Internet use	-0.0558	-0.3400	0.0237***	0.1101***
	(0.0856)	(0.3165)	(0.0051)	(0.0198)
Age	-0.020095***	-0.0819	-.0320***	-0.0159***
	(0.0025)	(0.0522)	(0.0016)	(0.0039)
Age squared	0.0002***	0.0007*	0.0003***	0.0001***
	(0.0000)	(0.0004)	(0.0000)	(0.0000)
Internet use * age		0.0112		-0.0041***
		(0.0093)		(0.0007)
Internet use * age squared		-0.0001		0.000045***
		(0.0001)		(0.0000)
Women	0.0349***	0.0353***	0.0740***	0.0760***
	(0.0106)	(0.0107)	(0.0.0081)	(0.0081)
Unemployment	-0.1336***	-0.1672***	-0.2445***	-0.2375***
	(0.0226)	(0.0128)	(0.0168)	(0.0169)
16-19 years of education	0.1113	0.0845	0.0731***	0.0667***
	(0.0789)	(0.0609)	(0.0128)	(0.0129)
20+ years of education	0.1986	0.1570	0.1617***	0.1559***
	(0.1285)	(0.1000)	(0.0158)	(0.0158)
Unmarried	-0.0941***	-0.0750***	-0.1649***	-0.1718***
	(0.0130)	(0.0089)	(0.0123)	(0.0123)
Divorced or separated	-0.1350***	-0.1355***	-.02344***	-0.2362***
	(0.0095)	(0.0095)	(0.0144)	(0.0144)
Widowed	-0.1446***	-0.1297***	-0.2108***	-0.1995***
	(0.0323)	(0.0240)	(0.0151)	(0.0152)
Other relationships	0.0041	0.0304	0.0178	0.0050
	(0.0271)	(0.0353)	(0.0483)	(0.0483)
Financial situation	0.5900***	0.5847***	0.9708***	0.9687***
	(0.0310)	(0.0278)	(0.0103)	(0.0103)
Living in a rural area or village	0.0050	0.0068	0.0352***	0.0357***
	(0.0173)	(0.0163)	(0.0093)	(0.0093)
Living in a large town	-0.0017	-0.0029	-0.0215**	-0.0219**
	(0.0134)	(0.0127)	(0.0101)	(0.0101)
Society level (above mid-point)	0.1646***	0.1560***	0.2576***	0.2562***
	(0.0297)	(0.0240)	(0.0091)	(0.0091)
White-collar	0.0920	0.0440	0.0547***	0.0740***
	(0.0762)	(0.0400)	(0.0133)	(0.0136)
Blue-collar	0.0132	-0.0191	-0.0083	0.0025
	(0.0199)	(0.0128)	(0.0143)	(0.0145)
Observations	98,681	98,681	98,681	98,681
Atanhrho			0.0282***	0.0225**

Heteroskedasticity-robust standard errors in parentheses. All regressions include time dummies and country fixed effects. * p<0.10; ** P<0.05; *** P<0.01.

