Internet Use and Health. Exploring the role of Social Interactions, Social Activities, and Social Cohesion*

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Abstract

This paper studies the effect of high-speed Internet on an individuals health, focusing on the role of social capital as a potential pathway through which Internet access affects health. We find that individuals with DSL access are more likely to be in poor health compared to their counterparts without DSL Internet, to declare mental health problems, and to report higher levels of BMI. Our findings suggest that social capital is indeed a key factor underlying the relationship between Internet use and health.

Keywords: Health, Internet, Social Capital.

JEL classification: I10, O33, A13.

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1 Introduction

Technological advancements have brought about substantial changes in our daily lives with relevant implications for individuals and their social behaviors. One of the areas in which technology has being playing a crucial role is health-care. Over the last half-century new technologies and medical techniques have contributed to improve the diagnosis and cure of several diseases with a resulting effect in terms of greater quality of life and higher life expectancy. For instance, in the U.S. the death rate due to heart diseases has dropped by nearly three times[1] while the cancer survival rate has increased by 30 percent over the last half century[2]. However, medical advances are not the only technological change that matter for health. The digital revolution has deeply affected both health and health-care in many, different ways that are still understudied.

With the advent of the Internet, more and more people have access to medical and health-related information, searching symptoms, specialists, treatments, and cures on-line. Health-related smartphone applications are extensively used to assist patients, to convey information concerning the delivery of health services, and to promote positive health behaviors. Digital therapy platforms provide on-line therapy sessions focused on patients' specific needs. As a result, Internet access can be assumed to have a strong positive effect on health outcomes, well-being (Castellacci and Tveito, 2018) and health behaviors (Guldi et al., 2017). At the same time, Internet access allows individuals to be constantly connected with a broader social network of virtual relationships. This state of constant connection can lead to small but reliable increase in depression, due to a raise of health-related anxiety (Bessière et al., 2010) and higher perceived digital stress (Lee et al., 2014), due to the fear of missing out potential social interactions (Reinecke et al., 2017). Lastly, extensive Internet use can lead to a sedentary lifestyle with a resulting negative effect in terms of physical health (Tsitsika et al., 2016). As a result, the very real effect of the Internet is, a priori, ambiguous.

In this paper we study the effect of high-speed Internet on an individuals mental and physical health, by specifically focusing on the role played by social capital as a potential mediator of this relationship. We therefore integrate two strands of literature, one on the effect of Internet on health, and one on the impact of Internet on social capital. Empirically, we exploit the richness of two data sources: the German Socio-Economic Panel (SOEP), a longitudinal panel dataset containing information on a rich set of individuals' socio-economic characteristics, and the German Time Use Survey (German TUS) provided by the German Federal Statistical Office.

Our findings reveal a negative impact of high-speed Internet on physical

[1] https://www.cdc.gov/nchs/fastats/heart-disease.htm

[2] https://www.cdc.gov/nchs/fastats/cancer.htm

and mental health. Individuals with DSL access tend to be 1.5 percent more likely to be in poor health compared to their Internet-less counterparts, 1.7 percent more likely to declare mental health problems, and to report higher levels of BMI. Furthermore, they are 2.5 percent more likely to be in time pressure. Our preliminary mediation analysis suggests that the increased availability of social capital brought about by high-speed Internet, may provide a source of social support with a resulting buffering effect in terms of self-reported health and mental health. However, it can simultaneously lead to a communication and social interactions overload with a resulting negative effect in terms of perceived time pressure. Furthermore, the reduction in social activities related to the increased availability of on-line resources can lead to a more sedentary lifestyle with deleterious effects on an individual's physical health.

The remainder of the paper is structured as follows. Section 2 briefly presents a conceptual framework of our study. Sections 3 and 4 describe the data and methods, respectively. Section 5 presents the preliminary results. Section 6 concludes.

2 Conceptual framework

This paper integrates two strands of research: the literature on Internet use and health, and the literature on Internet use and social capital.

While Internet use can improve health by promoting access to information concerning health outcomes and health behaviors, being constantly informed about diseases can lead to increased pessimism, depression and health-related anxiety (Bessière et al., 2010). Moreover, as people spend more time sitting in front of their personal computers, they may reduce time devoted to physical activities, embracing a more sedentary lifestyle. Furthermore, evidence also suggests that Internet overuse can lead to sleep problems (Shochat, 2012; Chen and Gau, 2016) with a resulting negative effect in terms of health.

The Internet may also influence physical and mental health by affecting an individual's social capital.

A growing body of literature shows that social capital is affected by communication and entertainment technologies, such as television and the Internet (e.g. La Ferrara et al., 2012; Bauernschuster et al., 2014). While some studies find a positive effect of communication technologies on social relations (Bauernschuster et al., 2014), others show that the more time people spend using information technologies for virtual interactions, the less time they devote to other social activities and, in particular, to face-to-face social interactions (Olkean, 2009; Rotondi et al., 2017).

