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

**Fulvio Castellacci and Henrik Schwabe**

TIK Centre, University of Oslo

Paper for the seminar at the Department of Economics, University of Oslo,
23 November 2018

## Abstract

Extant research shows that the relationship between age and well-being is U-shaped. One recent explanation for this empirical pattern is related to unmet aspirations theory, pointing out that optimism bias decreases life satisfaction at younger ages, whereas pessimism bias increases it at later stages of life. This paper investigates the effects of Internet use on subjective well-being over the life cycle. Our model investigates the proposition that Internet use affects aspirations, and that this effect is relatively stronger at younger and older ages. To investigate moderation effects of Internet use on the U-shape of life, we use the Eurobarometer annual surveys for the years 2010 to 2016, which provide rich information for around 150,000 individuals in all European countries. We focus on the *EU Digital Agenda* policy program, and exploit exogenous variation in broadband Internet take-up across European countries to identify the causal effects of Internet on life satisfaction for different age groups. The results of 2SLS estimations for a recursive bivariate ordered probit model show that active Internet users have a different well-being pattern over the life cycle compared to less active users. Specifically, we find that Internet use makes the U-shape of life steeper. Country-level evidence on aspiration levels for different demographic and Internet user groups suggest that our empirical results are consistent with unmet aspirations theory.

**Key words:** Internet use; subjective well-being; life satisfaction; age; 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 access information and communicate with each other. It is reasonable to think that online information and communication patterns may affect individuals' aspirations and their perceived 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 varying extent and for distinct 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). 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.

Recent research has put forward a new explanation of the U-shape relationship based on "unmet aspirations theory" (Schwandt, 2016). This argues that individuals make systematic forecast errors when they form expectations about future life satisfaction, and that these errors indicate optimism bias at early stages of life, and pessimism bias at older ages (Deaton, 2008). Since unmet aspirations depress life satisfaction for younger individuals, and, by contrast, unexpected well-being fosters life satisfaction for older people, this theory can explain the U-shape pattern that has been observed and confirmed in previous empirical studies.

We take this theory as a conceptual framework for our analysis, and we extend it by investigating the effects of Internet use. We present a simple model based on Schwandt (2016), in which Internet use increases individuals' aspirations, and relatively more so for more vulnerable age groups, such as younger and older individuals. Our model predicts that Internet use makes the U-shape relationship between age and well-being steeper, i.e. exacerbating optimism bias for the younger and pessimism bias for the older.

To empirically 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 six annual surveys that refer to the years 2010 to 2016, which provide a rich dataset for about 150,000 individuals. Our identification strategy is based on the *EU Digital Agenda* policy program, which was initiated in the late 2000s to foster digitalization and Internet access in member countries (EC, 2014). The EU Digital Agenda provides an exogenous source of variation in broadband Internet take-up across European countries and regions. In fact, as we will show in the paper, the implementation of the EU policy program in different countries and regions in Europe during the period 2010-2016 was characterized by substantial spatial and temporal variation, and the timing of the roll-out was not related to other factors driving life satisfaction and its correlates.

We exploit this exogenous variation to identify the causal effects of Internet on life satisfaction for different age groups. Our instrumental variables – 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 or region (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 result of this analysis is that the effects of Internet use on subjective well-being are heterogeneous, varying significantly with age. The econometric findings point out that active

Internet users have a more pronounced decrease in reported life satisfaction in their younger adult life, and an earlier and stronger recovery after the turning point of the U-shape, and steady growth throughout older adult life. In short, we find that Internet use makes the U-shape of life steeper. We then provide aggregate (country-level) empirical evidence that illustrates that this empirical result is consistent with the predictions of unmet aspirations theory, and the model presented in this paper.

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. This means 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 theoretical framework; section 4 outlines the data and empirical methods; section 5 presents and discusses the regression results; and section 6 summarizes 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-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.

[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).

[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.

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 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 may have positive effects on well-being by facilitating social contacts and communication, and thus decreasing 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

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

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]

The literature has recently advanced a possible explanation of this empirical regularity. This is related to "unmet aspirations" (Schwandt, 2016). A variety of empirical studies within psychology and behavioral economics has provided evidence that individuals often make forecast errors when they form expectations about the future, and that these prediction errors change along the life cycle (i.e. optimism bias prevails at younger ages, and pessimism bias at older life stages). According to this argument, the mismatch between expectations and realized life satisfaction may explain the observed decrease in well-being during the first part of life, and the corresponding increase at older ages (Deaton, 2018).

## 3. Theoretical framework

The simple model presented in this section provides the theoretical framework for the empirical analysis. The model is based upon a generalization of Schwandt's (2016) recent study of life satisfaction and unmet aspirations, and it extends his framework to investigate the effects of Internet use. In line with the literature on the determinants of well-being, we assume that individuals derive life satisfaction from different *domains of life* (e.g. working life, consumption, social life). Individual *i*'s life satisfaction at time *t* is given by the following equation:

$$LS(t) = \sum_{d=1}^{D} d(t)[x(d,t)] - \lambda(t) \sum_{\tau=0}^{t-t0} E(t-\tau-1)[LS(t-\tau)] - LS(t-\tau) \tag{1}$$

The first term on the RHS of the equation is the sum of life satisfaction derived from all domains of life *d* at time *t*. Each domain of life's satisfaction is achieved by means of the vector of commodities (or life achievements) *x*(*d,t*). The function *d*(*t*) can in principle change over the life cycle, because

[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.

individuals can change their preferences over time and may therefore derive different life satisfaction levels from the same vector of commodities at different ages.

The second term represents a forecast error that individuals make in their expectation formation about future life satisfaction. According to Schwandt (2016), individuals expect their future life satisfaction to be a function of their current satisfaction level. If this expectation is wrong, the resulting forecast error (unmet aspiration) will affect their current life satisfaction level. Specifically, when forecast errors are positive (negative), individuals systematically predict that their future life satisfaction will be higher (lower) than it will actually prove to be. In this second term of equation 1, $\lambda(t)$ is a so-called *regret* parameter, representing the negative effect of forecast error on current life satisfaction. The parameter ranges between 0 and 1; the higher it is, the stronger is the regret for past failures (or unmet aspirations).

The expectation that an individual forms at time $t$-$\tau$-$1$ about her life satisfaction at time $t$-$\tau$ is given by the expression:

$$E(t-\tau-1)[LS(t-\tau)] = [1+\ \beta(t-\tau-1)] \bullet LS(t-\tau-1) \tag{2}$$

Future expectations are positively affected by the variable $\beta(t)$, which represents individuals' *aspirations* about the future. In line with recent literature (Schwandt, 2016; Deaton, 2018), we postulate that aspirations will decrease over the life cycle, and that they will be positive (*optimism bias*) at younger ages until midlife ($t < t(M)$), and become negative (*pessimism bias*) at later stages of life (beyond midlife; $t > t(M)$).

$$\frac{\partial\beta(t)}{\partial t} < 0\ ; \beta(t) = \begin{cases} \beta > 0,\ t < t(M) \\ \beta\ < 0,\ t > t(M) \end{cases} \tag{3}$$

Introducing this expectation term in equation 1 yields:

$$LS(t) = \sum_{d=1}^{D} d(t)[x(d,t)] - \lambda(t)\sum_{\tau=0}^{t-t0}[1+\ \beta(t-\tau-1)] \bullet LS(t-\tau-1) - LS(t-\tau) \tag{4}$$

Writing the extended form for all periods τ from 0 to t0, and solving for $LS(t)$ gives the following expression:

$$LS(t) = \frac{\sum_{d=1}^{D} d(t)[x(d,t)]}{1-\lambda(t)} - \frac{\lambda(t)}{1-\lambda(t)} \sum_{\tau=1}^{t-t0} \beta(t-\tau) \bullet LS(t-\tau) \tag{5}$$

The first term on the RHS of this equation is the sum of life satisfaction that an individual derives from the set of commodities and achievements that she has available from all domains of life *d*, divided by the complement to 1 of the regret parameter. This term is hence magnified by the regret parameter: the higher the regret for past failures, the more important current satisfaction with domains of life will become for an individual's well-being (i.e. an individual with high regret must compensate these unmet aspirations with current life status). The second term on the RHS is the *optimism bias* term. As noted above, this term is affected by aspirations and it decreases over the life cycle.

This simple model can in principle generate a U-shaped relationship between age and well-being in two ways. The first is related to the second term on the RHS of equation 5, namely through optimism bias and unmet aspirations. As shown by Schwandt (2016), if the aspiration variable $\beta$ decreases over the life cycle – so that younger (older) people systematically overestimate (underestimate) their future life satisfaction – then the life satisfaction variable would follow a U-shape, because unmet aspirations would depress well-being at young ages, whereas the opposite mechanism would foster well-being later in life.[5]

A second way in which this model could generate a U-shaped relationship arises if life satisfaction related to one given domain of life changes over the life cycle following a non-monotonic relationship. Specifically, assuming for simplicity that the forecast error term is 0, this happens if the function *d(t)* is U-shaped, i.e. because individuals derive a satisfaction level from domain of life *d* that decreases until midlife, and then rises again at older ages. For instance, this would be the case if individuals change some of their life priorities over the life cycle, e.g. valuing differently the importance of their social life. This could be regarded as an important dimension of life satisfaction at younger ages, less important during midlife (when many individuals shift their focus to working life and career objectives), and then becoming again more important at later stages of life.

$$\frac{\partial d(t)}{\partial t} < 0\,; \frac{\partial \partial d(t)}{\partial t} > 0 \tag{6}$$

[5] This mechanism is also supported by Carstensen's (2006) "socioemotional selectivity theory", according to which the older are typically better able at self-regulating their emotions, more positive in their own assessment, and less prone to regret. According to this psychological theory, this may be explained by the sense of remaining time, namely that the older tend to change their own assessments as they sense their remaining lifetime is getting shorter.

In both of the cases noted here (decreasing aspirations or changing preferences over the life cycle), the resulting relationship between life satisfaction and age would be U-shaped:

$$\frac{\partial LS(t)}{\partial t} < 0\,; \frac{\partial\partial LS(t)}{\partial t} > 0 \qquad (7)$$

***Effects of Internet use on aspirations***

To investigate the effects of Internet use in this framework, suppose now that we have two types of individuals, one that is a high (active) Internet user (HI), and the other that is low (sporadic) Internet user (LI). Based on extant literature, we argue that the different intensity of Internet use between these individuals may affect the U-shape relationship between age and well-being. Active Internet use will expose individuals to a variety of online content that will foster social comparison mechanisms, and thereby affect individuals' expectation formation and raise their aspiration levels (Lohmann, 2015; Sabatini and Sarracino, 2016). According to extant literature on the effects of Internet on well-being, such online comparison mechanisms and the related aspiration effects will be different for distinct age groups. Aspiration effects may in fact be relatively stronger for more vulnerable age groups, such as the younger (McDool et al., 2016; Schwabe, 2018) and the older (Castellacci and Tveito, 2018). If this is the case, the aspiration variable $\beta(t)$ will have a steeper (negative) trend for the group of active Internet users than for sporadic users:

$$\beta(t)^{HI} > \beta(t)^{LI} \qquad (8)$$

Under these conditions, it follows that Internet use will make the U-shape relationship between life satisfaction and age steeper. This means that the decrease in life satisfaction in early stages of life (before the turning point $t(M)$) would become more pronounced for active Internet users due to stronger optimism bias, and that, correspondingly, the increase in life satisfaction after midlife ($t > t(M)$) would also become swifter because of stronger pessimism bias:

**Proposition 1:**

$$\beta(t) = \begin{cases} \dfrac{\partial LS(t)^{HI}}{\partial t} < \dfrac{\partial LS(t)^{LI}}{\partial t}, & t < t(M) \\ \dfrac{\partial LS(t)^{HI}}{\partial t} > \dfrac{\partial LS(t)^{LI}}{\partial t}, & t > t(M) \end{cases}$$

This is the proposition that will be empirically tested and discussed in the subsequent sections.

