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SOCIAL MEDIA USE AND CHILDREN'S WELLBEING

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Abstract

Childhood circumstances and behaviours have been shown to have important persistent effects in later life. One aspect of childhood that has changed dramatically in the past decade, and is causing concern among policy makers and other bodies responsible for safeguarding children, is the advent of social media, or online social networking. This research explores the effect of children's digital social networking on their subjective wellbeing. We use a large representative sample of 10-15 year olds over the period 2010 to 2014 from the UK Household Longitudinal Study, and estimate the effect of time spent chatting on social websites on a number of outcomes which reflect how these children feel about different aspects of their life, specifically: school work; appearance; family; friends; school attended; and life as a whole. We deal with the potential endogeneity of social networking via an instrumental variables approach using information on broadband speeds and mobile phone signal strength published by Ofcom. Our results suggest that spending more time on social networks reduces the satisfaction that children feel with all aspects of their lives, except for their friendships; and that girls suffer more adverse effects than boys. As well as addressing policy makers' concerns about the effects of digital technology on children, this work also contributes to wider debates about the socioeconomic consequences of the internet and digital technologies more generally, a debate which to date has largely been based on evidence from outside of the UK.

JEL Codes: D60; I31; J13

Key Words: digital society, social media, wellbeing, children.

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1. INTRODUCTION

Childhood circumstances and behaviours have been shown to have important persistent effects in later life (see for example Heckman (2008), Almond and Currie (2011)). One aspect of childhood that has changed dramatically in the past 10 years, but has received scant attention in the economics literature, is the advent of social media, or online social networking. Social media are computer-mediated tools that allow people, and organisations, to create, share, or exchange information in virtual communities and networks. The growth of social media has been extremely rapid; these sites started among university students in the US in the early 2000s, but their use has quickly spread around the world. Facebook, the most well-known social networking site, was launched in February 2004, initially only for Harvard University students. Today it has over 1.7 billion active users around the world;[1] 31 million of these users are in UK – almost half of the UK population.

Perhaps unsurprisingly, young people have been heavy adopters of social media; today's generation of teenagers is the first cohort to have grown up with online social networking. A survey in 2015 revealed that, in the UK, 92% of 16 to 24 year olds had used social networks in the last three months.[2] Along with these teenagers, younger children are also increasingly users of social media; while most sites stipulate a minimum user age of 13, few require any validation, and a survey for the children's BBC channel found that more than three quarters of 10 to 12 year olds had social media accounts.[3]

Social media are a core part of young people's lives. Social networks such as Facebook, Snapchat, WhatsApp and Instagram are their primary interface with the internet. These portals are generally used in an 'always on' state, often via smartphones and tablets, such that many children are permanently connected to their virtual social network, continually receiving and checking feed, and regularly posting their own updates (Boyd, 2014). This social media access serves a multiplicity

[1] www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/
[2] www.ons.gov.uk/ons/guide-method/method-quality/specific/business-and-energy/e-commerce-and-ict-activity/social-networking/index.html
[3] www.bbc.co.uk/news/education-35524429

of functions. It is a tool for developing and maintaining interpersonal relationships, a real-time portal for accessing information, news, advice and support, as well as a canvas for sketching a selective and idealised self-portrait. However, despite its practical uses, worries about the effects of social media use on children persist. While it is generally acknowledged that social media can have a positive impact on the social capital of children, for example by enhancing friendships and decreasing loneliness (Wood et al., 2016), there are concerns that 'excessive' time spent on social media is associated with low self-esteem, common mental health problems, and socioemotional difficulties (e.g., Beardsmore, 2015; Kross, 2013). The UK children's charity the National Society for the Prevention of Cruelty to Children has recently cited social media as a major cause of the dramatic increase in the numbers of children admitted to hospital as a result of self-harming.[4] Further there have been a number of high profile cases involving teenagers taking their own lives in part because of being harassed over the internet (Hinduja and Patchin, 2010). In the UK, concerned that children are now more likely to turn to social media and the internet for information, rather than other more 'traditional' sources, the House of Lords launched an enquiry into 'children and the internet' in July 2016.[5]

Given the importance of children's use of social media in the twenty first century, and its possible long-term detrimental effects, it is perhaps surprising that the economics research community has not paid more attention to this topic. A systematic review of studies on online communication, social media and adolescent wellbeing in 2014 identified no economic studies (Best et al., 2014). However, this phenomenon is worthy of economic study because it is clearly a significant component of youth time use, and its effects on utility, or wellbeing, are ambiguous, (Kalmus et al., 2014). Further, it has been shown in previous work that circumstances and behaviours in childhood can have persistent effects into adulthood.[6] Indeed, the economics of

[4] http://news.sky.com/story/social-media-to-blame-for-14-rise-in-self-harm-hospital-admissions-10688539
[5] www.parliament.uk/documents/lords-committees/communications/children-internet/CfEChildren-internet.pdf
[6] See for example, Frijters et al. (2014), who show that having behavioural problems at ages 7 and 11 predicts lower adult life satisfaction, conditioning on an adult's socioeconomic characteristics. Also data from the Whitehall study

childhood wellbeing is now a growing literature given the importance of experience early in life in shaping future outcomes, see Conti and Heckman (2014) for a review.