Social capital constitutes an important source of social support and, as a consequence, is a key determinant of an individual's health. Existing literature shows that social support has a positive effect on mental and physical health. As an example, while participation in social activities is found to improve older adults' ability to perform daily life's activities (Tomioka et al., 2016), perceived social isolation is linked to an increase in the stress hormone cortisol, high blood pressure and inflammation in the body (Cole et al., 2015). Accordingly, loneliness can be related to higher rates of morbidity and mortality (Cacioppo and Cacioppo, 2014), social isolation to increased chance of premature death (Luo et al., 2012), and low social trust to higher rates of psychosomatic symptoms, musculoskeletal pain, and depression (Åslund et al., 2010). While the effect of social capital on mental health is generally robust, few studies report that, although increased access to social capital has been found to be correlated to a significantly higher level of quality of life, it had no independent effect on the course of depression (Webber et al., 2011).

This inconclusiveness can be related to the fact that, today, the term "social capital" describes more a strand of the literature than a specific concept.[3] While this paved the way to a genuine interchange among scholars from different disciplines, the array of definitions and measurement methods used in the empirical literature has often made it difficult to compare the results of different studies and to formulate any general assessment about the effects of social capital (Sobel, 2002).

One of the reasons behind this difficulty is the practice, very common in economics, to use the label "social capital" to indicate one of its components, thus measuring a part for the whole. Social capital arises from social networks and it is the use that individuals make of them that may produce social capital. As in Bourdieu (1986) and Coleman (1994), social capital is therefore *intangible*. In order to possess social capital, a person must be related to others and it is those others, not himself, who are the actual source of his social capital (Lin et al., 2001). In fact, the existence of social capital depends on the quality of the networks, on their ability in promoting and socializing trust (Sabatini, 2009), on the actions undertaken by individuals in building trust and reciprocity inside and towards those networks, and on the resources available to their connections (Portes, 2000). The literature usually defines trust as the *cognitive* component of social capital, while networks are generally referred to as its *structural* component (Burt, 2000). While trust is more linked to individuals' perceptions, and it is therefore more difficult to measure, networks are usually identified through observation of reality (e.g., participation in voluntary activities).[4]

[3]For a discussion regarding whether the concept of social capital is indeed a good social science concept see Bjrnskov and Snderskov (2013).

[4]The structural and cognitive components of social capital are inextricably linked, either positively or negatively (Sabatini, 2009). Trust, for instance, can confer legitimacy to cooperative behaviors that can result in the formation of networks. These networks, in turn, strengthen trust and reciprocity. Conversely, certain types of networks hamper trust by restricting others, outside the network, in accessing it (Woolcock, 2001).

In this paper we claim that it is the structural component of social capital, with respect to its cognitive component, that matter for health. More specifically, we focus on three sub-dimensions of structural social capital, namely social interactions, social activities and social cohesion. In economics, a relatively small part of existing literature, has defined these sub-dimensions of social capital as relational goods. Uhlaner (1989) and Gui (1987) define relational goods as goods that "can only be possessed by mutual agreement that exist, after appropriate joint actions taken by a person and non-arbitrary others" (1989, p. 254). As such, relational goods cannot be enjoyed by an isolated individual but should be shared with others (Bruni and Stanca, 2008). When relational goods are consumed, they produce positive externalities. While the primary producers of these goods are family and friends, social events, such as concerts and sport events (Becchetti et al., 2008), or the active engagement in volunteering associations, can also produce them. A few papers to date show that relational goods have a positive effect on well-being (Bruni and Stanca, 2008; Becchetti et al., 2008; Stanca, 2009; Becchetti et al., 2011; Colombo et al., 2017).

Our hypothesis is that the increased availability of social relations brought about by Internet access can play a double role for an individual's health. On the one hand, given that social capital is a source of social support it can play a crucial role as a buffering factor for the negative effect of techno-stress (Lee et al., 2014) in terms of health. On the opposite, the communication and social interactions overload brought about by over connection might have detrimental effects in terms of health. Furthermore, the replacement of real relationships with virtual ones generated by the availability of remote connection with people not physically present, and the possibility of carrying out more and more activities without moving from home (think for example to the increasing connectivity of mobile phones) has a negative effect on health because it increases sedentary life. While it is not easy to formulate a precise assessment on which of these two effects prevails, our hypothesis suggests that the direction of the effect depends crucially on the outcome being it mental or physical health.

3 Data

Our empirical analysis aims at studying the effect of broadband Internet access on health by focusing specifically on the role played by social capital. The data used for this purpose are drawn from two main sources: the German Socio-Economic Panel (SOEP) and the German Time Use Survey (TUS).

The SOEP is uniquely suited for this purpose. First, it contains information on several health metrics, such as self-assessed health status, satisfaction with health, and doctor-assessed disability. Second, it provides information on Internet access and, specifically, on whether Internet access is based on a

DSL technology. Therefore, our key explanatory variable is a dummy that indicates whether a household has a DSL connection. Third, our dataset contains information on several formal and informal social activities and networks, for instance: the frequency of meeting with friends, relatives, or neighbors; helping out friends, relatives or neighbors; involvement in a citizens' group, political party, or local government; volunteer work in clubs or social services; doing sports; going to cultural events; going to the movies, pop music concerts, dancing, disco, or sports events, as well as artistic or musical activities.