## 4. 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 annual surveys that refer to the years 2010 to 2016, which provide a pooled cross-sectional dataset for around 150,000 individuals. These surveys 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:

$$\mathrm{LS}_{ict} = \alpha + \gamma \mathrm{INT}_{ict} + \delta \mathbf{X}_{ict} + \eta_c + \theta_t + \varepsilon_{ict} \tag{9}$$

$$\mathrm{INT}_{ict} = \lambda + \varrho \mathbf{X}_{ict} + \mu \mathrm{Z}_{ict} + \sigma_{ict} \tag{10}$$

where LS stands for life satisfaction, INT is internet use intensity, and **X** is a vector of covariates (control variables).[6] The sub-indexes *i*, *c* and *t* indicate individuals, countries and years respectively. $\eta_c$ is a set of country-specific effects, and $\theta_t$ is a set of time dummies. The variable Z in equation (2) is an exogenous instrumental variable that is correlated with INT but not correlated with the error term of the outcome equation, as explained further below.

An identification strategy for this model has to consider two aspects. The first one is to formulate a comprehensive specification of equation 10, 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 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. For this purpose, we exploit cross-country differences in broadband take-up among European nations and regions as a source of exogenous variation.

In the late 2000s, the EU initiated a new policy to foster access and use of broadband Internet in European countries. The *EU Digital Agenda*, introduced in May 2010, formulated a set of objectives that national Member States have to achieve to increase their degree of digitalization, and particularly their Broadband Internet take-up (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. Cross-country differences have been 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).[7] Supply-side factors are also related to geographical factors and pre-existing phone and

[6] 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".

[7] 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.

Internet infrastructures, which affect the pace at which broadband transmission centrals and local access points are built up in different regions and countries. 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).[8]

Figure 1 shows the distribution of broadband Internet take-up across countries and regions in Europe, and its evolution during the time span considered in this paper. The graphs show that spatial and temporal variation in broadband coverage is substantial. Using this source of variation to identify the causal effects of Internet use on life satisfaction relies upon two features of the EU digital policy program (Bhuller et al., 2013: 1250). First, that the supply and demand factors that affected the development of broadband Internet take up during this period did not vary substantially over time; second, that the timing of the broadband Internet expansion does not co-vary with other factors that are correlated with the outcome variable life satisfaction. We will empirically assess these two assumptions in the next sub-section.

Based on this exogenous source of variation, we make use of two instrumental variables that measure the diffusion of broadband Internet (fixed broadband take-up per 100 people) in European countries and regions during the period: one is defined at the country-level, and the other is defined at the regional level. 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- or region-year shocks (Angrist and Pischke, 2009: 192-197). We carried out all estimations and robustness tests using the two instruments in separate exercises. The baseline results we present in the manuscript are those for the fixed broadband take-up at the country-level, and the additional results reported in the appendix are those for the corresponding variable measured at the regional level.

Note that 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 specified in equation 10, but also on the overall level of diffusion of broadband Internet in the country (or region). The idea that peer effects affect Internet use intensity is in line

[8] 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).

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).

The key assumption of this identification strategy is that these 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, or region, in which $i$ lives is determined by a set of dimensions that cannot be affected by each individual (and particularly so since our instruments *predate* the individual-level outcome variable). The next sub-sections will empirically assess the validity of this assumption for our dataset.

After clarifying the identification strategy, we now briefly point out the methods that 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. We expect the use of Internet may 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).[9]

We estimate equations (9) and (10) through a 2SLS recursive bivariate ordered probit model, which simultaneously estimates the two equations adopting an ordered probit approach, given the

[9] Note that when we will include such interaction variables in the regressions, we will instrument them by using the corresponding interactions between the instrument and the age and age-squared variables, respectively. For a further discussion of econometric tests of U-shaped relationships, see Lind and Mehlum (2010).

categorical nature of both the outcome and treatment 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 >**

## 5. Results

### *5.1 First stage results and LATE analysis*

Before presenting the estimation results for the first stage, we seek to shed further light on the variability of our instrumental variables. First, we further assess the assumption that the timing of the broadband Internet expansion does not co-vary with other factors that are correlated with the outcome variable life satisfaction. Table 2 presents the results of regressions in which the dependent variable is the annual growth rate of the instrumental variable, and the RHS variables are the country average of the control variables at the beginning of the period. Table 2 shows that the timing of broadband Internet expansion is uncorrelated with the set of control variables that supposedly affect life satisfaction (e.g. education, occupation type, gender, age, marital status, financial situation, unemployment).

In table 3, we report the results of some balancing regressions (OLS), in which the dependent variables are some of the main socio-economic control variables in the model (income status, education, unemployment), and on the RHS we include future broadband take-up (in addition to lagged take-up and other control variables). The results indicate that the estimated coefficient for future take-up is not significant, ruling out the further the possibility that broadband Internet expansion co-varies with other determinants of life satisfaction.

Table 4 presents the results of the first stage estimations (equation 10), in which the dependent variable is the intensity of Internet use of each individual. The baseline results presented in the first column of table 4 show that 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;

[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 could in principle 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).

Kiiski and Pohjola, 2002; Chinn and Fairlie, 2006). The table indicates that Internet use intensity decreases with age. It is higher for people in the workforce that have higher education level and white-collar occupations, and that report a good financial situation. Unemployed workers have lower Internet use intensity than average, arguably because they do not use the Internet for professional activities. Further, Internet use is on average higher for individuals that live in a large town as opposed to those in a rural area.

The most important finding in table 4 is 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. We obtain the same result when the instrumental variable is defined at the regional level (see table A.2 in the appendix). As explained in the previous section, this finding corroborates the importance of "peer effects" as a determinant of Internet use, i.e. based on the idea that an individual is more likely to adopt and actively use Internet if many other individuals in the same country (or region) 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 5, we report the estimated coefficients of the effect of the instrumental variable on Internet use intensity (first stage regressions using a linear IV model) for different age sub-groups.

The table shows that individuals that respond more actively to increases in fixed broadband infrastructures are middle-aged adults (between 25 and 54), and less so younger and older Internet users. The pattern for middle-aged age groups is reasonable, since individuals in this stage of life typically 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 result that younger individuals (15-24 years old) increase their Internet use only marginally when their peers do

[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.

is somewhat surprising. A possible explanation of this pattern is that younger people in our sample are those that in the period 2010-2016 increasingly begun to use wireless mobile broadband, which gradually substituted the use of fixed broadband. Hence, it may simply be the case that our instrument (based on fixed broadband development) underestimates compliers effects for adolescents and young Internet users because it neglects the early phase of diffusion of mobile broadband.

**< Tables 2, 3, 4 and 5 here >**

### *5.2 Second stage results*

Table 6 presents the results of the second stage (equation 9), in which the dependent variable is the life satisfaction reported by each individual. 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 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 6 indicates that the relationship between age and life satisfaction is U-shaped, with lowest reported subjective well-being for middle-aged individuals. We will elaborate further on this U-shaped relationship later in this section. Among other control variables, highly educated individuals report higher life satisfaction than less educated people; unemployed individuals substantially lower satisfaction levels than employed people; and life satisfaction is higher for those individuals that have a good financial situation.

The top part table 6 reports the estimation results for the main variable of interest: Internet use intensity. This has a positive and significant effect on life satisfaction. Marginal effects of the Internet use variable, not reported here, are positive and significant too. The next columns in the table report some additional tests in order to assess the robustness of this result and the validity of our identification strategy. First, the second column of table 6 includes an additional control variable – the country-level time trend of life satisfaction in the period before the broadband Internet expansion. The inclusion of this additional regressor does not change the result for the Internet use variable, which is still positive and significant. This rules out the possibility that the positive effect of Internet use on life satisfaction is driven by pre-existing trends in outcome (we have carried out the same test and obtained the same result for region-specific life satisfaction time trends).

Second, the third column reports the results of a placebo test, which tests whether Internet take-up at *t+1* affects current life satisfaction at time *t*. In this placebo regression, we exclude the Internet use variable and correspondingly include the lead value of the instrumental variable (i.e. measured one year *after* the life satisfaction and other control variables). The future broadband take-up variable is not significant in the estimations, ruling out the possibility that our results are driven by some omitted variables that are related to both life satisfaction and broadband Internet expansion.

Third, the fourth column of table 6 includes an additional set of control variables, cohort effects, in order to test whether the U-shape relationship between age and well-being is a methodological artefact driven by the omission of cohort effects in life satisfaction regressions (Ree and Alessie, 2011; Hellevik, 2017). The estimation results, though, are in line with the other findings in the table: life satisfaction is U-shaped in age, and Internet has a direct positive effect on the dependent variable.

Finally, after presenting these robustness tests, we shift the focus to the point of our main interest: the moderation effects of Internet 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 fifth column of table 6 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] Table 7 provides similar evidence by running the same 2SLS oprobit regressions separately for four sub-groups of individuals (15-24; 25-39; 40-54; 55+). The results confirm that the effects of Internet use on life satisfaction are positive and significant, but they vary substantially with age.

**< Tables 6 to 8 here >**

Moderation effects of Internet on the age-well-being relationship can have two 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

[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 6, the marginal effect of the interaction variable is positive and significant. The slope analysis reported below in this section will elaborate further on this result.

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. From a conceptual point of view, the latter effect is more interesting and relevant than the former. However, the two effects are obviously related to each other, and we will therefore analyze them both.

Tables 9, 10 and 11 report the results of tests of these moderation effects. First, table 9 presents the results of second-stage estimations for seven sub-samples, each defined by a distinct Internet use intensity (i.e. sub-sample 1 (sub-sample 7) only refers to those individuals that report no Internet use (highest Internet use)). The estimated coefficients for the age and age-squared variables in table 9 indicate that the slope and curvature of the U-shape of life change as we move from lower to higher levels of Internet use intensity.

We calculated the turning points of the U-shape (i.e. age of midlife crisis) for the seven regressions reported in table 9. Table 10 reports the turning point for different levels of the Internet use intensity, and it shows that this moves towards the left as Internet use intensity increases (from around 53 to 50 years old), meaning that active Internet users, on average, begin a recovery period after the midlife crisis somewhat *earlier* than individuals who use Internet less actively.