We contribute to the literature by providing valuable evidence on the effects of social media use on the subjective wellbeing of children in the UK. This is a rare economic study on a phenomenon which is a pervasive and much debated feature of modern life. We improve on the vast majority of existing evidence on the effects of social media use by, firstly, using a large nationally representative sample of children, rather than a small survey of a selective group. Secondly, we utilise measures of domain satisfaction which enable us to explore which aspects of children's lives are most affected. Thirdly, we explore causal mechanisms by considering three theories that can help to explain why extensive social media use may have a negative effect on children's wellbeing. Finally, we attempt to derive causal estimates, rather than associations, by adopting an instrumental variable (IV) framework, which deals with the endogeneity of social media use in our empirical model by exploiting exogenous variation in internet connection speeds accessed via both broadband and the mobile 3G network at disaggregated local levels. Our results are worrying for anyone concerned with children's subjective wellbeing and its potential long-term effects. We show a substantial negative association between time spent socialising via social media sites and satisfaction in four of the five domains, as well as life overall, and this adverse effect remains when we deal with the endogeneity of social media use in an IV setting.

2. SOCIAL MEDIA USE AND WELLBEING

There are three, complementary, theories that help to explain why extensive social media use may have a negative effect on children's wellbeing. All of these theories draw on research from both economics and psychology, and it is likely that they are not mutually exclusive, but rather that all of them contribute to altered wellbeing in individuals who use social media. The first, which we term 'social comparison' theory, posits that increased social media use is linked to more frequent social

suggests that early life circumstances are all predictive of entry grade and promotion to higher grade in Whitehall (Case and Paxson, 2011).

comparisons with others (Zuo, 2014). These comparisons are more likely to be ‘upward’ (negative) in direction, given that the material people choose to present online represents selectively idealised versions of their true appearance, activities, and achievements (Mendelson and Papacharissi, 2010). Most direct empirical support for this theory comes from studies in university student samples. Chou and Edge (2012) found that students who spent more time on Facebook were more likely to think that other people were happier and had better lives than their own. Feinstein et al. (2013) reported a significant positive effect of Facebook social comparisons on depressive symptoms. Zuo (2014) reported negative associations between daily Facebook use and measures of self-esteem, which were explained by increased social comparisons. Furthermore, a growing body of research attests to the mediating role of envy in the relationship between Facebook use and decreased affective wellbeing (e.g., Tandoc Jr. et al., 2015; Verduyn et al., 2015). In economic research, social comparisons, largely related to relative income, have been shown to be an important determinant of subjective wellbeing. For example, Ferrer-i-Carbonell (2005) uses data from a large German panel to show that individuals are happier the larger their income is in comparison with the income of the reference group, and that this effect is asymmetric, with individuals largely making upward comparisons; similar results are found by McBride (2001), Luttmer (2005) and Card et al. (2012) for the US. Further, Clark and Oswald (1996) use data on 5,000 British workers to show that workers' reported satisfaction levels are inversely related to their comparison wage rates.

Among economic research that has explicitly considered the role of the internet, Sabatini and Saracino (2016) find that social network users in Italy have a higher probability of making social comparisons than non-users, and that this tendency is greatest in younger people. In related work Clark and Senik (2010) found that, in Europe, people with internet access attach more importance to income comparisons that those without, and Lohmann (2015) finds that people who regularly use the internet as a source of information derive less satisfaction from their income. Further, in related work a number of studies have found that television viewing makes people less happy, less satisfied with their income, and more prone to material aspirations e.g. Hyll and

Schneider (2013); Frey et al. (2007); Bruni and Stanca (2006). Solnick and Hemenway (1998) show that positional concerns are also strong for attractiveness and praise from supervisors.

A second theory, which we call ‘finite resources’, suggests that extensive time spent on social media encroaches on other activities known to be beneficial for psychological wellbeing, such as face-to-face socialising, sports or exercise participation, and mental relaxation (Moreno et al., 2013; Wallsten, 2013). Recent work has shown that the link between Facebook use and subsequent negative mood may be mediated by the interpretation that people have wasted their time on an activity that was meaningless (Sagioglu and Greitemeyer, 2014), and there is evidence that passive use of social networking is worse for wellbeing than active usage (e.g., Verduyn et al., 2015). In similar vein Bryson and Mackerron (2016) find, from the large scale Mappiness experience sampling data set,[7] that the overall effect of texting, email and social media use upon happiness when also ‘working or studying’ is negative and significant. Helliwell and Huang (2013) compare face-to-face (or ‘real’) friends with online social networks in an adult Canadian sample. They find a positive correlation between the size of real and online social networks, but further find that only increases in the number of ‘real’ friends increase’s subjective wellbeing, and this effect remains after they control for income, demographic characteristics and personality traits. There is also an interesting line of research emerging demonstrating a detrimental effect of social media use (particularly at night) on sleep quantity and quality (e.g., Levenson et al., 2016), and decreased wellbeing (e.g., Woods and Scott, 2016).