Our variable of interest are operationalized as follows: poor health is a dummy variable taking value 1 if the respondents' self-reported health status is less than good, and zero otherwise. The mental health variables are indicators that take value 1 if the frequency of the depressive symptoms are assessed "always" or "very often". As far as social capital is concerned, we consider three main measures of "structural social capital": social interactions defined as the frequency of meeting with friends or helping out friends; social cohesion as involvement in a citizens' group, political party, or local government as well as volunteer work; and social activities as going to movies, concerts and artistic or musical activities.

Summary statistics for the main variables are reported in table 1.

The second source of information is the TUS. Surveys about time use allocation are an important source of information for empirical research (Aguiar and Hurst, 2007; Aguiar et al., 2013) and are more reliable and accurate than estimates obtained from direct questions (Kan, 2008). More specifically, we make use of the last wave of the German TUS (2012-2013). This is the third and most recent wave provided by the German Federal Statistical Office. Each person in the household, aged 10 years and above, is requested to fill in a personal diary during two weekdays and one weekend day. This diary provides information on all performed activities recorded in ten-minute intervals. Socio-demographic and socio-economic characteristics of individuals and households are collected using individual and household questionnaires. For a detailed description of the survey, see Stuckemeier and Kühnen. In our analyses, we restrict the sample to individuals between 18 and 59 years old. After this restriction, our sample consists of 10,869 diary observations resulting from about 5,587 individuals.

Summary statistics for this dataset during week days and during weekends are reported in table 2 and 3, respectively. .

Such data allow us to measure the social activities dimension of social capital as hours spent in social events (i.e., cinema, theaters, concerts, opera, museums, libraries, sporting events, zoo, circuses, parks, caffes, brewery, discotheques, and any other form of entertainment and culture). Moreover, since we are interested in testing whether Internet access leads to a more sedentary lifestyle, we build a "sport" variable that account for any hour

Table 1: Summary statistics: SOEP

Variable	Mean	Std. Dev.	Min.	Max.	N
Dependent variables (y_{it})					
Health					
Poor health	0.45	0.5	0	1	39379
BMI	25.9	4.75	15.03	54.43	38911
Poor mental health	0.56	0.5	0	1	39351
High time pressure	0.74	0.44	0	1	39337
Social capital					
Social interactions	0.46	0.5	0	1	35921
Social cohesion	0.11	0.31	0	1	35839
Social activities	0.17	0.38	0	1	35924
Explanatory variable (x_{1i})					
DSL subscription in HH	0.75	0.43	0	1	39379
Covariates (x_{2i})					
Age	43.31	12.76	18	64	39379
Age sq.	2038.14	1071.3	324	4096	39379
Not working	0.07	0.26	0	1	39379
Unemployed	0.07	0.25	0	1	39379
Retired	0.06	0.24	0	1	39379
Blue collar	0.22	0.42	0	1	39379
White collar	0.42	0.49	0	1	39379
Entrepreneur	0.07	0.26	0	1	39379
Apprentice	0.08	0.27	0	1	39379
Household income (log)	7.87	0.6	0	12.21	39379
Widowed	0.02	0.14	0	1	39379
Divorced	0.09	0.29	0	1	39379
Single	0.29	0.45	0	1	39379
Married	0.6	0.49	0	1	39379
Secondary School Degree	0.02	0.15	0	1	39379
Intermediate School Degree	0.24	0.43	0	1	39379
Technical School Degree	0.35	0.48	0	1	39379
Upper Secondary Degree	0.31	0.46	0	1	39379
Other Degree	0.06	0.24	0	1	39379
Homeowner	0.53	0.5	0	1	39379
Number of children	0.86	1.05	0	10	39379

Table 2: Summary Statistics: TUS, weekdays

	N	Mean	Std. dev.	Min	Max
social_capital_hours	10903	0.75999	1.263887	0	21.66667
sport_hours	10903	0.307882	0.773111	0	8
overall_index	10903	1.067871	1.481283	0	21.66667
pcuse_smartphone_hours	10903	0.373613	0.831047	0	11
pcgames_hours	10903	0.112874	0.634259	0	13.83333
age	10903	41.33275	11.54643	18	59
female	10903	0.558195	0.496625	0	1
owner	10903	0.619921	0.485428	0	1
hhincome	10903	3.939741	1.197189	1	5
bornabroad	10903	0.045217	0.207789	0	1
occupation_headhh	10903	3.127029	1.382168	1	6
nchild_below10	10903	0.371733	0.710172	0	4
west	10903	0.796295	0.402771	0	1
tagnr	10903	1.599009	0.66512	1	3
weekday	10903	1	0	1	1
low_educated	10903	0.0897	0.285765	0	1
medium_educated	10903	0.53068	0.499081	0	1
high_educated	10903	0.37962	0.485315	0	1
single	10903	0.301844	0.459079	0	1
married	10903	0.575897	0.494229	0	1
separated	10903	0.111346	0.314574	0	1
widowed	10903	0.010914	0.103905	0	1
selfemployed	10903	0.143447	0.350544	0	1
civilservant	10903	0.137118	0.343988	0	1
employee	10903	0.406494	0.491201	0	1
worker	10903	0.168944	0.37472	0	1
retired	10903	0.049895	0.217737	0	1
notemployed	10903	0.094103	0.291985	0	1
below_1100euro	10903	0.054939	0.227872	0	1
between_1100_1700euro	10903	0.101899	0.302529	0	1
between_1700_2300euro	10903	0.11318	0.316827	0	1
between_2300_3600euro	10903	0.308447	0.461874	0	1
above_3600euro	10903	0.421535	0.493828	0	1