Table 11 shifts the focus to the second type of moderation effect, which is the one of our main interest. The table reports the estimated slope of the U-shape at six different ages (25, 35, 45, 55, 65, 75 and 85) and for each Internet use intensity level (1 to 7). We also tested the slope difference for four different years around the turning point (following the method described in Haans et al., 2016: 1195). The slopes reported in table 11 show a clear and consistent pattern. First, the slopes are obviously negative before the turning point and positive thereafter. Second, and more relevant, a comparison of slopes between different Internet user groups shows that Internet use intensity makes the U-shaped relationship between age and life satisfaction *steeper*. This finding is also consistent with the positive sign of the estimated interaction effect *Internet * age-squared* previously reported in table 6. This means that Internet use accelerates the decline in life satisfaction that characterizes young adults and middle-aged individuals until the midlife crisis; and that it strengthens the subsequent growth and recovery period for older adults. After the turning point of the U-shape, active Internet users turn out to experience a much more pronounced and rapid recovery from the midlife crisis, reporting steadily increasing levels of life satisfaction.

**< Tables 9 to 11 here >**

### *5.3 Discussion*

What can explain these empirical results? The simple theoretical framework outlined in section 3 points to the role of unmet aspirations (Schwandt, 2016; Deaton, 2018), and how these are affected by Internet use for different age groups. The main idea put forward in our model is twofold. First, the framework assumes that aspirations decrease over the life cycle, leading to optimism bias in the first part of life, and pessimism bias at older ages. It is such decreasing trend of aspirations that explains a U-shaped relationship between age and well-being. Second, our model points out that if aspirations decline over time more rapidly for Internet users than non-users, Internet use would make the U-shape of life steeper (which is precisely the main empirical result that has been shown by the regression analysis above).

In our dataset, we are not able to empirically test these two properties of the model at the individual level (differently from Schwandt, 2016, who had available a panel dataset that enables the test of this assumption). However, the Eurobarometer survey dataset has a few questions about individuals' expectations on their future life satisfaction that can be used to provide aggregate evidence on the relevance of unmet aspirations theory. Specifically, we have used the following four variables that can be constructed based on survey questions about individuals' expectations on their life in the following 12 months: (1) life as a whole; (2) working life; (3) financial situation; (4) social life. Each variable is defined on a 1-3 scale (1: worse than today; 2: same as today; 3: better than today). Since our dataset is not a panel, we are not able to match individuals' responses to the life satisfaction and expectations questions at time $t$ (which would provide a direct measure of unmet aspirations at the individual level). Instead, we have collapsed these four expectation variables at the country-level, and calculated their average for different age groups and different Internet users groups, in order to provide aggregate evidence on the relationships between expectations, life satisfaction and Internet use.

Figure 2 shows the trend of life satisfaction and expectations about life as a whole for four different age groups. The graph shows that expectations are on average higher for younger age groups, and decrease progressively for older age groups. The expectation line is above 2 (indicating that individuals do on average expect a better life in the future) until about the age group 40-54, and it then goes below 2 thereafter (indicating expectations of a worse future). This aggregate evidence is therefore in line with the model's main assumption that the aspiration variable (here proxied by expectations about the future) decreases over time, shifting from optimism bias to pessimism bias throughout the life cycle (see equation 3, in section 3). This pattern is consistent with the main idea of unmet aspiration theory (Schwandt, 2016; Deaton, 2018).

Figure 3 depicts the trends of expectations for different age groups, and comparing active Internet users from less active (or sporadic) users. The four panels in figure 4 focus on expectations about life as a whole, working life, financial situation and social life, respectively. These figures illustrate two patterns. The first is that, for all age groups, Internet users have on average higher expectations than non-users. This is in line with recent literature suggesting that Internet increases aspirations (e.g. Lohmann, 2015; Sabatini and Sarracino, 2016; Schwabe, 2018). The second pattern is that in all four figures the expectation variable decreases with age, and this decline is relatively faster for active Internet users than for sporadic users. This is consistent with the main property of our model that Internet use affects aspirations more strongly for individuals in younger and in older age groups (see equation 8, in section 3).

Further, the figures also show that the point at which the life satisfaction curve meets the expectation line comes earlier for Internet users than for non-users. This point indicates the stage at which expectations begin to be lower than realized life satisfaction, and hence when optimism bias of younger ages is substituted by pessimism bias typical of older life stages. On the whole, this aggregate evidence is consistent with the main properties of the model presented in section 3, suggesting that the effects of Internet on the U-shape of life can be explained in terms of aspiration effects and their evolution over the life cycle.[13]

**< Figures 2 and 3 here >**

[13] However, it is important to acknowledge that our empirical result of a moderation effect of Internet on life satisfaction may in principle be explained by a different mechanism that is not related to unmet aspirations theory. In fact, as pointed out in section 3 (see equation 6), it is theoretically possible to assume that life satisfaction related to one given domain of life changes over the life cycle following a non-monotonic relationship, thus generating a U-shaped relationship between age and well-being. For instance, consider as an example the social life domain. Individuals may value it differently throughout the life cycle. Social life could be regarded as an important dimension of life satisfaction at younger ages, less important during midlife (when many individuals shift their focus to working life and career objectives), and then becoming again more important at later stages of life. Internet use could also be thought to have different effects on social life for different age groups (e.g. through different social media and online communication behavior). In this example, the U-shape of life would be explained by changing preferences and values over time, and moderation effects of Internet would be related to its heterogenous effects on the social life of different demographic groups. In this paper, we have not been able to investigate this second possible explanation in further details, in lack of an adequate theory and empirical evidence on this second mechanism. It is therefore important that future research will test and compare the predictions of unmet aspirations theory with those of other different explanations of the U-shape of life.

## 7. Conclusions

Empirical research has consistently shown that the relationship between age and life satisfaction is U-shaped, and the present study has investigated whether, and the extent to which, Internet use moderates the U-shape of life. According to recent research (Schwandt, 2016; Deaton, 2018), one possible explanation of the U-shape relationship is related to unmet aspirations, pointing out that individuals make systematic forecast errors when they form expectations about future life satisfaction, and that these errors indicate optimism bias at early stages of life, and pessimism bias at older ages. Since unmet aspirations depress life satisfaction for younger individuals, and, by contrast, unexpected well-being fosters life satisfaction for older people, this theory can explain the U-shape pattern that has been observed and confirmed in many empirical studies.

The present paper takes this theory as a conceptual framework, and it extends it by investigating the effects of Internet use. Our main proposition is that Internet tends to increase aspirations, and that this effect will be stronger for more vulnerable age groups, such as younger individuals and older groups. If this is true, Internet use would make the U-shape relationship steeper, i.e. exacerbating optimism bias for the younger and pessimism bias for the older.

To empirically investigate this proposition, we used the Eurobarometer surveys for the years 2010 to 2016, and exploited exogenous variation in broadband Internet take-up across European countries and regions to identify the causal effects of Internet use on well-being for different age groups. The results of 2SLS bivariate ordered probit estimations are twofold. First, Internet use has a positive and significant effect on subjective well-being. Second, Internet use does also moderate the U-shaped relationship between age and well-being by making it steeper. Specifically, we find that Internet users experience a more pronounced decrease in reported life satisfaction in their younger adult life, and then an earlier and stronger recovery after the turning point (midlife crisis).

According to our model, the interpretation of this result is related to the effects of Internet on individuals' aspirations, and how these effects differ for distinct age groups. As noted above, our dataset does not enable to carry out a proper empirical test of unmet aspirations theory at the individual level. However, we have reported aggregate (country-level) evidence showing that our empirical results are consistent with the main predictions of the unmet aspirations model. This evidence shows in fact that: (1) aspirations decline over the life cycle; (2) active Internet users have on average higher aspirations than less active users; (3) the effect of Internet use on aspirations is stronger for younger and older groups. In short, this aggregate evidence corroborates an unmet aspirations explanation of our econometric results.

However, as discussed above, it is also important to acknowledge that this country-level evidence does not represent a full-fledged test of the theoretical framework adopted in this paper. The U-shape of life could in principle be explained by other mechanisms, such as e.g. changing preferences and values over the life cycle. Therefore, we cannot rule out the possibility that our econometric results on the moderation effects of Internet may be driven not only by aspiration-related patterns, but also be explained by age-specific effects of Internet in specific domains of life. This calls for further research investigating how the effects of Internet on well-being vary with age, employing individual-level data and variables that enable a test of possible alternative explanations.

## Acknowledgments

Financial support from the Research Council of Norway's Samansvar program is gratefully acknowledged. We wish to thank Manudeep Bhuller, Monica Guillen-Royo and Philippe Larédo for the comments they provided on a previous draft of this paper.

## References

Agarwal, R., Animesh, A. and Prasad, K. (2009). Social Interactions and the "Digital Divide": Explaining Variations in Internet Use. *Information Systems Research*, 20(2): 277-294.

Akerman, A., Gaarder, I. and Mogstad, M. (2015). The skill complementarity of broadband Internet. *Quarterly Journal of Economics*, 1781-1824.

Angrist, J. and Pischke, J. (2009): *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press, Princeton and Oxford.

Baetschmann, G. (2013). Heterogeneity in the relationship between happiness and age: Evidence from the German socio-economic panel. *German Economic Review*, 15, 393-410.

Bauernschuster, S., Falck, O. and Woessmann, L. (2014). Surfing alone? The internet and social capital: Evidence from an unforesseable technological mistake. *Journal of Public Economics*, 117: 73-89.

Bhuller, M., Havnes, T., Leuven, E. and Mogstad, M. (2013). Broadband Internet: An Information Superhighway to Sex Crime? *Review of Economic Studies*, 80: 1237-1266.

Blanchflower, D. and Oswald, A. (2004). Well-being over time in Britain and the USA. *Journal of Public Economics*, 88, 1359-1386.

Blanchflower, D. and Oswald, A. (2008). Is well-being U-shaped over the life cycle? *Social Science & Medicine*, 66, 1733-1749.

Blanchflower, D. and Oswald, A. (2009). The U-shape without controls: A response to Glenn. *Social Science & Medicine*, 69, 486-488.

Bruni, L. and Stanca, L. (2006). Income aspirations, television and happiness: Evidence from the world values survey. *Kyklos*, *59*(2), 209-225.

Bruni, L. and Stanca, L. (2008). Watching alone: relational goods, television and happiness. *Journal of Economic Behavior & Organization*, *65*(3), 506-528.

Cambini, C. and Jiang, Y. (2009). Broadband investment and regulation: A literature review. *Telecommunications Policy*, 33: 559-574.

Carstensen, L. (2006), The influence of a sense of time on human development, *Science*, 312, 1913-1915.

Castellacci, F. (2010). Structural change and the growth of industrial sectors: Empirical test of a GPT model. *Review of Income and Wealth,* 56(3): 449-482.

Castellacci, F. and Tveito, V. (2018). Internet Use and Well-being: A Survey and a Theoretical Framework. *Research Policy*, 47: 308-325.