A third theory, which we call ‘cyberbullying’, relates to the fact that children who spend more time on social networks have a greater chance of being the victim of cyberbullying or direct attacks from others on their sense of self, wellbeing, and self-esteem. Sampasa-Kanyinga and Hamilton (2015) reported a significant increase in the odds of being victimised for every hour spent using social networking sites. Cyberbullying is associated with negative impacts on children’s emotional health and wellbeing (Cowie, 2013). While cyberbullying victimization often overlaps

[7] www.mappiness.org.uk/

and correlates with traditional ‘offline’ bullying, the former may be particularly pernicious because of children’s perceptions of continual connectedness, and that they cannot escape criticism and ridicule (Slonje et al., 2012). A number of economic studies have illustrated the potential negative and persistent effects of being bullied in childhood. For example, Eriksen et al. (2014) find detrimental effects of being bullied on educational attainment at ages 15-16, in a large Danish sample. Using Finnish data, Varhama and Bjorkqvist (2005) find a positive association between long-term unemployment and whether an individual was bullied during childhood. Using the National Child Development Study for the UK, Brown and Taylor (2008) find that being bullied at school has an adverse effect on human capital accumulation both at and beyond school; it influences wages received in adulthood, as well as indirectly influencing wages via educational attainment. Further, Powdthavee (2012) finds that those children who report fear of bullying subsequently suffer larger psychological effects of unemployment in later life; and this association remains after controlling for personality traits.

There are two important shortcomings with much of the existing evidence on social media and individual wellbeing outcomes. The first is that wellbeing is often conceptualised differently across studies, or treated as a unitary construct. However, children’s overall satisfaction with life can be meaningfully subdivided into multiple domains, such as their satisfaction with school, with their friends, with their appearance, and so on (Diener et al., 1999; Van Praag et al., 2003). Thus, it is possible that social media use may affect discrete aspects of children’s wellbeing differently, and perhaps even in opposing ways. For example, social media use has been shown to be positively associated with heightened social capital (Antoci et al., 2012; Ellison et al., 2007),[8] while simultaneously having a negative impact on educational outcomes (Jacobsen and Forste, 2011).

A second important caveat that needs to be taken into account is the proposed directionality of effects. It is possible that people with lower levels of psychological wellbeing, may choose to

[8] Although in contrast with this, Sabatini and Sarracino (2015) find that in Italy the use of social networking sites is associated with lower trust.

spend more time on social media, perhaps in preference to interacting with others in person. Ellison et al. (2007) reported greater positive effects of Facebook usage on 'bridging' social capital for participants scoring lower on life satisfaction and self-esteem indicators.[9] There is also evidence that some people may use social media to combat loneliness and enhance self-esteem (e.g., Song et al., 2014; Gonzales and Hancock, 2011; McKenna and Bargh, 2000). It is also possible that 'third variable' problems exist, with other constructs, such as loneliness, driving both lower levels of wellbeing and greater social media use. In this paper we explicitly address both shortcomings, using a multiple domain wellbeing outcome, and an IV approach to account for the endogeneity problems of reverse causation between social networking and domain satisfaction, and unobserved effects influencing both variables. Our analysis uses a large, representative sample of children in the UK.

3. DATA AND METHODOLOGY

In this paper we utilise data from *Understanding Society* – The UK Household Longitudinal Study (UKHLS), a representative sample of over 40,000 households across the UK; where individuals and households can be tracked over time since it is panel data (University of Essex, 2015). Data collection for the UKHLS began in 2009, with information being provided on social and economic circumstances, attitudes, behaviours and health. Six waves of data are currently available; respondent interviews were conducted between 2009 and 2011 for wave 1 which provided data on over 50,000 individuals. In wave 6, over 45,000 individuals were interviewed between 2014 and 2016. All adult members of each household are interviewed along with children aged 10 to 15 years old. In this analysis, waves 2 to 4 are used where these waves provide data on just under 4,000 of these children, who are the focus of the empirical analysis.[10]

Children's data is derived from the Youth Self-completion Questionnaire, and this is used alongside data from the Adult Self-completion Questionnaire, which provides information on

[9] Putnam (2000) stresses two forms of social capital, 'bonding' (or exclusive), which is inward looking and reinforces strong ties among close groups, such as families, and 'bridging' (or inclusive), which is more outward looking and based on weaker ties between people from more diverse social groupings, such as groups of work colleagues.

[10] We are not able to use waves 1 and 6 of the UKHLS because the Ofcom data that we use for the instrumental variables (see below) is not available for these years.

household and parent characteristics such as household income, homeownership and parental education. The outcomes of interest relate to the domain satisfaction of children obtained by asking how they feel about different aspects of their life, specifically: *school work; appearance; family; friends; school attended; and life as a whole*. Full information on the question asked to children is provided in the Appendix. We reorder the responses to each question to range from "1=not happy at all" through to "7= completely happy", where we define $j(=1,..,7)$.