Table 3: Summary Statistics: TUS, weekend

	N	Mean	Std. dev.	Min	Max
social_capital_hours	6065	1.256499	1.824554	0	13.16667
sport_hours	6065	0.56947	1.14255	0	10.83333
overall_index	6065	1.825969	2.071052	0	14.33333
pcuse_smartphone_hours	6065	0.42726	0.949171	0	10.5
pcgames_hours	6065	0.157983	0.771994	0	11.5
tvvideodvd_hours	6065	2.136603	1.937857	0	13.5
age	6065	41.38813	11.53172	18	59
female	6065	0.560759	0.496336	0	1
owner	6065	0.619786	0.485479	0	1
hhincome	6065	3.940148	1.195809	1	5
edu_isced	6065	2.290025	0.617047	1	3
bornabroad	6065	0.042374	0.201458	0	1
occupation_headhh	6065	3.127782	1.388915	1	6
nchild_below10	6065	0.377082	0.711827	0	4
west	6065	0.804617	0.396528	0	1
tagnr	6065	2.720363	0.511693	1	3
weekday	6065	0	0	0	0
low_educated	6065	0.087387	0.282424	0	1
medium_educated	6065	0.535202	0.4988	0	1
high_educated	6065	0.377411	0.484779	0	1
single	6065	0.302721	0.459473	0	1
married	6065	0.573784	0.494567	0	1
separated	6065	0.111954	0.315336	0	1
widowed	6065	0.011542	0.106819	0	1
selfemployed	6065	0.145425	0.352558	0	1
civilservant	6065	0.135367	0.342143	0	1
employee	6065	0.406266	0.491176	0	1
worker	6065	0.167848	0.373762	0	1
retired	6065	0.049134	0.216166	0	1
notemployed	6065	0.09596	0.294561	0	1
below_1100euro	6065	0.055565	0.229098	0	1
between_1100_1700euro	6065	0.100577	0.300793	0	1
between_1700_2300euro	6065	0.111459	0.314726	0	1
between_2300_3600euro	6065	0.312943	0.46373	0	1
above_3600euro	6065	0.419456	0.493511	0	1

spent doing physical activity: walking outside, jogging, bicycling, playing with the ball, doing gymnastics, doing water sports, or doing any another form of physical activity. As a further round of analysis we also use an index of social and pyshical activities together (overall index), that is the raw sum of the social events and sport variables.

4 Methods

We are interested in estimating the parameters characterizing the relationship between broadband Internet availability and health. The identification of a causal effect is difficult due to endogeneity issues. Access to high-speed Internet is likely to be correlated with many unobservable determinants of health, which may confound our relationship of interest. Unobserved factors (such as unobserved socioeconomic determinants of health, time preferences, genetics, and risk aversion) might simultaneously affect the willingness to pay for DSL subscription and health. Assuming that the omitted variables do not change over time, we can exploit the time dimension of the data set to eliminate the effect of unobservable factors. More specifically, we can make use of a panel estimator as the one depicted in (1):

$$y_{ist} = \beta_1 x_{1ist} + \beta_2 x_{2i} + \mu_t + \lambda_s + \gamma_s^1 t + \alpha_i + \eta_{ist} \tag{1}$$

where y_{ist} denotes the health of individual i residing in state s at the year of interview t, x_{1ist} is a dummy variable tacking value 1 if the respondent has access to high speed Internet, 0 otherwise. x_{2i} is our set of control variables as detailed in Table 1.[5] The estimated equation also includes a full set of federal state fixed-effects (λ_s) as well as a set of linear state-specific time trends ($\gamma_s^1 t$). The former are meant to capture unobservable, time-constant differences across states that may affect the health of the individuals, the latter unobserved cross-state differences in health over time. η_{ist} is the idiosyncratic error component, i.i.d. $(0, \sigma_\eta^2)$, uncorrelated with $(x_{1it}, x_{2i}, \alpha_i)$, and α_i is i.i.d. $(0, \sigma_\alpha^2)$, potentially correlated with x_{1it} and x_{2i}. Equation (1) is estimated via OLS. Provided that η_{ist} and x_{1ist} are uncorrelated at all leads and lags, this estimator is consistent even in the presence of unobservable effects correlated with the controls. Throughout the analysis, we cluster the standard errors at the individual level. Since it is plausible to assume that the impact of high speed Internet on health is heterogeneous across age and educational status, we formally test for heterogeneous effects by estimating equation (1) separately by age groups (18-30, 31-50, and 50+) and education (low-educated vs high educated). Examining the heterogeneity of the effects

[5] Age and age squared, a set of secondary school track effects (basic, intermediate or academic track), indicators for marital status, occupational status, a dummy indicating the ownership of a house or flat, and the logarithm of net household income.

across age and education groups provide further insights on the mechanisms through which Internet use may affect health.