Chen, Y., Persson, A. (2002). Internet use among young and older adults: relation to psychological well-being. *Educational Gerontology*, 28 (9), 731–744.

Chinn, M. and Fairlie, R. (2006). The determinants of the global digital divide: A cross-country analysis of computer and internet penetration. *Oxford Economic Papers*, 59: 16-44.

Clark, A. E., Frijters, P., & Shields, M. A. (2008). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic Literature*, 95-144.

Clarke, R. (2014). Expanding mobile wireless capacity: The challenges presented by technology and economics. *Telecommunications Policy*, 38: 693-708.

Czernich, N., Falck, O., Kretschmer, T. and Woessmann, L. (2011). Broadband infrastructure and economic growth. *Economic Journal*, 121: 502-532.

De Ree, J. and Alessie, R. (2011): Life satisfaction and age: Dealing with underidentification in age-period-cohort models. *Social Science and Medicine*, 73, 177-182.

Deaton, A. (2013). Through the darkness to a brighter future. In Palacios-Huerta, I. (ed.), 100 Years: Leading Economists Predict the Future, MIT Press, London.

Deaton, A. (2018). What do self-reports of wellbeing say about life-cycle theory and policy? *Journal of Public Economics*, 162, 18-25.

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, 29(1), 94-122.

Easterlin, R. A. (1995). Will raising the incomes of all increase the happiness of all? *Journal of Economic Behavior & Organization*, 27(1), 35-47.

EC (2014): Study on National Broadband Plans in the EU-28. Final Report, European Commission.

Falck., O., Gold, R. and Heblich, S. (2014). E-lections: Voting Behavior and the Internet. *American Economic Review*, 104(7): 2238-2265.

Ford, G.S., Ford, S.G. (2009). Internet use and depression among the elderly. Phoenix Center Policy Paper. pp. 38.

Franzen, A. (2003). Social capital and the Internet: Evidence from Swiss panel data. *Kyklos*, 56(3), 341-360.

Frey, B. S., & Stutzer, A. (2002). What can economists learn from happiness research? *Journal of Economic Literature*, 40(2), 402-435.

Frijters, P. and Beatton, T. (2012). The mystery of the U-shaped relationship between happiness and age. *Journal of Economic Behavior & Organization*, 82, 525-542.

Ganju, K.K., Pavlou, P.A. and Banker, R.D. (2015). Does information and communication technology lead to the well-being of nations? A Country-Level Empirical Investigation. *MIS Quarterly*, 40(2): 417-430.

Goolsbee, A. and Klenow, P. (2002). Evidence on learning and network externalities in the diffusion of home computers. *Journal of Law and Economics*, XLV, 317-343.

Graham, C., & Nikolova, M. (2013). Does access to information technology make people happier? Insights from well-being surveys from around the world. *Journal of Socio-Economics, 44*, 126-139.

Greene, W. (2003). Econometric Analysis. Fifth Edition, Upper Saddle River, N.J., Prentice Hall.

Gruber, H., Hatonen, J. and Koutrompis, P. (2014). Broadband access in the EU: An assessment of future economic benefits. *Telecommunications Policy*, 38: 1046-1058.

Haans, R., Pieters, C. and He Z-L. (2016). Thinking About U: Theorizing and Testing U- and Inverted U-Shaped Relationships in Strategy Research. *Strategic Management Journal*, 37, 1177-1195.

Hellevik, O. (2017). The U-shaped age-happiness relationship: real or methodological artifact? *Quality and Quantity*, 51, 177-197.

Jackson, L.A., Fitzgerald, H.E., Zhao, Y., Kolenic, A., Von Eye, A., Harold, R. (2008), Information Technology (IT) use and children's psychological well-being. *Cyberpsychology Behavior*, 11 (6), 755–757.

Kahneman, D. and Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences*, 107(38), 16489-16493.

Kahneman, D. and Krueger, A. B. (2006). Developments in the measurement of subjective well-being. *Journal of Economic Perspectives*, 20(1), 3-24.

Kavetsos, G. and Koutroumpis, P. (2011). Technological affluence and subjective well-being. *Journal of Economic Psychology*, *32*(5), 742-753.

Kiiski, S. and Pohjola, M. (2002). Cross-country diffusion of the Internet. *Information Economics and Policy*, 297-310.

Lelkes, O. (2013). Happier and less isolated: internet use in old age. *Journal of Poverty and Social Justice*, 21, 33-46.

Lind. J.T. and Mehlum, H. (2010). With or without U? The appropriate test for a U-shaped relationship. *Oxford Bullettin of Economics and Statistics*, 72 (1), 109-118.

Lohmann, S. (2015). Information technologies and subjective well-being: does the Internet raise material aspirations? *Oxford Economic Papers*, 67(3), 740-759.

MacKerron, G. (2012). Happiness economics from 35 000 feet. *Journal of Economic Surveys*, 26(4), 705-735.

McDool, E., Powell, P., Roberts, J. and Taylor, K. (2016). Social Media Use and Children's Wellbeing. IZA Discussion Paper 10412.

Monfardini, C. and Radice, R. (2008). Testing Exogeneity in the Bivariate Probit Model: A Monte Carlo Study. *Oxford Bulletin of Economics and Statistics*, 70 (2): 271–282.

Pénard, T., Poussing, N., & Suire, R. (2013). Does the Internet make people happier?. *The Journal of Socio-Economics*, *46*, 105-116.

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal*, 11(2): 159-206.

Rotondi, V., Stanca, L., & Tomasuolo, M. (2016). Connecting Alone: Smartphone Use, Quality of Social Interactions and Well-being. DEMS Working Paper 357.

Sabatini, F. and Sarracino, F. (2017). Online networks and subjective well-being. *Kyklos,* 70(3): 456-480.

Sabatini, F. and Sarracino, F. (2016). Keeping up with the e-Joneses: Do online social networks raise social comparisons?. MPRA Working Paper 69201.

Sajaia, Z. (2008). Maximum likelihood estimation of a bivariate ordered probit model: Implementation and Monte Carlo simulations. *The Stata Journal*, 4(2): 1-18.

Schwabe, H. (2018): Internet use and expectation formation over the life cycle, TIK Working Paper, forthcoming.

Schwandt, H. (2016). Unmet aspirations as an explanation for the age U-shape in wellbeing. *Journal of Economic Behavior and Organization*, 122, 75-87.

Senik, C. (2005). Income distribution and well‐being: what can we learn from subjective data? *Journal of Economic Surveys, 19*(1), 43-63.

Serdarevic, G., Hunt, M., Ovington, T. and Kenny, C. (2016). Evidence for a Ladder of Investment in Central and Eastern European countries. *Telecommunications Policy, 40: 515-531*.

Troulos, C. and Maglaris, V. (2011): Factors determining municipal broadband strategies across Europe. *Telecommunications Policy*, 35: 842-856.

# Tables and figures

**Table 1: Descriptive statistics**

| | Mean | St.dev. | Min | Max | Obs |
|---|---|---|---|---|---|
| Life satisfaction | 2.93 | 0.80 | 1 | 4 | 157,693 |
| Internet use | 5.42 | 2.26 | 1 | 7 | 157,693 |
| Age | 47.27 | 18.21 | 15 | 99 | 157,693 |
| Women | 0.52 | 0.50 | 0 | 1 | 157,693 |
| Financial situation | 2.65 | 0.77 | 1 | 4 | 157,693 |
| Up to 15 years of education | 0.24 | 0.43 | 0 | 1 | 157,693 |
| 16-19 years of education | 0.44 | 0.50 | 0 | 1 | 157,693 |
| 20+ years of education | 0.32 | 0.47 | 0 | 1 | 157,693 |
| Unemployment | 0.09 | 0.29 | 0 | 1 | 157,693 |
| Divorced | 0.07 | 0.26 | 0 | 1 | 157,693 |
| Widow | 0.08 | 0.28 | 0 | 1 | 157,693 |
| Living in a rural area or village | 0.33 | 0.47 | 0 | 1 | 157,693 |
| Living in a small/middle sized town | 0.39 | 0.49 | 0 | 1 | 157,693 |
| Living in a large town | 0.27 | 0.45 | 0 | 1 | 157,693 |
| White-collar | 0.36 | 0.48 | 0 | 1 | 157,693 |
| Blue-collar | 0.14 | 0.35 | 0 | 1 | 157,693 |
| Fixed broadband take-up | 27.84 | 6.67 | 14.85 | 43.39 | 157,693 |