The main independent variable of interest is obtained by firstly asking: *Do you belong to a social web-site such as Bebo, Facebook or Myspace?* 77% of the respondents were members of a social network and were subsequently asked: *How many hours do you spend chatting or interacting with friends through a social web-site like that on a normal school day?* The response to this question ranges from "1=none", "2=less than an hour", "3=1-3 hours", "4=4-6 hours", and "5=7 or more hours", where we define $k(=1,..,5)$. The responses to this question are coded into the variable, $netchat$. After conditioning on missing values for key explanatory variables we create an unbalanced panel of 3,971 children, providing 6,788 observations between waves 2 to 4, which covers the period 2010/11 through to 2013/14.

For each ordered outcome of different aspects of child wellbeing we condition upon a set of covariates and the extent to which the child uses social media. Hence, the initial models we estimate are of the following form:

$$y_{iw}^{*} = \boldsymbol{X}'_{iw}\boldsymbol{\beta} + \phi netchat_{iw} + \varepsilon_{iw} \qquad (1)$$

where $i(=1,..,3971)$, $w(=2,3,4)$ denote the child and wave of interview respectively. The error term is normally distributed $\varepsilon_{iw} \sim N(0,\Sigma)$. The outcome, y_{iw}^{*}, is observed in discrete form through a censoring mechanism as follows: $y_{iw} = j$ if $\mu_{j-1} < y_{iw}^{*} \leq \mu_j$, $j(=1,..,7)$. Equation (1) is estimated as a random effects ordered probit model where the primary variable of interest $netchat$

is treated as being exogenous.[11] Our interest lies in the sign and statistical significance of the estimate $\hat{\phi}$. Control variables appear in the vector $\boldsymbol{X}$ and are described in detail below.

We also employ an IV approach to overcome the potential endogeneity issue when investigating the impact of social network usage on domain satisfaction outcomes, where we model the child's social media use and the outcome of interest simultaneously via a bivariate random effects ordered probit model, see Maddala (1983), as follows:

$$netchat_{iw}^{*} = \boldsymbol{X}_{iw}'\boldsymbol{\beta}_1 + \gamma Z_{iw} + \varepsilon_{1iw} \tag{2a}$$

$$y_{iw}^{*} = \boldsymbol{X}_{iw}'\boldsymbol{\beta}_2 + \theta netchat_{iw}^{*} + \varepsilon_{2iw} \tag{2b}$$

Where $netchat_{iw}^{*}$ and y_{iw}^{*}, are observed in discrete form through a censoring mechanism as follows: $y_{iw} = j$ if $\mu_{j-1} < y_{iw}^{*} \leq \mu_{j,}$ $j(= 1,..,7)$ and $netchat_{iw} = k$ if $\psi_{k-1} < netchat_{iw}^{*} \leq \psi_k,$ $k(= 1,..,5)$. The vector of covariates, in $\boldsymbol{X}$, influence both the outcome of interest and social media use. The equation for social media use is identified by the instrumental variable Z_{iw} (discussed in detail below). The error terms are jointly normally distributed, $\varepsilon_{1iw}, \varepsilon_{2iw} \sim N(0, \Sigma)$, and are allowed to be correlated across the two equations revealing whether there is interdependency between the child's wellbeing and social media use. If the correlation is statistically significant this endorses the joint modelling approach and provides efficient parameter estimates. We use a Conditional Mixed Process (CMP) estimator available in Stata v14 (see Roodman, 2011), to jointly estimate equations (2a) and (2b). CMP is an appropriate estimator in this context given that there is simultaneity between social media use and the outcome(s) of interest, but the availability of instruments allows the construction of a recursive set of equations, similar to a two-stage least squares (2SLS) regression. In the estimation of equations (2a) and (2b), CMP is a limited information maximum likelihood (LIML) estimator where the first stage parameters are

[11] For simplicity in this model we also treat $netchat$ as continuous. Robustness checks show that specifying $netchat$ as an ordinal variable, i.e. replacing the index with binary indicators, does not change the story we report in this paper. Essentially the action occurs for values of $netchat$ of 3, 4, and 5, with the expected gradient over these values.

structural and the second stage parameters are reduced form. In the context of the above IV model the estimated parameter of interest in terms of sign and statistical significance is $\hat{\theta}$.