As a way on interpreting the results, we estimate equation (1) by using as dependent variables different measures of social capital as detailed in table 1.

As a further way of interpreting the results, we exploit time use data (TUS) to explore the relationship between digital devices and social capital. More specifically, we look at the association between social capital variables with electronic media use (i.e., playing video games, and use of computers and smartphones). We include in the regression model control variables comparable to those included in (1): gender, age and age squared, number of children, indicators of their educational attainment, marital status, occupational status, migration background and net household income. We also include indicators for the day of interview and a dummy of whether the respondent lives in Western Germany. For the sake of completeness, this last model is estimated both by including and not including individual-level fixed effects.

5 Preliminary results

This section presents the preliminary results of the empirical analysis. We start by estimating the effect of broadband Internet on health. We then present heterogeneous effects and some robustness checks. Finally, in order to assess the interpretation of the results, we investigate the role of social capital as a mediator of the relationship between broadband Internet and health.

5.1 Effects of broadband Internet on health

Table 4 presents panel data fixed effect estimation results for equation (1). Columns 1-4 show that broadband Internet has a negative effect in terms of both physical and mental health. Indeed, the main effect is sizable in absolute and relative terms, ranging from 0.015 for self reported health (Column 1) to 0.059 for BMI (Column 2).

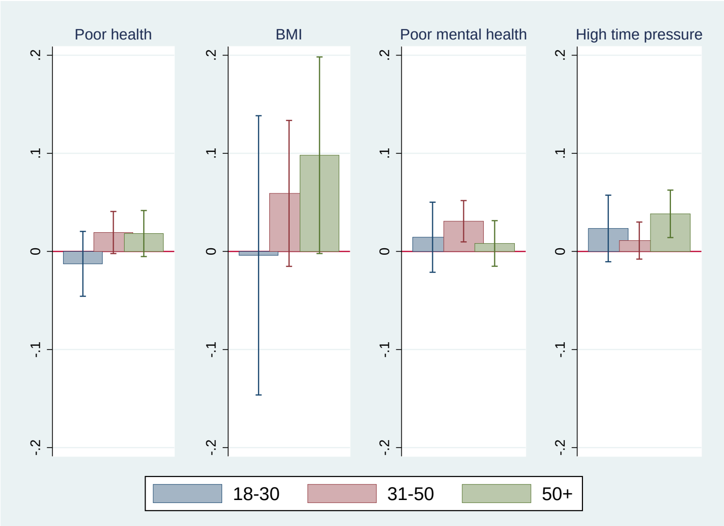
Figure 1 and 2 provide the fixed effect model estimation results by age and education group, respectively. Looking at the heterogeneous effects by age group (see Figure 1), we observe that middle-age and older individuals are those who respectively experience worse mental health and higher perceived time pressure as a consequence of high-speed Internet access. Such effects might be explained by a communication overload that could lead to stronger negative effects for adults compared to younger adults. Less clear-cut are the differential effects by age of Internet on BMI and self-assessed health.

Table 4: Effects of broadband Internet on health: Fixed effect panel model

	(1) Poor health	(2) BMI	(3) Poor mental health	(4) High time pressure
DSL subscription in HH	0.015*	0.059*	0.017**	0.023***
	(0.008)	(0.032)	(0.008)	(0.008)
Age	0.020*	0.337***	0.011	0.027***
	(0.012)	(0.049)	(0.012)	(0.010)
Age sq.	-0.000	-0.003***	0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Not working	-0.016	0.157	0.057	-0.078
	(0.047)	(0.278)	(0.072)	(0.074)
Unemployed	0.016	0.050	0.119*	-0.130*
	(0.046)	(0.278)	(0.071)	(0.073)
Retired	-0.078	0.069	0.051	-0.146*
	(0.048)	(0.289)	(0.073)	(0.076)
Blue collar	-0.009	-0.130	0.107	0.088
	(0.045)	(0.275)	(0.071)	(0.072)
White collar	-0.017	-0.210	0.085	0.099
	(0.045)	(0.274)	(0.071)	(0.072)
Entrepreneur	-0.071	-0.020	0.075	0.064
	(0.049)	(0.283)	(0.073)	(0.075)
Apprentice	-0.020	-0.136	0.084	0.088
	(0.042)	(0.267)	(0.068)	(0.071)
Household income (log)	-0.010	0.081**	-0.015	-0.000
	(0.010)	(0.041)	(0.011)	(0.010)
Widowed	0.076	-0.728	-0.019	-0.038
	(0.119)	(0.728)	(0.153)	(0.092)
Divorced	0.137	-0.018	-0.083	-0.035
	(0.105)	(0.663)	(0.140)	(0.080)
Single	0.097	-0.396	-0.086	-0.058
	(0.102)	(0.654)	(0.140)	(0.078)
Married	0.112	-0.152	-0.097	-0.027
	(0.103)	(0.662)	(0.140)	(0.079)
Secondary School Degree	0.968***	-0.669	-0.620***	-0.067
	(0.112)	(0.691)	(0.198)	(0.095)
Intermediate School Degree	0.940***	-0.820***	-0.560***	0.025**
	(0.011)	(0.047)	(0.012)	(0.011)
Technical School Degree	0.978***	-0.785	-0.597***	-0.119
	(0.119)	(0.659)	(0.190)	(0.093)
Upper Secondary Degree	0.880***	-0.607	-0.693***	-0.120
	(0.112)	(0.685)	(0.195)	(0.094)
Homeowner	-0.014	-0.017	-0.000	-0.017
	(0.014)	(0.061)	(0.016)	(0.014)
Number of children	-0.002	-0.006	-0.007	-0.000
	(0.006)	(0.026)	(0.007)	(0.006)
N.	40139	39669	40111	40097