**Figure 1: Distribution of fixed broadband across EU countries (above) and regions (below)**

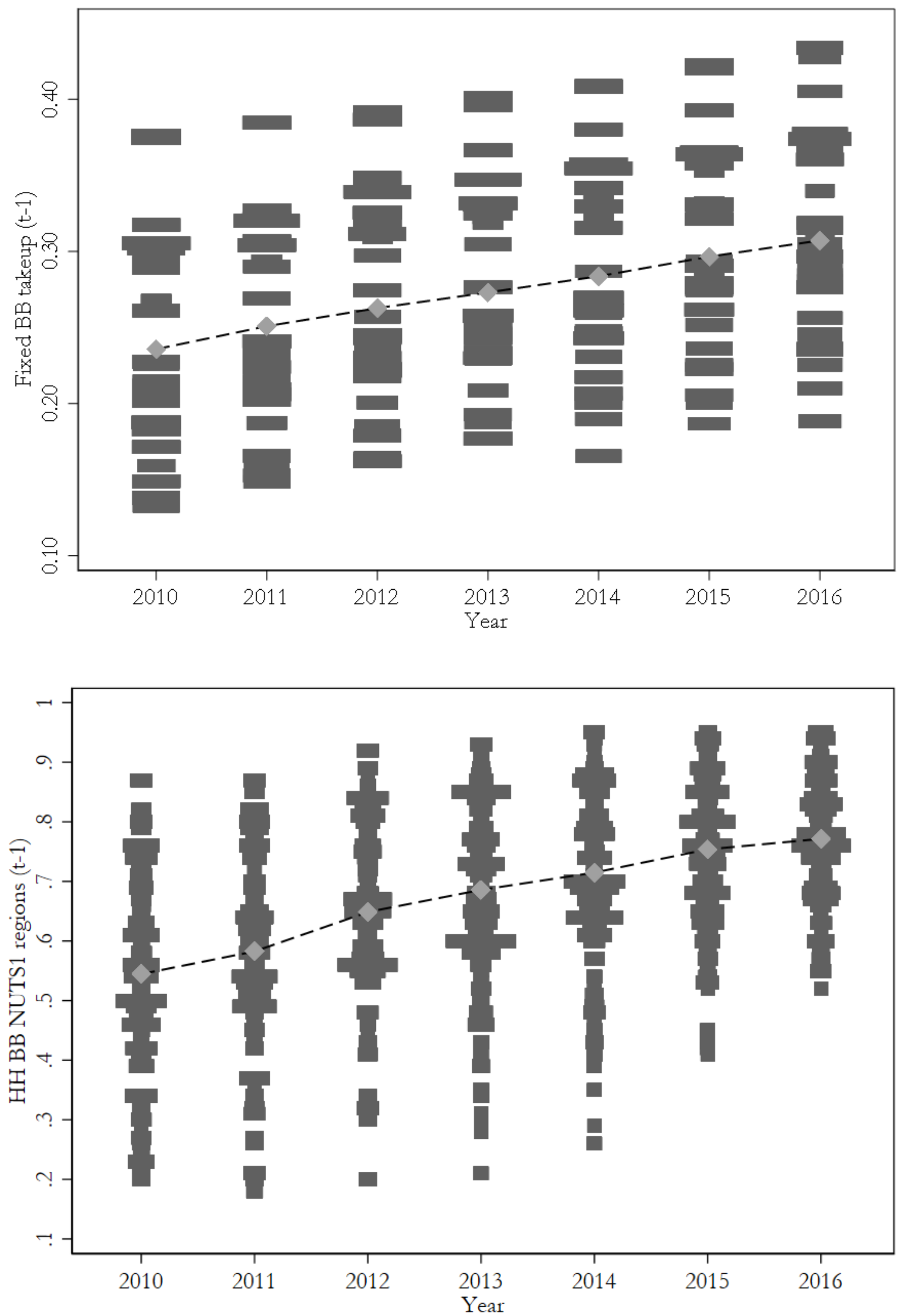


**Table 2: Timing of broadband Internet variation.**

| | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|
| Education level | 11.297** | 2.825 | 6.589 | 2.062 | 3.814 |
| Women | 4.699 | 19.146 | 2.118 | -1.790 | -38.126 |
| Urbanization | -0.052 | 4.278 | -5.473 | -3.098 | 0.481 |
| Unemployment | -16.952 | 10.851 | 3.967 | -8.345 | 15.817 |
| Age | -0.467 | 0.393 | 0.264 | -0.239 | 0.075 |
| Financial situation | 0.346 | -2.309 | -2.781 | -1.055 | 3.901 |
| Divorces | -44.397 | 23.519 | 4.476 | 9.312 | 17.147 |
| Widowers | 62.058 | -70.526 | -133.491 | -22.544 | 3.714 |
| Blue-collar jobs | 54.491 | -12.548 | 11.021 | 5.987 | 17.124 |
| White-collar jobs | -1.281 | -2.274 | -13.970 | -18.894** | -11.149 |

*Note:* The table reports estimated coefficients from a regression of the growth rate of broadband Internet on the time trend of covariates for the years 2012 to 2016. The regression is based on a panel of 207 country-year observations.
* p<0.10; ** p<0.05; *** p<0.01

**Table 3: First stage results. Balancing regressions.**

| | Financial situation | Education | Unemployment |
|---|---|---|---|
| Fixed broadband take-up t-1 | 0.011*** | -0.007** | 0.001 |
| | (0.003) | (0.003) | (0.001) |
| Fixed broadband take-up t+1 | -0.003 | 0.004 | -0.000 |
| | (0.002) | (0.003) | (0.001) |

The table reports the estimated coefficients of lagged and lead broadband Internet take-up in three balancing regressions. These regress the dependent variables financial situation, education and unemployment, respectively, on the set of covariates included in the model plus the lead and lagged instruments. Heteroskedasticity-robust standard errors in parentheses. All regressions include a full set of control variables, time dummies and country fixed effects. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

**Table 4: First stage results. Baseline estimations and balancing tests.**

| | Baseline | Balancing test |
|---|---|---|
| Fixed broadband take-up t-1 | 0.048*** | 0.037*** |
| | (0.005) | (0.006) |
| Age | -0.035*** | -0.035*** |
| | (0.002) | (0.002) |
| Age squared | -0.000*** | -0.000*** |
| | (0.000) | (0.000) |
| Women | -0.094*** | -0.094*** |
| | (0.009) | (0.009) |
| Financial situation | 0.322*** | 0.322*** |
| | (0.007) | (0.007) |
| 16-19 years of education | 0.582*** | 0.581*** |
| | (0.014) | (0.014) |
| 20+ years of education | 1.103*** | 1.103*** |
| | (0.015) | (0.015) |
| Unemployment | -0.205*** | -0.205*** |
| | (0.020) | (0.020) |
| White-collar job | 0.450*** | 0.449*** |
| | (0.014) | (0.014) |
| Blue-collar job | -0.137*** | -0.138*** |
| | (0.017) | (0.017) |
| Divorced | 0.020 | 0.023 |
| | (0.019) | (0.019) |
| Widowed | -0.530*** | -0.529*** |
| | (0.019) | (0.019) |
| Living in a rural area or village | -0.157*** | -0.158*** |
| | (0.010) | (0.010) |
| Living in a large town | 0.155*** | 0.155*** |
| | (0.010) | (0.010) |
| _cons | 4.806*** | 5.045*** |
| | (0.131) | (0.629) |
| N | 157,693 | 157,693 |
| F-value (instrument) | 92.12 | |

Heteroskedasticity-robust standard errors in parentheses. The second column includes a full set of controls that was averaged and lagged over country-years (i.e. $\overline{x'_{c,t}}$, and $\overline{x'_{c,t-1}}$) time dummies and country fixed effects. * p<0.10; ** p<0.05; *** p<0.01.

**Table 5: LATE results: compliers for different age groups.**

| | | P[X=x] | Coefficient of fixed broadband take-up |
|---|---|---|---|
| **Age groups** | | | |
| | Young (15-24) | 0.089 | 0.041*** |
| | Younger adults (25-39) | 0.222 | 0.078*** |
| | Middle-aged (40-54) | 0.258 | 0.088*** |
| | Older adults (55+) | 0.431 | 0.030** |

*Note:* Column 1 reports the relative shares of each age group of the total sample. The second column reports the first stage coefficients on our instrument (based on a linear model). The regressions include time and country dummies. * p<0.10; ** p<0.05; *** p<0.01.

**Table 6: Second stage results. Baseline estimations.**

| | Baseline | Pre-reform trend | Placebo | Cohort | Full model |
|---|---|---|---|---|---|
| Internet use | 0.042*** | 0.042*** | | 0.053*** | 0.117*** |
| | (0.004) | (0.004) | | (0.004) | (0.018) |
| Internet use X age | | | | | -0.004*** |
| | | | | | (0.001) |
| Internet use X age squared | | | | | 0.000** |
| | | | | | (0.000) |
| Age | -0.028*** | -0.028*** | -0.030*** | -0.025*** | -0.012*** |
| | (0.001) | (0.001) | (0.001) | (0.003) | (0.005) |
| Age squared | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Women | 0.055*** | 0.055*** | 0.051*** | 0.058*** | 0.057*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Financial situation | 0.782*** | 0.782*** | 0.799*** | 0.781*** | 0.781*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.009) |
| 16-19 years of education | -0.013 | -0.013 | 0.008 | -0.011 | -0.012 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.014) |
| 20+ years of education | 0.079*** | 0.079*** | 0.115*** | 0.081*** | 0.083*** |
| | (0.012) | (0.012) | (0.011) | (0.012) | (0.024) |
| Unemployment | -0.273*** | -0.273*** | -0.284*** | -0.250*** | -0.259*** |
| | (0.014) | (0.014) | (0.015) | (0.014) | (0.014) |
| White-collar job | -0.032*** | -0.032*** | -0.017 | -0.011 | -0.008 |
| | (0.010) | (0.010) | (0.010) | (0.011) | (0.022) |
| Blue-collar job | -0.120*** | -0.120*** | -0.134*** | -0.094*** | -0.103*** |
| | (0.011) | (0.011) | (0.012) | (0.012) | (0.013) |
| Divorced | -0.190*** | -0.190*** | -0.187*** | -0.191*** | -0.192*** |
| | (0.012) | (0.012) | (0.013) | (0.012) | (0.012) |
| Widowed | -0.177*** | -0.177*** | -0.203*** | -0.166*** | -0.168*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.014) |
| Living in a rural area or village | 0.040*** | 0.040*** | 0.036*** | 0.036*** | 0.040*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| Living in a large town | -0.020** | -0.020** | -0.010 | -0.025*** | -0.020** |
| | (0.008) | (0.008) | (0.009) | (0.008) | (0.009) |
| Pre-reform trend in life satisfaction (linear) | | -0.052*** | | | |
| | | (0.019) | | | |
| Fixed broadband take-up t-1 | | | 0.028*** | | |
| | | | (0.006) | | |

| | | | | | |
|---|---|---|---|---|---|
| Fixed broadband take-up t+1 | | | -0.001<br>(0.005) | | |
| N | 157,693 | 157,693 | 132,933 | 157,693 | 157,693 |
| Atanhrho | -0.094***<br>(0.009) | | | -0.019**<br>(0.009) | |

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 7: Second stage results. Separate estimations for different age groups.**

| | ***15-24*** | ***25-39*** | ***40-54*** | ***55+*** |
|---|---|---|---|---|
| Internet use | 0.079*** | 0.023** | 0.014* | 0.027*** |
| | (0.021) | (0.010) | (0.009) | (0.006) |
| Women | 0.008 | 0.086*** | 0.060*** | 0.052*** |
| | (0.021) | (0.014) | (0.013) | (0.010) |
| Financial situation | 0.710*** | 0.755*** | 0.808*** | 0.802*** |
| | (0.019) | (0.013) | (0.012) | (0.009) |
| 16-19 years of education | -0.062 | 0.021 | 0.035 | 0.036** |
| | (0.046) | (0.027) | (0.024) | (0.014) |
| 20+ years of education | -0.071 | 0.127*** | 0.139*** | 0.144*** |
| | (0.055) | (0.029) | (0.029) | (0.019) |
| Unemployment | -0.452*** | -0.250*** | -0.129*** | -0.208*** |
| | (0.053) | (0.030) | (0.028) | (0.028) |
| White-collar job | -0.182*** | 0.001 | 0.139*** | -0.035** |
| | (0.052) | (0.025) | (0.024) | (0.017) |
| Blue-collar job | -0.203*** | -0.108*** | 0.036 | -0.129*** |
| | (0.052) | (0.027) | (0.024) | (0.019) |
| Divorced | -0.243** | -0.255*** | -0.186*** | -0.195*** |
| | (0.121) | (0.033) | (0.020) | (0.017) |
| Widowed | 0.037 | -0.227* | -0.197*** | -0.128*** |
| | (0.236) | (0.118) | (0.043) | (0.014) |
| Living in a rural area or village | 0.055** | 0.062*** | 0.043*** | 0.014 |
| | (0.026) | (0.016) | (0.015) | (0.011) |
| Living in a large town | -0.028 | 0.006 | -0.049*** | -0.018 |
| | (0.026) | (0.016) | (0.016) | (0.013) |
| N | 14,099 | 34,94 | 40,706 | 67,940 |