An alternative approach is also adopted in order to examine the robustness of our results. In particular, the above models are based upon ordered random effects panel estimators and hence a potential criticism might be that there are unobservable fixed effects (FE), e.g. either at the household level or child specific, which we are not allowing for and could potentially influence the parameter estimates. We therefore seek to control for unobserved child heterogeneity, or omitted variable bias, by employing a difference estimator as follows:

$$\Delta y_i^{(w4-w2)} = \Delta \boldsymbol{X}_i^{(w4-w2)'} \boldsymbol{\pi}^{FD} + \mu^{FD} \Delta netchat_i^{(w4-w2)} + \nu_i \quad (3a)$$

The change in each measure of the child's wellbeing between wave 4 and wave 2, $\Delta y_i^{(w4-w2)}$, is conditioned on the change in time varying covariates, $\Delta \boldsymbol{X}_i^{(w4-w2)}$, and the change in social media use, $\Delta netchat_i^{(w4-w2)}$. Each measure of wellbeing is measured on a scale of 1 to 7 and hence the difference ranges from -6 to +6; the distribution is approximately normal and we treat the outcome as continuous. The first difference model in equation (3a) is equivalent to a FE estimator (given the focus on just two periods), as follows:

$$y_{iw} = \boldsymbol{X}'_{iw} \boldsymbol{\pi}^{FE} + \mu^{FE} netchat_{iw} + \alpha_i + \nu_{iw} \quad (3b)$$

where $w(= 2,4)$, α_i is a child fixed effect, $\nu_{iw} \sim N(0, \Sigma)$, $\boldsymbol{\pi}^{FD} = \boldsymbol{\pi}^{FE}$ and $\mu^{FD} = \mu^{FE}$. Our focus in estimating equation (3b) is on the sign and statistical significance of the estimate $\hat{\mu}$. The advantage of the outcome being continuous is that the analysis can also be extended to an IV setting as follows:

$$y_{iw} = \boldsymbol{X}'_{iw} \boldsymbol{\lambda} + \delta netchat_{iw} + \alpha_i + \nu_{iw} = \boldsymbol{Q}'_{iw} \boldsymbol{\psi} + \alpha_i + \nu_{iw} \quad (4)$$

where $\boldsymbol{Q}_{iw} = [\boldsymbol{G}_{iw}, netchat_{iw}]$ and $\boldsymbol{G}_{iw} = [\boldsymbol{X}_{iw}, Z_{iw}]$, with Z_{iw} being the potential instrument(s), defined below, which satisfy the following condition $E[Z_{iw}, \nu_{iw}] = 0$. Equation (4) is an IV FE estimator which with two periods (waves 2 and 4 only) is equivalent to an IV first difference approach. Using the within group transformation, which eradicates the child fixed effect, α_i, from the model, a two stage least squares estimator can be used by regressing, $\tilde{y}_{iw}$, on $\widetilde{\boldsymbol{Q}}_{iw}$ with instruments $\widetilde{\boldsymbol{G}}_{iw}$.[12] We estimate equation (4) using the xtivreg command in Stata v14. Hence this approach simultaneously controls for unobserved child fixed effects and endogeneity.

The covariates included in vector $\boldsymbol{X}$ control for individual child, parent, household and local area characteristics and comprise: age controls, specifically whether aged 10, 11, 12, 13 or 14 (with aged 15 as the omitted category); whether male; whether white ethnicity; the number of hours spent watching television; the number of friends that the child has; whether the child's parent is employed; whether the child's parent has a degree or equivalent qualification; the natural logarithm of real equivalised net household income; the number of children aged 0-2, 3-4, 5-11 or 12-15 in the household;[13] whether the child's parent(s) own the house; the number of times in last 7 days the child has eaten an evening meal with their family; whether the child wants to go college or university after finishing school; whether the child has played truant from school in the past year; whether the child has ever smoked; whether during the past month the child has stayed out after 9pm without their parent(s) knowing their whereabouts; whether the household lives in an urban area; and the local area district unemployment rate to attempt to proxy for local economic conditions.[14] We also include wave and Government office regional dummies.

Data are available from Ofcom, the communications regulator in the UK, for the potential instruments, Z, which are measures of the speed of internet access in the local area.[15] The first two variables are measures of broadband connection speeds; these are the average synchronisation speed of existing broadband connections (*avsyncspeed*), and the percentage of homes with broadband

[12] Note that $\tilde{y}_{iw} = y_{iw} - \bar{y}_{i.} + \bar{y}$, where $\bar{y}_{i.} = [1/n \sum_{t=1}^{2} y_{it}]$ and $\bar{y} = [(1/n) \sum_{i=1}^{n} \sum_{t=1}^{2} y_{it}]$. $\widetilde{\boldsymbol{Q}}_{iw}$ and $\widetilde{\boldsymbol{G}}_{iw}$ are based upon corresponding transformations.

[13] For the categories 5-11 and 12-15 the number of children excludes the respondent, given that the child interviews cover those individuals aged 10 to 15.

[14] Local area district unemployment rates are obtained from www.nomisweb.co.uk which is a service provided by the Office for National Statistics containing official labour market statistics.