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

Figure 1: Estimated effects of broadband Internet on health: age



(a) *Note:* Covariates as described in Table 1. Panel data fixed effect model.

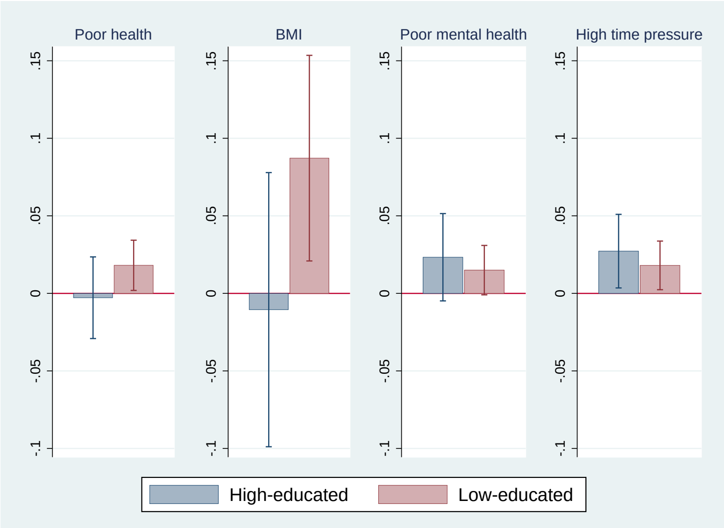
Figure 2 shows an interesting digital divide effect of Internet access on poor health and, most of all, on BMI. Lower educated individuals, compared to higher educated ones, show a much higher and significant likelihood of experiencing poor health and being overweight when they have access to high-speed Internet. Such heterogeneous effect by educational level may be explained by different uses of the Internet (i.e., digital divide). Higher educated individuals may use the Internet to (i) access health-related or lifestyle-related useful information, or (ii) as a communication tool, which in turn might lead to communication overload that would explain a higher perceived time pressure experienced by this educational group. Conversely, lower educated people may use the Internet mostly for leisure activities, such as on-line gaming, leading them to have a more sedentary lifestyle.

As a way to interpret these results we turn on TUS data. Table 5 and 6 depict the correlations between the hours spent on digital activities (operationalized as hours spent using PCs or smartphones and in gaming activities) and three different measures of social and physical activities, as described in section 3 during weekdays and weekends, respectively. Both tables show a negative and significant association between time spent using digital devices and such activities.

5.1.1 Robustness

Assuming that the omitted variables are time-invariant (with time-invariant effects), a fixed effect panel estimator may provide a means for controlling for omitted variable bias. However, it is not efficient. We therefore also consider

Figure 2: Estimated effects of broadband Internet on health: education



(a) *Note:* Covariates as described in Table 1. Panel data fixed effect model.

Table 5: Effect of technology on social capital, working days, full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES		**social_capital_hours**			**sport_hours**			**overall_index**	
pcuse_smartphone_hours	-0.080***			-0.033**			-0.112***		
	(0.022)			(0.015)			(0.025)		
pcgames_hours		-0.075*			-0.030			-0.105**	
		(0.042)			(0.025)			(0.044)	
Observations	10,903	10,903	10,903	10,903	10,903	10,903	10,903	10,903	10,903
R-squared	0.009	0.008	0.038	0.002	0.001	0.005	0.011	0.009	0.044
Number of id_persx	5,592	5,592	5,592	5,592	5,592	5,592	5,592	5,592	5,592
Mean of Dep. Var.	0.760	0.760	0.760	0.308	0.308	0.308	1.068	1.068	1.068
Std.Err. of Dep. Var.	1.264	1.264	1.264	0.773	0.773	0.773	1.481	1.481	1.481

Note: Covariates as described in Table 2. Individual fixed effects. * p<0.10, ** p<0.05, *** p<0.01

a random effect model, an estimator that is more efficient and allows to estimate the parameters of time-invariant regressors but it is inconsistent in the presence of unobservable effects correlated with the included controls. Given the comparison of the estimates for the fixed and random effects models, we perform Hausman tests of the null hypothesis that the individual-specific component of the error term (α_i) is uncorrelated with the regressors. The results are reported in Table 7.