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 8: Second stage results. Separate estimations for different Internet use groups.**

| | *No access* | *Never use* | *Less often* | *2-3 times a month* | *About once a week* | *2-3 times a week* | *Every day* |
|---|---|---|---|---|---|---|---|
| Age | -0.011** | -0.020*** | -0.037*** | -0.034*** | -0.030*** | -0.032*** | -0.033*** |
| | (0.005) | (0.003) | (0.009) | (0.012) | (0.008) | (0.005) | (0.002) |
| Age squared | 0.000* | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Women | 0.077*** | 0.037*** | 0.054 | 0.030 | 0.120*** | 0.060*** | 0.062*** |
| | (0.025) | (0.014) | (0.044) | (0.062) | (0.039) | (0.022) | (0.009) |
| Financial situation | 0.836*** | 0.801*** | 0.766*** | 0.741*** | 0.830*** | 0.806*** | 0.758*** |
| | (0.021) | (0.013) | (0.038) | (0.057) | (0.035) | (0.021) | (0.008) |
| 16-19 years of education | 0.073*** | 0.037** | 0.077 | 0.066 | -0.026 | 0.010 | -0.076*** |
| | (0.028) | (0.017) | (0.061) | (0.078) | (0.057) | (0.034) | (0.016) |
| 20+ years of education | 0.230*** | 0.140*** | 0.092 | 0.177* | -0.018 | 0.078** | 0.030* |
| | (0.044) | (0.025) | (0.074) | (0.094) | (0.069) | (0.038) | (0.017) |
| Unemployment | -0.245*** | -0.120*** | -0.285*** | -0.166 | -0.036 | -0.315*** | -0.295*** |
| | (0.048) | (0.029) | (0.080) | (0.115) | (0.080) | (0.047) | (0.020) |
| White-collar job | 0.017 | 0.075*** | 0.134** | 0.055 | 0.032 | -0.044 | -0.017 |
| | (0.054) | (0.027) | (0.065) | (0.087) | (0.055) | (0.032) | (0.015) |
| Blue-collar job | -0.058 | -0.023 | -0.062 | 0.110 | 0.011 | -0.155*** | -0.124*** |
| | (0.043) | (0.023) | (0.066) | (0.093) | (0.059) | (0.036) | (0.018) |
| Divorced | -0.158*** | -0.202*** | -0.325*** | -0.113 | -0.217*** | -0.203*** | -0.198*** |
| | (0.044) | (0.025) | (0.070) | (0.095) | (0.062) | (0.037) | (0.017) |
| Widowed | -0.153*** | -0.107*** | -0.193** | -0.140 | -0.164** | -0.197*** | -0.263*** |
| | (0.030) | (0.018) | (0.081) | (0.113) | (0.079) | (0.054) | (0.027) |
| Living in a rural area or village | 0.056** | 0.047*** | 0.084* | -0.017 | 0.062 | 0.075*** | 0.033*** |
| | (0.026) | (0.016) | (0.050) | (0.068) | (0.044) | (0.025) | (0.011) |
| Living in a large town | -0.017 | -0.062*** | -0.089 | -0.065 | -0.089* | 0.015 | -0.012 |
| | (0.032) | (0.019) | (0.055) | (0.076) | (0.051) | (0.028) | (0.011) |
| N | 11126 | 33003 | 3516 | 1951 | 4391 | 14357 | 89349 |

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 9: 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 | 55.29 |
| Never use Internet | 52.78 |
| Less than 2-3 times per month | 51.18 |
| 2-3 times per month | 50.08 |
| About once a week | 49.27 |
| 2-3 times per week | 48.65 |
| Everyday | 48.16 |

**Table 10: Moderation effects of Internet use on the U-shape curvature: Estimated slopes at different ages.**

| | Internet use category | | | | | | |
|---|---|---|---|---|---|---|---|
| | *1* | *2* | *3* | *4* | *5* | *6* | *7* |
| **Age** | | | | | | | |
| ***25*** | -0.006 | -0.011 | -0.019 | -0.015 | -0.014 | -0.016 | -0.017 |
| ***35*** | -0.004 | -0.007 | -0.011 | -0.008 | -0.008 | -0.010 | -0.011 |
| ***45*** | -0.001 | -0.003 | -0.004 | -0.001 | -0.002 | -0.004 | -0.004 |
| ***55*** | 0.001 | 0.001 | 0.003 | 0.007 | 0.004 | 0.002 | 0.002 |
| ***65*** | 0.003 | 0.004 | 0.010 | 0.014 | 0.010 | 0.008 | 0.009 |
| ***85*** | 0.007 | 0.012 | 0.025 | 0.029 | 0.023 | 0.021 | 0.021 |

**Figure 2: Aggregate life satisfaction and expectations, by age group.**

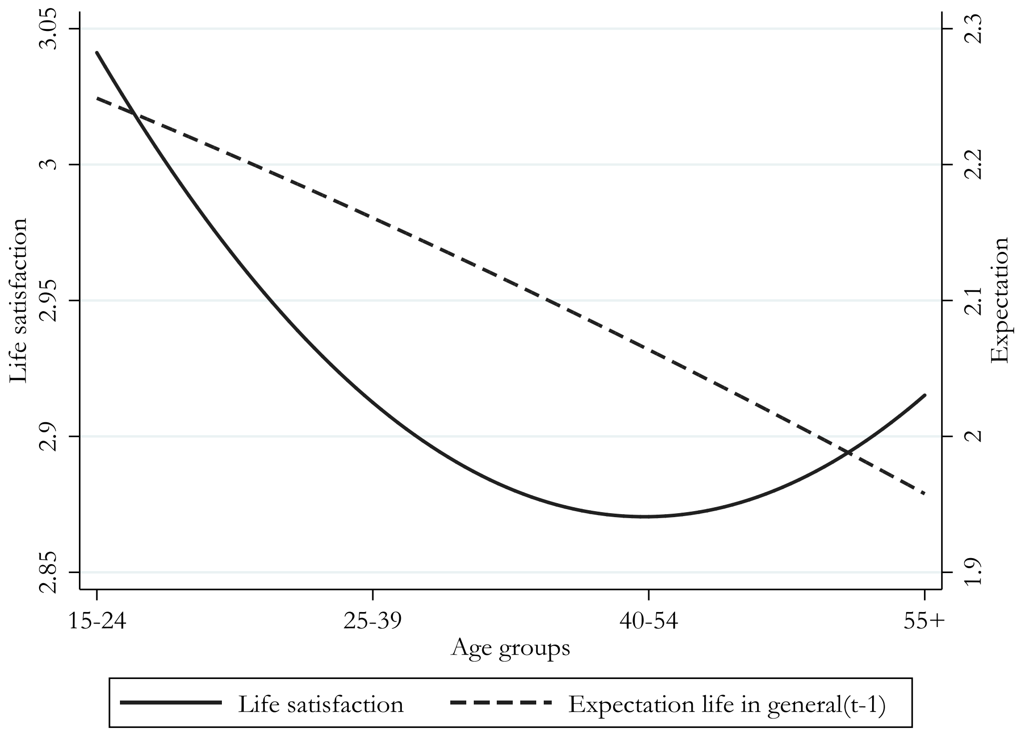
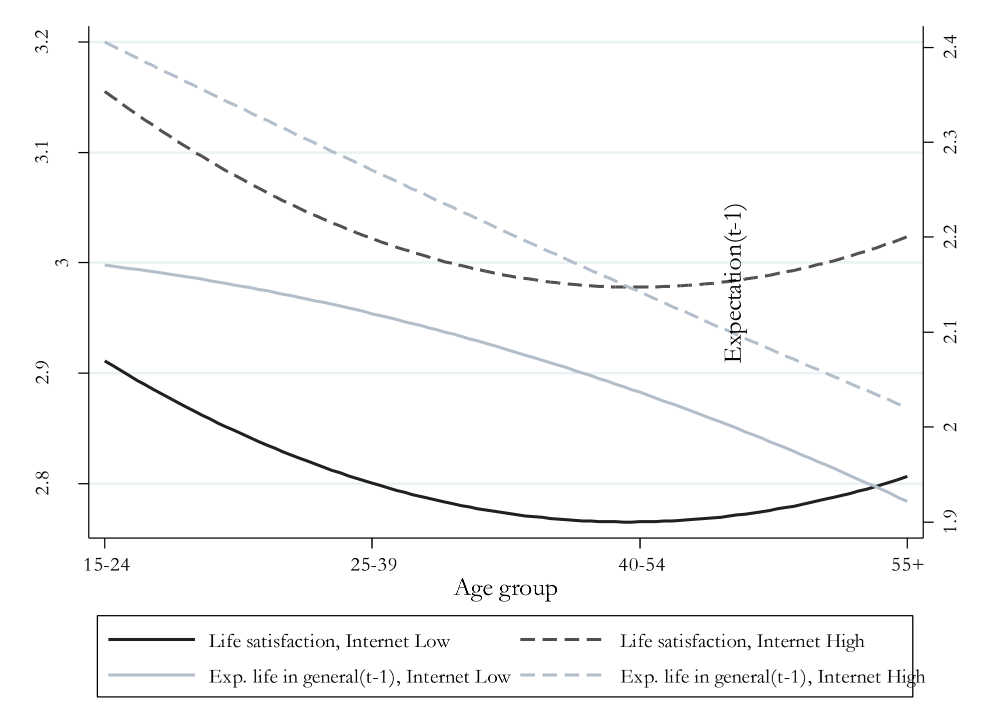
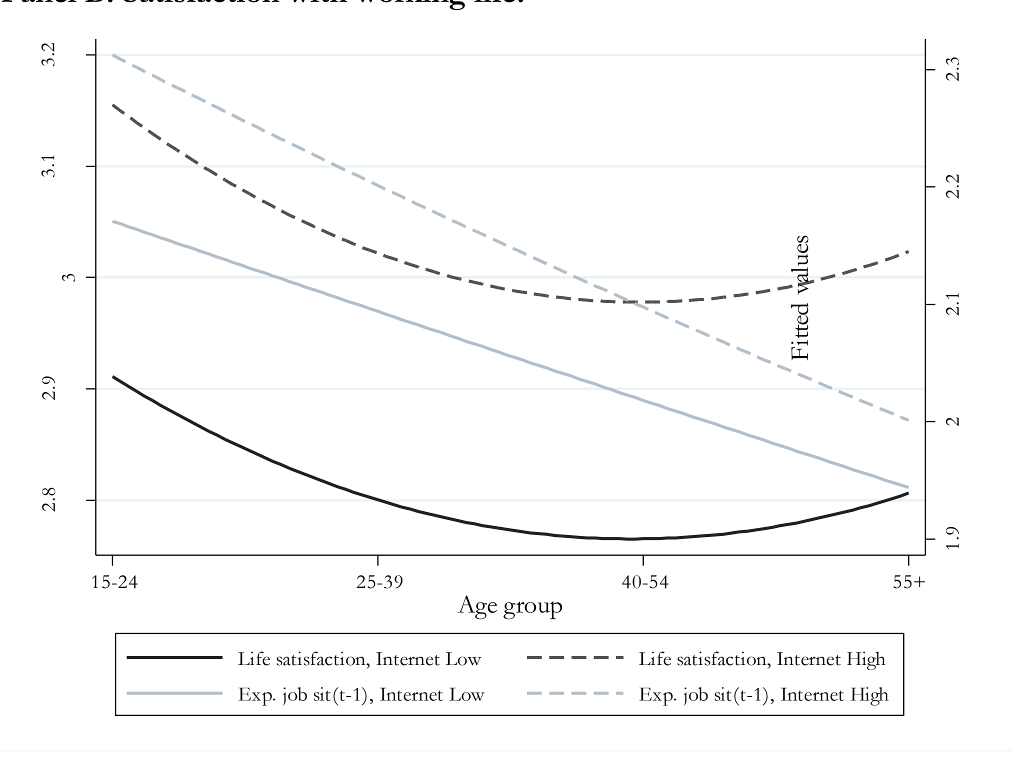