[15] The data are available from www.ofcom.org.uk.

currently not achieving a download speed of 2 megabits per second (Mbit/s) (*notrec2mb*). The third variable is a measure of how easy it is to connect to the internet via a mobile phone signal; the percentage of landmass with 'third generation' (3G) mobile signal outdoor coverage from all phone operators (*signal3G*).[16] 3G technology was introduced in the UK in 2004 and offered substantially higher download speeds than older mobile communication protocols. The Ofcom data are available both at the local authority level, and in some areas within England, at the unitary authority level.[17] The UKHLS provides detailed information on the Local Authority District (LAD) in which an individual resides,[18] allowing us to merge in the instruments from the Ofcom data (and the local unemployment rate control variable). The instrument data are available across all years from 2011 to 2013; the data are therefore matched to the corresponding waves of the UKHLS survey with the 2011 data merged with wave 2 of the survey, 2012 with wave 3 and finally, 2013 Ofcom data merged with wave 4.[19] The assumption for the use of Z as instruments, is that conditional on the vector of covariates $\boldsymbol{X}$, Z has no direct influence on children's wellbeing outcomes; the effect of Z on these outcomes operates only indirectly through $netchat$. This seems like a reasonable assumption, and we investigate it empirically below. Firstly, the children in our sample live with their parents, hence do not choose the location of their home; thus we can assume they do not choose to live in areas of good broadband and 3G coverage. Secondly, we have a rich set of control variables in $\boldsymbol{X}$ that reflect individual, household and local area characteristics, and thus can be expected to purge any remaining correlation between Z and y.[20]

Full variable definitions are given in the Appendix. Summary statistics for the dependent variables, y_{iw}, key explanatory variable, $netchat_{iw}$, other control variables, $\boldsymbol{X}$, and the instrumental variables, Z, are shown in Table 1. Figures 1 and 2 provide histograms of the distribution of each

[16] We do not use information on 'fourth generation' (4G) mobile signal technology because this was not widely available in the UK until after the time period covered by our data.

[17] Where possible LAD data are merged with the LAD identifiers given in the UKHLS; where the LAD is unavailable, the local area broadband data are based on the larger area level unitary authority.

[18] UKHLS LAD identifiers are available under Special Licence. There are 355 LADs represented in UKHLS.

[19] Only 32 individuals fail to be matched to the Ofcom data and these individuals are predominantly from the Outer Hebrides (Western Isles) council area of Scotland.

[20] This identification strategy is similar to that used by Sabatini and Sarracino (2015) in their study of social networking and trust in Italy.

dependent variable and social media usage respectively; Figure 3 shows the distribution of each alternative instrumental variable. Clearly, across each of the wellbeing questions on average children report towards the upper of the scale, although for feelings about their *school work* and *appearance* the mean response is lower and the standard deviation is higher in comparison to the other domains. This is also reflected in less than 20% of respondents stating that they are 'completely happy' with their *school work* and/or *appearance,* which is much lower than the other wellbeing domains. Approximately 45% of children report spending less than 1 hour per school day using social media, although perhaps worryingly around 10% of respondents spend 4 or more hours.

On average children have 5-6 close friends, 42% are aged 13 or 14 (the two dominant age groups), 47% are male, and children spend an average of 3 hours watching television per day.[21] In terms of family background 84% of children have at least one parent who is either an employee or self-employed, 26% live in a single parent household and the average real net equivalised family income is £624 per month; 68% of parents own their home either outright or with a mortgage; on average children eat an evening meal together with the rest of your family on 3 to 5 occasions during the week; 70% of children aspire to either go to college or university after finishing school; and 9% of children reporting have played truant from school in the last year. In terms of the instrumental variables at the local level 52% have 3G outdoor coverage from all operators whilst 12% of homes have a broadband connection speed below 2Mbits per second.

Table 2a provides the raw correlation coefficient between the child's social media usage, $netchat_{iw}$, and each of the instrumental variables, Z, whilst in Table 2b the average value of each instrumental variable is given by each category of $netchat_{iw}$. Clearly, social media usage is correlated with each of the instruments at the 1% level of statistical significance and is negatively associated with both the average synchronisation speed and 3G outdoor coverage, i.e. children

[21] Both the number of friends the child has and the number of hours that they spend watching TV are positively and significantly correlated with $netchat$, where the correlation coefficients are 0.071 and 0.171 respectively.

spend less time on the using social networks the better the connection. This is also confirmed in the raw data by positive correlation with the percentage of households not achieving broadband speeds of 2Mbits per second. However, interestingly Table 2b reveals that there is not a monotonic relationship between the mean value of the instruments and the time spent on social media. The mean value of each instrument also varies by the categories of $netchat_{iw}$, i.e. both the aggregate mean and the LAD mean over time, hence the null hypothesis of a constant mean across the values of the endogenous variable is always rejected which suggests that the instruments are appropriate.

4. RESULTS

Table 3a presents the coefficients from estimation of equation (1), a random effects ordered probit model where $netchat$ is treated as an exogenous influence on each of the outcome variables. Before discussing the role of social networks we initially look at the results for some of the control variables. Each column in Table 3a reports a different child wellbeing outcome. Interestingly, where statistically significant younger children feel happier than those aged 15 (the omitted category), this is true, with the exception of *school attended* for children aged between 10 and 12. Boys feel less happy than girls about *school work*, but conversely, are happier about their general *appearance* and *life overall*. Interestingly, there is little role for hours spent watching television, with the exception of how children feel about their *school work*, a finding which is at odds with Frey et al. (2007). There is no association between household income and how children feel across the different domains. This finding is consistent with Anand and Roope (2016) who consider child wellbeing employing a random sample survey from Germany, the German Socio-Economic Panel (GSOEP).[22,23] Those UK children residing in a single parent household have lower wellbeing across the majority of outcomes. Children who frequently eat an evening meal with their parents and/or aspire to go to university are happier across each outcome, whilst conversely those that have played

[22] It should be noted that the children in the GSOEP analysis are much younger than the ones in the UKHLS, aged just 2 or 3.