The Hausman test statistics depicted at the bottom of Table 7 strongly reject the null hypothesis that the errors are uncorrelated with the regressors suggesting that there is indeed positive correlation between unobserved effects and time varying controls. The Hausman tests therefore suggest that the preferred model is the fixed effects one and that, failing to account for

Table 6: Effect of technology on social capital, weekend, full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**social_capital_hours**			**sport_hours**			**overall_index**		
pcuse_smartphone_hours	-0.260***			-0.002			-0.262***		
	(0.085)			(0.027)			(0.081)		
pcgames_hours		-0.093			0.003			-0.090	
		(0.107)			(0.044)			(0.086)	
Observations	6,065	6,065	6,065	6,065	6,065	6,065	6,065	6,065	6,065
R-squared	0.025	0.006	0.053	0.023	0.023	0.024	0.021	0.002	0.056
Number of id_persx	5,638	5,638	5,638	5,638	5,638	5,638	5,638	5,638	5,638
Mean of Dep. Var.	1.256	1.256	1.256	0.569	0.569	0.569	1.826	1.826	1.826
Std.Err. of Dep. Var.	1.825	1.825	1.825	1.143	1.143	1.143	2.071	2.071	2.071

Note: Covariates as described in Table 2. Individual fixed effects. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Effects of broadband Internet on health: Random effect panel model, robustness

	(1) Poor health	(2) BMI	(3) Poor mental health	(4) High time pressure
DSL subscription in HH	0.005	0.053*	0.004	0.017***
	(0.006)	(0.030)	(0.006)	(0.006)
Hausmann test χ^2	182.29	397.98	45.38	33.45
Hausmann test $Prob > \chi^2$	0.0000	0.0000	0.0015	0.0415
N.	40139	39669	40111	40097

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

unobserved heterogeneity, would lead to mis-estimating the impact of broadband Internet on health.

5.2 Broadband Internet, social capital and health: Potential pathways

Our proposed interpretation for the negative effect of broadband Internet on health is that the Internet increases social capital. However, while this increased availability of social capital may provide a source of social support with a resulting positive effect in terms of health, it can simultaneously provoke a communication and social interactions overload with a resulting negative effect in terms of health. In order to assess this interpretation, we focus on the estimation of equation (1) using as dependent variables three dummies measuring different dimensions of an individual's social capital.

Table 8 shows that broadband Internet connection is positively and significantly associated to social interactions (Column 1). The effect turns out to be positive and not significant for social cohesion (Column 2) and negative and not significant for social activities (Column 3).

So far, the estimated specification did not include potential pathways, i.e., did not include indicators of social capital. As in Dave and Kelly (2012), we therefore proceed by including in the estimated models the three measures of social capital to gauge the extent to which the estimated effect of high-speed Internet on health can be explained by them. To put it differently, we condition on social capital, which is influenced by Interned access, and, in turn, affects an individuals' health, and examine the change in the estimate of the impact of DSL subscription on health. The results of this exercise are reported in Table 9.

Each column of each panel of Table 9 presents estimates controlling alternately for the three variables of social capital used in Table 8 (i.e., social interactions, social cohesion, and social activities) while column 4 controls for them jointly.

Focusing on Panel 1 and Panel 3, controlling for any social capital dimensions causes the effect on reporting poor health and poor mental health to become smaller and not significant[6] suggesting that social capital is indeed a mediator of the relationship between Internet use, self-reported health and mental health. More specifically, it suggests that self reported health and mental health respond positively to increased availability of social support embedded in social relations, social cohesion, and social activities. On the opposite, panel 2 shows that social interactions and social cohesion do not play a significant role as mediators of the relationship between Internet and BMI, while the detrimental effect of high speed Internet in terms of participating

[6]Only slightly significant in Column 1 of Panel 3.

Table 8: Effects of broadband Internet on social capital: Fixed effect panel model