**Figure 3: Aggregate life satisfaction and expectations, by age group and Internet users group.**

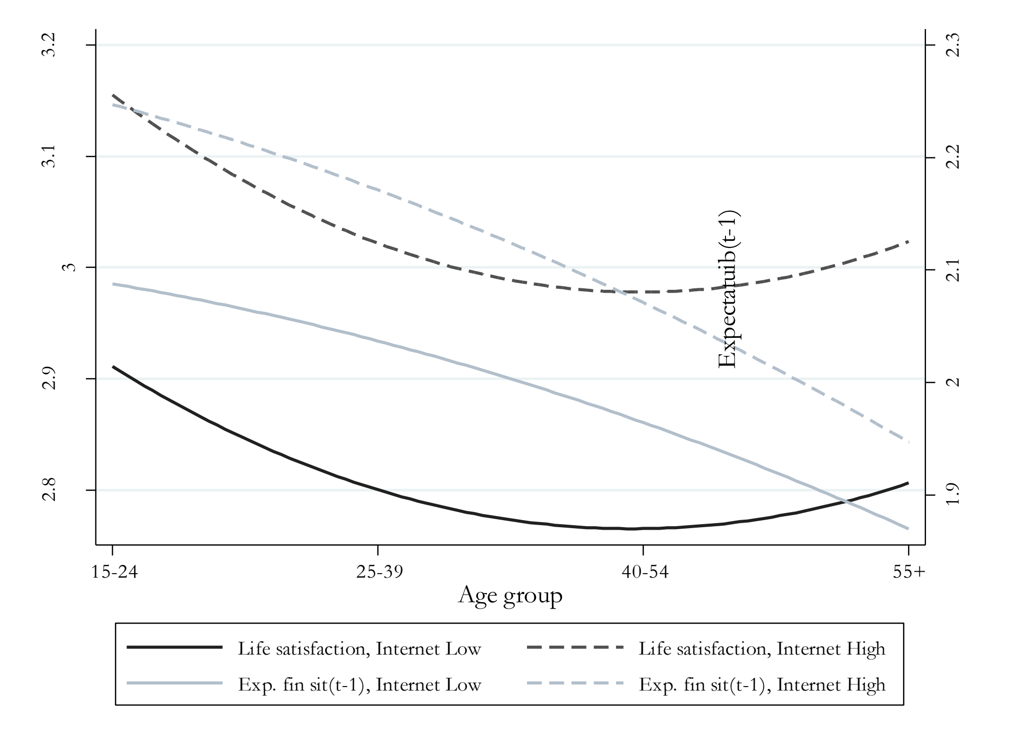
**Panel A: Satisfaction with life as a whole.**



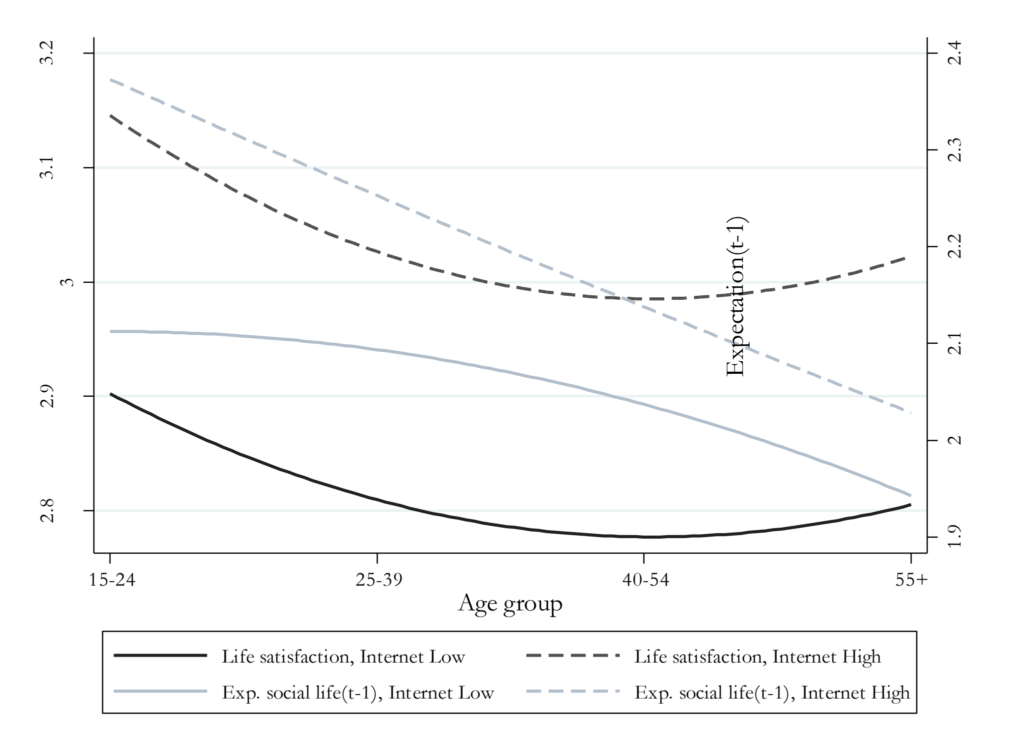

**Panel B: Satisfaction with working life.**



**Panel C: Satisfaction with financial situation.**




**Panel D: Satisfaction with social life.**



# Appendix: Results for region-level instrument

**Table A.1: Descriptive statistics**

| | Mean | St.dev. | Min | Max | Obs |
|---|---|---|---|---|---|
| Life satisfaction | 2.92 | 0.81 | 1 | 4 | 139,865 |
| Internet use | 5.46 | 2.25 | 1 | 7 | 139,865 |
| Age | 47.18 | 18.15 | 15 | 99 | 139,865 |
| Women | 0.52 | 0.50 | 0 | 1 | 139,865 |
| House/apartment ownership | 0.74 | 0.44 | 0 | 1 | 139,865 |
| Up to 15 years of education | 0.25 | 0.43 | 0 | 1 | 139,865 |
| 16-19 years of education | 0.43 | 0.50 | 0 | 1 | 139,865 |
| 20+ years of education | 0.32 | 0.47 | 0 | 1 | 139,865 |
| Unemployment | 0.10 | 0.30 | 0 | 1 | 139,865 |
| Divorced | 0.07 | 0.26 | 0 | 1 | 139,865 |
| Widow | 0.08 | 0.28 | 0 | 1 | 139,865 |
| Living in a rural area or village | 0.33 | 0.47 | 0 | 1 | 139,865 |
| Living in a small/middle sized town | 0.39 | 0.49 | 0 | 1 | 139,865 |
| Living in a large town | 0.28 | 0.45 | 0 | 1 | 139,865 |
| White-collar | 0.36 | 0.48 | 0 | 1 | 139,865 |
| Blue-collar | 0.14 | 0.35 | 0 | 1 | 139,865 |
| HH broadband connection | 0.72 | 0.13 | 0.20 | 0.95 | 139,865 |

**Table A.2: Timing of broadband Internet variation.**

| | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|
| Education level | 0.017 | -0.028 | -0.006 | -0.051* | 0.015 |
| Women | 0.014 | 0.088 | 0.032 | -0.005 | -0.009 |
| Urbanization | 0.002 | 0.022 | -0.008 | 0.011 | 0.012 |
| Unemployment | -0.254 | 0.105 | 0.045 | -0.003 | 0.131 |
| Age | -0.000 | 0.004* | 0.000 | 0.003 | 0.002 |
| House/apartment ownership | 0.004 | -0.051 | -0.074 | -0.016 | -0.062* |
| Divorces | -0.149 | -0.356** | -0.440** | -0.312** | -0.155 |
| Widowers | -0.060 | 0.069 | 0.093 | -0.222 | 0.172 |
| Blue-collar jobs | -0.027 | 0.096 | -0.004 | 0.036 | -0.030 |
| White-collar jobs | -0.229 | 0.240** | 0.100 | -0.062 | 0.037 |

*Note:* The table reports estimated coefficients from a regression of the growth rate of broadband Internet on the time trend of covariates for the years 2012 to 2016. The regression is based on a panel of 598 region-year observations.
* p<0.10; ** p<0.05; *** p<0.01

**Table A.3: Balancing regressions.**

| | Financial situation | Education | Unemployment |
|---|---|---|---|
| HH broadband connection t-1 | -0.014 | -0.099 | -0.036 |
| | (0.072) | (0.107) | (0.037) |
| HH broadband connection t+1 | 0.113 | 0.064 | -0.173*** |
| | (0.105) | (0.110) | (0.049) |

The table reports the estimated coefficients of lagged and lead broadband Internet take-up in three balancing regressions. These regress the dependent variables financial situation, education and unemployment, respectively, on the set of covariates included in the model plus the lead and lagged instruments. Heteroskedasticity-robust standard errors in parentheses. All regressions include a full set of control variables, time dummies and country fixed effects. * p<0.10; ** p<0.05; *** p<0.01.

**Table A.4: First stage results. Baseline estimations and balancing tests.**

| | Baseline | Balancing test |
|---|---|---|
| HH broadband connection t-1 | 0.789*** | 0.792*** |
| | (0.217) | (0.214) |
| Age | -0.045*** | -0.045*** |
| | (0.008) | (0.008) |
| Age squared | -0.000*** | -0.000*** |
| | (0.000) | (0.000) |
| Women | -0.096*** | -0.095*** |
| | (0.020) | (0.020) |
| House/apartment ownership | 0.209*** | 0.211*** |
| | (0.022) | (0.022) |
| 16-19 years of education | 0.638*** | 0.639*** |
| | (0.070) | (0.070) |
| 20+ years of education | 1.177*** | 1.178*** |
| | (0.069) | (0.069) |
| Unemployment | -0.308*** | -0.308*** |
| | (0.039) | (0.039) |
| White-collar job | 0.501*** | 0.499*** |
| | (0.068) | (0.068) |
| Blue-collar job | -0.083* | -0.082 |
| | (0.049) | (0.049) |
| Divorced | -0.000 | -0.000 |
| | (0.036) | (0.036) |
| Widowed | -0.558*** | -0.558*** |
| | (0.047) | (0.047) |
| Living in a rural area or village | -0.182*** | -0.183*** |
| | (0.023) | (0.023) |
| Living in a large town | 0.165*** | 0.166*** |
| | (0.021) | (0.021) |
| _cons | 6.518*** | 6.519*** |
| | (0.214) | (0.218) |
| N | 139,865 | 139,865 |
| F-value (instrument) | 13.22 | |

Robust standard errors clustered at the NUTS1 level in parentheses. The second column include a full set of controls that was averaged and lagged over region-years (i.e. $\overline{x'_{r,t}}$, and $\overline{x'_{r,t-1}}$) time dummies and region fixed effects. * p<0.10; ** p<0.05; *** p<0.01.