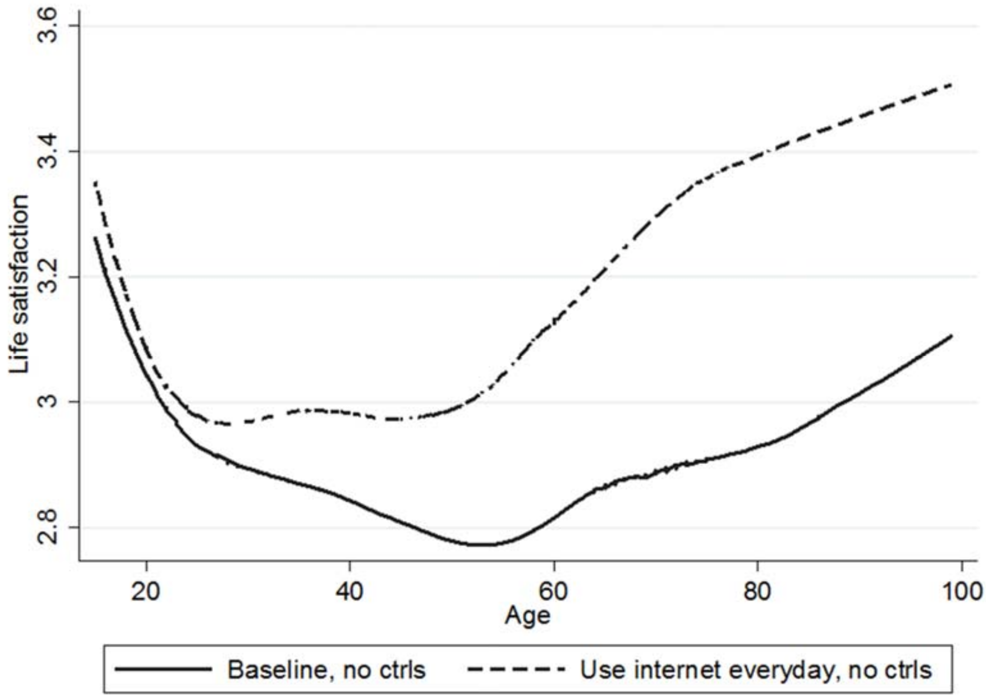
Table 5: Moderation effects of Internet use on the location of turning point of U-shape.

Internet use intensity	Turning point of U-shape
No Internet access	51.85
Never use Internet	50.76
Less than 2-3 times per month	50.02
2-3 times per month	49.49
About once a week	49.08
2-3 times per week	48.76
Everyday	48.50

Table 6: Moderation effects of Internet use on the curvature of U-shape.

Years around the turning point	Change of slope (Internet everyday – no Internet)
-10	+0.0054
-5	+0.0027
+5	-0.0.0027
+10	-0.0054

Figure 2: U-shaped relationship between age and life satisfaction. Whole sample vs. sub-sample of active Internet users



Appendix: Test of validity of instruments

We initially considered four instrumental variables: (1) fixed broadband take-up (subscriptions/100 people); (2) percentage of households having a fixed broadband connection (3) percentage of individuals accessing the Internet through a mobile phone via UMTS (3G); (4) wireless mobile broadband subscriptions. To test their validity, table 2.1 shows that when we include each instrument in the outcome equation (2nd stage) the two variables measuring households having a fixed broadband connection and wireless mobile broadband subscriptions are significantly correlated with the outcome variable, thus violating our exclusion restriction. Table 2.2 reports results of overidentification tests. The second column in this table indicates that the system is overidentified when we include together the two instruments that do not violate the exclusion restriction, fixed broadband take-up and 3G mobile broadband, and these should therefore be included in separate regressions rather than using them together. However, first stage regressions show that only the instrumental variable fixed broadband take-up is positively and significantly related to individuals Internet use intensity. For these reasons, the results presented in the paper have only used this instrumental variable and neglected the other three.

Table A.1: Instrument in outcome equation

	Panel A: Fixed broadband take-up	**Panel B: Households with broadband**
Instrument	0.0044 (0.0059)	-0.0040*** (0.0013)
Internet use	0.0279*** (0.0023)	0.0256*** (0.0022)
	Panel C: 3G mobile broadband	**Panel D: Wireless mobile subscriptions**
Instrument	0.0006 (0.0009)	0.0010* (0.0006)
Internet use	0.0255*** (0.0022)	0.0264*** (0.0026)

Table A.2 Sargan tests of overidentification

Instrument pair	Fixed take-up & Households with broadband	Fixed take-up & 3G mobile broadband	Fixed take-up & Wireless subscriptions	Households with broadband & 3G mobile broadband	Households with broadband & Wireless subscriptions	3G mobile broadband & Wireless subscriptions
J ($\chi^2(1)$)	19.1086***	2.9574*	2.0070	6.4602**	2.6897	0.0614
p(J)	0.0000	0.0855	0.1566	0.0110	0.1010	0.8043