[23] Analysis from the US reveals that parental earnings are positively associated with childhood wellbeing, Mazumder and Davis (2013). However, their study is not based upon measures of children's subjective wellbeing but reported health outcomes such as current health status, hospital admission, and whether health limits school work, and so is quite different from the analysis herein.

truant, smoked and/or stay out late at night are less happy.[24] Interestingly, across the majority of domains – including how children feel about their lives as a whole – the local level unemployment rate does not influence subjective wellbeing, the exceptions to this are how they feel about their *friends* and the *school attended*.

We now turn our key explanatory variable $netchat$, focusing upon the estimates of ϕ from equation (1). The first row of results in columns (1) to (6) shows that time spent chatting on social networks is negatively associated with how children feel about their *school work, appearance, family, school attended* and *life overall*, but it has no significant association with how they feel about their *friends*. The finding that internet use has a detrimental effect upon children's wellbeing is consistent with the analysis of Kraut et al. (1998). Looking at the marginal effects reported in Table 3b we can see that for all outcomes except *friends*, spending more time chatting on social networks increases the probability of not being happy with the outcome and decreases the probability of being happy with it. In Table 3b column (6), for example, spending an hour a day chatting on social networks (the average time in our data) reduces the probability of being completely happy with *life overall* by approximately 3 percentage points.[25,26]

Turning to Table 4a, this reports coefficient estimates for equation (2b), where $netchat$ is treated as endogenous, and this is dealt with using an IV approach via simultaneous estimation of equations (2a) and (2b). In particular our focus is upon the estimate of θ. We have three alternative instruments all derived from Ofcom data on the quality of internet access in the local area. The main results in Table 4a Panel A use average synchronisation speed (*avsyncspeed*); Panel B in the bottom part of the table shows the coefficient for $netchat$ where the percentage of homes with broadband currently not achieving 2 megabits per second (*notrec2mb*) is used as an instrument; Panel C uses

[24] Recent evidence has revealed that in the US smoking is associated with lower adult subjective wellbeing, see Weinhold and Chaloupka (2016).

[25] From Table 1 the mean value of $netchat$ is 2.4 this equates to approximately 1 hour based upon the definition of this ordinal variable, see Section 3 and the Appendix. Hence, the size of the effect is calculated as follows: -0.029×1×100=2.9.

[26] In robustness checks we have estimated these models excluding children aged below 13, since most sites stipulate this as the minimum user age. This results in a sample of NT=4,250 comprising 2,844 children. The estimates are very similar to those reported here for the full sample of children aged 10 to 15, full details are available upon request.

percentage of landmass with 3G outdoor coverage from all operators (*signal3G*). There is a large degree of consistency in the results regardless of which instrument is used. In all cases the results suggest that spending more time on social networks reduces the extent of happiness with five of the six outcome measures. However, for *friends* (column 4) the findings are not always consistent. Only using *signal3G* to instrument $netchat$ shows a negative relationship with the way children feel about their *friends*; using *avsyncspeed* suggests that $netchat$ causes an increase in happiness with *friends*; and using *notrec2mb* suggests no significant association with the outcome. Pre-empting some of the later discussion it is worth noting here that while in general our instruments are valid for the other five outcome measures; they do not perform as well for the *friends* outcome.

Turning to the marginal effects in Table 4b; as in Table 3b, where $netchat$ was treated as exogenous, for all outcomes except *friends*, spending more time chatting on social networks increases the probability of not being happy with the outcome and decreases the probability of being very happy with it. Looking in more detail at Panel A, where *avsyncspeed* is used as the instrument, there is some variation in where the 'tipping point' occurs on the outcome scale that ranges from '1=not at all happy' to '7=completely happy'. For *school work, appearance* and *school attended*, $netchat$ increases the chance of giving a happiness response of 1 to 5, and decreases the chance of the highest responses (6 or 7); whereas for *family* and *life overall*, the tipping point is only for the completely happy response (7).[27] Quantitatively, looking at Panel A, where *avsyncspeed* is the instrument, spending an hour a day chatting on social networks (the average time in our data) reduces the probability of being completely happy with *school work* and *appearance* by approximately 7 percentage points; for *family* and *school attended* and effect is larger at 13 percentage points. Focusing upon how children feel about their *life overall* spending an hour a day chatting on social networks reduces the probability of being completely satisfied with life overall by approximately 14 percentage points. This is a substantial effect; it is three times as large as the

[27] No clear pattern emerges if we relate this to the distribution of the outcome measures shown in Figure 1. The outcomes have similar distributions. For *school work, appearance* and *life overall*, the modal response is 6, for *family* and *friends* it is 7, and for *school attended* 6 and 7 are equally popular.

estimated adverse effect on wellbeing of being in a single parent household (4.6 percentage points) and is also larger than the effect of playing truant (10.3 percentage points). These effects are similar when the other instruments are used as reported in Panels B and C.