**Table A.5: LATE results: compliers for different age groups.**

| | | P[X=x] | Coefficient of HH broadband connection |
|---|---|---|---|
| **Age groups** | | | |
| | Young (15-24) | 0.092 | 1.205** |
| | Younger adults (25-39) | 0.226 | 1.900*** |
| | Middle-aged (40-54) | 0.259 | 1.721*** |
| | Older adults (55+) | 0.423 | 0.194 |

*Note:* Column 1 reports the relative shares of each age group of the total sample. The second column reports the first stage coefficients on our instrument. The regressions include time and region dummies. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

**Table A.6: Second stage results. Baseline estimations.**

| | Baseline | Pre-reform trend | Placebo | Cohort | Full model |
|---|---|---|---|---|---|
| Internet use | 0.059*** | 0.059*** | | 0.072*** | 0.120*** |
| | (0.006) | (0.006) | | (0.007) | (0.029) |
| Internet use X age | | | | | -0.004 |
| | | | | | (0.003) |
| Internet use X age squared | | | | | 0.000** |
| | | | | | (0.000) |
| Age | -0.043*** | -0.043*** | -0.045*** | -0.042*** | -0.047*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.012) |
| Age squared | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Women | 0.029*** | 0.029*** | 0.024*** | 0.033*** | 0.049*** |
| | (0.007) | (0.007) | (0.008) | (0.007) | (0.009) |
| House/apartment ownership | 0.198*** | 0.198*** | 0.208*** | 0.189*** | 0.163*** |
| | (0.017) | (0.017) | (0.017) | (0.017) | (0.025) |
| 16-19 years of education | 0.022 | 0.022 | 0.060*** | 0.024 | -0.075 |
| | (0.016) | (0.016) | (0.019) | (0.016) | (0.048) |
| 20+ years of education | 0.179*** | 0.179*** | 0.249*** | 0.182*** | 0.016 |
| | (0.019) | (0.019) | (0.022) | (0.020) | (0.087) |
| Unemployment | -0.518*** | -0.518*** | -0.532*** | -0.486*** | -0.445*** |
| | (0.021) | (0.021) | (0.022) | (0.020) | (0.030) |
| White-collar job | 0.077*** | 0.078*** | 0.108*** | 0.109*** | 0.103** |
| | (0.015) | (0.015) | (0.015) | (0.016) | (0.052) |
| Blue-collar job | -0.091*** | -0.091*** | -0.097*** | -0.054*** | -0.034 |
| | (0.017) | (0.017) | (0.017) | (0.018) | (0.021) |
| Divorced | -0.285*** | -0.285*** | -0.285*** | -0.287*** | -0.291*** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.016) |
| Widowed | -0.251*** | -0.251*** | -0.281*** | -0.238*** | -0.101** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.040) |
| Living in a rural area or village | 0.017 | 0.018 | 0.006 | 0.014 | 0.036** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.018) |
| Living in a large town | -0.002 | -0.002 | 0.007 | -0.009 | -0.021 |
| | (0.016) | (0.016) | (0.017) | (0.016) | (0.018) |
| Pre-reform trend in life satisfaction (linear) | | -0.022 | | | |
| | | (0.064) | | | |
| HH broadband connection t-1 | | | 0.013 | | |
| | | | (0.261) | | |

| | | | | | |
|---|---|---|---|---|---|
| HH broadband connection t+1 | | | 0.672<br>(0.419) | | |
| N | 139,865 | 139,865 | 137,978 | 139,865 | 157,693 |
| Atanhrho | 0.016<br>(0.015) | | | -0.007<br>(0.015) | |

Robust standard errors clustered at the NUTS1 level in parentheses. All regressions include time dummies and region fixed effects. * p<0.10; ** p<0.05; *** p<0.01.

**Table A.7: Second stage results. Separate estimations for different age groups.**

| | *15-24* | *25-39* | *40-54* | *55+* |
|---|---|---|---|---|
| Internet use | 0.087*** | 0.033*** | 0.016 | 0.038*** |
| | (0.023) | (0.013) | (0.010) | (0.009) |
| Women | -0.023 | 0.065*** | 0.058*** | 0.012 |
| | (0.024) | (0.015) | (0.014) | (0.012) |
| House/apartment ownership | 0.185*** | 0.164*** | 0.208*** | 0.211*** |
| | (0.030) | (0.023) | (0.026) | (0.021) |
| 16-19 years of education | -0.048 | 0.029 | 0.077** | 0.098*** |
| | (0.050) | (0.038) | (0.030) | (0.021) |
| 20+ years of education | -0.049 | 0.218*** | 0.260*** | 0.276*** |
| | (0.066) | (0.041) | (0.042) | (0.031) |
| Unemployment | -0.606*** | -0.461*** | -0.377*** | -0.511*** |
| | (0.064) | (0.038) | (0.030) | (0.030) |
| White-collar job | -0.114** | 0.139*** | 0.322*** | 0.035 |
| | (0.056) | (0.032) | (0.034) | (0.027) |
| Blue-collar job | -0.183*** | -0.054 | 0.120*** | -0.138*** |
| | (0.067) | (0.035) | (0.029) | (0.021) |
| Divorced | -0.235* | -0.371*** | -0.292*** | -0.286*** |
| | (0.136) | (0.034) | (0.023) | (0.019) |
| Widowed | 0.154 | -0.353*** | -0.321*** | -0.151*** |
| | (0.212) | (0.102) | (0.040) | (0.016) |
| Living in a rural area or village | 0.077*** | 0.033 | 0.001 | -0.008 |
| | (0.029) | (0.021) | (0.016) | (0.016) |
| Living in a large town | 0.009 | 0.022 | -0.032 | -0.012 |
| | (0.030) | (0.022) | (0.028) | (0.019) |
| N | 12863 | 31645 | 36210 | 59147 |

Robust errors clustered at the NUTS1 level in parentheses. All regressions include time dummies and region fixed effects. * p<0.10; ** p<0.05; *** p<0.01.

**Table A.8: Second stage results. Separate estimations for different Internet use groups.**

| | ***No access*** | ***Never use*** | ***Less often*** | ***2-3 times a month*** | ***About once a week*** | ***2-3 times a week*** | ***Every day*** |
|---|---|---|---|---|---|---|---|
| Age | -0.029*** | -0.024*** | -0.036*** | -0.045*** | -0.041*** | -0.047*** | -0.051*** |
| | (0.007) | (0.005) | (0.012) | (0.017) | (0.010) | (0.005) | (0.003) |
| Age squared | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Women | 0.051 | 0.035** | 0.077* | 0.051 | 0.130*** | 0.017 | 0.030*** |
| | (0.032) | (0.018) | (0.046) | (0.066) | (0.044) | (0.020) | (0.009) |
| Financial situation | 0.251*** | 0.173*** | 0.054 | 0.149* | 0.130** | 0.186*** | 0.210*** |
| | (0.037) | (0.025) | (0.058) | (0.084) | (0.054) | (0.034) | (0.021) |
| 16-19 years of education | 0.175*** | 0.110*** | 0.105* | 0.102 | 0.023 | 0.073** | -0.068*** |
| | (0.034) | (0.021) | (0.062) | (0.079) | (0.060) | (0.031) | (0.024) |
| 20+ years of education | 0.385*** | 0.275*** | 0.239** | 0.205** | 0.047 | 0.177*** | 0.104*** |
| | (0.042) | (0.029) | (0.094) | (0.103) | (0.077) | (0.039) | (0.027) |
| Unemployment | -0.436*** | -0.411*** | -0.522*** | -0.431*** | -0.265*** | -0.559*** | -0.504*** |
| | (0.043) | (0.034) | (0.077) | (0.123) | (0.084) | (0.055) | (0.028) |
| White-collar job | 0.146** | 0.176*** | 0.276*** | 0.087 | 0.175*** | 0.086** | 0.106*** |
| | (0.063) | (0.041) | (0.071) | (0.101) | (0.063) | (0.039) | (0.023) |
| Blue-collar job | 0.026 | 0.004 | -0.026 | 0.060 | 0.024 | -0.111*** | -0.075*** |
| | (0.055) | (0.029) | (0.067) | (0.109) | (0.079) | (0.034) | (0.027) |
| Divorced | -0.223*** | -0.282*** | -0.358*** | -0.183 | -0.342*** | -0.314*** | -0.299*** |
| | (0.044) | (0.029) | (0.075) | (0.113) | (0.075) | (0.033) | (0.020) |
| Widowed | -0.140*** | -0.176*** | -0.208** | -0.166 | -0.255*** | -0.253*** | -0.337*** |
| | (0.031) | (0.020) | (0.094) | (0.104) | (0.067) | (0.053) | (0.028) |
| Living in a rural area or village | 0.031 | 0.038 | 0.084 | 0.024 | -0.004 | 0.027 | 0.015 |
| | (0.041) | (0.025) | (0.054) | (0.092) | (0.060) | (0.030) | (0.013) |
| Living in a large town | -0.025 | -0.050** | -0.136* | -0.042 | -0.126* | -0.017 | 0.012 |
| | (0.055) | (0.024) | (0.081) | (0.104) | (0.072) | (0.034) | (0.017) |
| N | 9237 | 28738 | 2972 | 1697 | 3816 | 12418 | 80987 |

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 A.9: 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 | 50.76 |
| Never use Internet | 47.83 |
| Less than 2-3 times per month | 45.05 |
| 2-3 times per month | 42.41 |
| About once a week | 39.91 |
| 2-3 times per week | 37.52 |
| Everyday | 35.25 |

**Table A.10: Moderation effects of Internet use on the U-shape curvature.**

| | Internet use category | | | | | | |
|---|---|---|---|---|---|---|---|
| | *1* | *2* | *3* | *4* | *5* | *6* | *7* |
| **Age** | | | | | | | |
| ***25*** | -0.014 | -0.012 | -0.016 | -0.021 | -0.018 | -0.023 | -0.025 |
| ***35*** | -0.009 | -0.007 | -0.009 | -0.011 | -0.008 | -0.013 | -0.014 |
| ***45*** | -0.003 | -0.002 | -0.001 | -0.001 | 0.001 | -0.003 | -0.004 |
| ***55*** | 0.003 | 0.003 | 0.007 | 0.009 | 0.010 | 0.007 | 0.007 |
| ***65*** | 0.009 | 0.008 | 0.015 | 0.019 | 0.020 | 0.017 | 0.018 |
| ***85*** | 0.020 | 0.018 | 0.030 | 0.038 | 0.039 | 0.036 | 0.039 |