	(1) Social interactions	(2) Social cohesion	(3) Social activities
DSL subscription in HH	0.021**	0.005	-0.007
	(0.009)	(0.005)	(0.006)
Age	-0.042***	0.006	-0.032***
	(0.007)	(0.004)	(0.005)
Age sq.	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)
Not working	-0.036	-0.109*	-0.055
	(0.060)	(0.059)	(0.072)
Unemployed	0.001	-0.095	-0.050
	(0.060)	(0.058)	(0.072)
Retired	0.055	-0.086	-0.058
	(0.062)	(0.060)	(0.073)
Blue collar	-0.007	-0.092	-0.055
	(0.059)	(0.058)	(0.072)
White collar	-0.029	-0.099*	-0.056
	(0.059)	(0.058)	(0.072)
Entrepreneur	-0.031	-0.066	-0.059
	(0.062)	(0.060)	(0.074)
Apprentice	-0.023	-0.068	-0.063
	(0.057)	(0.059)	(0.070)
Household income (log)	-0.021**	-0.014**	-0.008
	(0.010)	(0.006)	(0.008)
Widowed	-0.030	0.006	-0.059
	(0.150)	(0.083)	(0.090)
Divorced	0.038	0.042	-0.045
	(0.134)	(0.076)	(0.085)
Single	-0.005	0.040	-0.022
	(0.132)	(0.077)	(0.086)
Married	-0.032	0.038	-0.060
	(0.133)	(0.077)	(0.085)
Secondary School Degree	1.089***	0.020	-0.490***
	(0.087)	(0.026)	(0.184)
Intermediate School Degree	1.023***	-0.009**	-0.000
	(0.008)	(0.005)	(0.006)
Technical School Degree	1.107***	-0.016	-0.472**
	(0.091)	(0.046)	(0.193)
Upper Secondary Degree	1.194***	-0.014	-0.573***
	(0.085)	(0.017)	(0.181)
Homeowner	-0.017	0.003	0.006
	(0.017)	(0.009)	(0.012)
Number of children	-0.004	-0.005	0.001
	(0.007)	(0.004)	(0.005)
N.	36635	36547	36635

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

Table 9: Internet, Social capital and health: pathways

	(1)	(2)	(3)	(4)
Panel 1				
Dep. var.: **Poor health**				
DSL subscription in HH	0.011	0.011	0.011	0.010
	(0.008)	(0.008)	(0.008)	(0.008)
Social interactions	X			X
Social cohesion		X		X
Social activities			X	X
Panel 2				
Dep. var.: **BMI**				
DSL subscription in HH	0.060*	0.061*	0.062*	0.059*
	(0.033)	(0.033)	(0.033)	(0.033)
Social interactions	X			X
Social cohesion		X		X
Social activities			X	X
Panel 3				
Dep. var.: **Poor mental health**				
DSL subscription in HH	0.014*	0.013	0.014	0.014
	(0.008)	(0.008)	(0.008)	(0.008)
Social interactions	X			X
Social cohesion		X		X
Social activities			X	X
Panel 4				
Dep. var.: **High time pressure**				
DSL subscription in HH	0.025***	0.025***	0.025***	0.025***
	(0.008)	(0.008)	(0.008)	(0.008)
Social interactions	X			X
Social cohesion		X		X
Social activities			X	X

Note: Covariates as described in Table 1. (d) indicates discrete change of dummy variable from 0 to 1. Cluster-robust standard errors reported in brackets. * p<0.10, ** p<0.05, *** p<0.01

in social activities can strengthen its negative effect in terms of BMI. Accordingly, panel 3 shows that the increased availability of social interactions are a major pathway underlying the link between Internet use and perceived time pressure. We interpret this result as being driven by an increased communication and social relations overload. Summing up, these models highlight that social capital is a key factor underlying the relationship between Internet use and health. However, the direction of the mediation effect depends on the outcome we are considering. In fact, social capital seems to act as a buffer against the negative effect of high speed Internet in terms of reporting poor (mental) health through increased availability of social support embedded in social relations. On the opposite, it seems to contribute to a reduction in health through reduced social activities and more sedentary lifestyle and through increased social interactions overload. However, the very fact that a significant effect of Internet use on BMI and time pressure remains after controlling for social capital as a mediator, suggests that other mechanisms that we are not accounting for might also be playing a role. As an example, Internet use can cause a shift in risk preferences therefore changing the relative cost of healthy behaviors. Accordingly, Internet access can have an effect on time preference and time allocation, with a deleterious effect in terms of health (Shochat, 2012).

6 Concluding remarks

Internet is a technological shift that also shapes an individuals health. Our results suggest that, overall, the effect of broadband Internet connection on both physical and mental health is negative. Social capital may indeed act as a mediator of this relationship by providing social support and, at the same time, by increasing social interactions overload. While the first path translates into a buffering effect of social capital in terms of self reported (mental) health, the second path contributes to increase time pressure. Although we are aware of the fact that our estimates should be interpreted with caution since social capital and health can also be related by an exactly reversed path, the correlations emerging in the analysis point to important policy implications.

First, the Internet revolution permeates our daily life and can be empowering in many respects. However, the changes brought about by this relatively new technology require a better understanding of the mechanisms through which they occur in our daily life. Second, our findings suggests that social capital plays a relevant role in the transmission of the health effects of Internet access. Social capital may provide social support, a sense of belonging, can mobilize human and material resources that can dampen the negative effect of Internet access therefore affecting *individual* health. However, when we conceptualize social capital as relational goods, we implicitly recognize its collective dimension. As a result, we implicitly assume that social capital can be crucial also in terms of *public* health. While this last pattern has not been explored in this paper, it can constitute and interesting extension of our current framework.

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