Table 5 reports diagnostic statistics for the main models to help judge the validity of our instruments. The random effects ordered probit models presented in Table 4a are estimated via simultaneous estimation of equations (2a) and (2b) and the cross-equation correlation statistics in the first row of Panels A to C in Table 5 show the correlation in the error terms from these two equations, ε_{1iw} and ε_{2iw}. For all outcomes except *friends* this correlation is positive and significant, showing interdependency between the outcome (happiness with the domain) and social media use. This is true for all three instruments, and endorses our joint modelling approach. For *friends*, the correlation is only positive and significant if *signal3G* is used to instrument $netchat$. In the first stage regressions (equation 2a) all instruments are significant at p<0.001 with the expected sign, meaning that the instruments are significant predictors of $netchat$, even after conditioning on the full set of individual, household and area level controls in $\boldsymbol{X}$. *Avsyncspeed* and *signal3G* are negatively related to $netchat$ and *notrec2b* is positively related.[28] The next two rows of Panels A to C report the coefficients on each instrument, Z, and $netchat$ if we include the instrument in the main outcome equation; this is single equation estimation of equation (2b) but with Z also included as an explanatory variable. As we would expect for a good instrument, in all cases, except for *friends*, and for all three instruments, they are not statistically significant in the outcome equation, but $netchat$ remains significant when Z is included. However, it appears that two of the instruments, *avsyncspeed* and *notrec2mb*, have a statistically significant direct association with how children feel about their *friends*; this is negative for the former instrument and positive for the latter. These results cast doubt on the validity of these instruments in the *friends* model. The results of the Sargan (1958) test when pairs of instruments are used together are shown in Panel D. For all

[28] These results are not reported here for conciseness.

outcomes, using *signal3G* paired with either *avsynchspeed* or *notrec2b*,[29] the null hypothesis that the over-identifying restrictions are valid cannot be rejected. In addition the F-tests for joint significance of the instruments in the first stage are all highly significant and exceed the minimum threshold suggested by Stock et al. (2002).[30] Overall then, apart from for the *friends* outcome, our instruments appear to be valid, providing support for the results reported in Tables 4a and 4b.

An alternative approach to examine the robustness of our results is presented in Table 6. In Panel A $netchat$ is treated as exogenous and the results show the coefficient estimates from a FE model (difference model) to control for unobserved child heterogeneity, as specified in equations (3a, b), where our key parameter of interest is μ. The significant negative association of $netchat$ with how children feel about the different domains still exists for *appearance, family, school attended* and *life overall;* in contrast with the results in Table 4a there is no significant association with how children feel about their *friends* or *school work*; this suggests that the association between time spent on social networks and happiness with these two outcomes may have been driven by unobserved confounding effects.[31] We extend this analysis to instrument $netchat$ employing an IV FE approach, equation (4). The results are shown in Table 6, Panels B to D, which report specifications based upon our three alternative instruments; and the results are similar regardless of which is used. There is a negative relationship between most of the dimensions of wellbeing and social media use, even after controlling for unobserved effects and endogeneity issues; for *school work*, the significant relationship exists only when *notrec2mb* is used as the instrument.

In Section 2 we outlined three theories that can help to explain why social media use may have a negative effect on children's wellbeing. Table 7 presents results which explore whether there is any support for these theories in our data, by carrying out analysis on a number of sub-groups where we re-estimate equation (1) and equations (2a, b). In all the panels we report the coefficient

[29] These pairs were chosen to represent access to the internet over a broadband (*avsyncspeed/notrec2mb*) or phone connection (*signal3G*).
[30] These results are not reported here for conciseness.
[31] However, the p-value for α_i in the *friends* model suggests that the individual effects are not significant.

on $netchat$, and we include the same control variables as in Tables 3a and 4a and we also report results assuming both exogeneity of $netchat$ and using our IV strategy. As explained above, we have confidence in our IV results, except possibly for the *friends* outcome so we focus largely on the IV results here.

In order to explore the social comparisons theory outlined in Section 2, in Panel A we explore the effects of time spent on chatting on social media for children with high (above mean) vs. low (below or equal to mean) self-esteem defined using a psychological measure called the Rosenberg self-esteem scale. There are more adverse effects of social network use for those with lower self-esteem. For those with high self-esteem, more time on social media decreases satisfaction only with *friends* and *school attended*; whereas for those with low self-esteem there are adverse effects on all aspects of life, except *friends*. These results provide some support for the social comparisons theory as those with lower self-esteem are more prone to make negative social comparisons (Gibbons and Buunk, 1999).

Panel B explores the finite resources theory by classifying children according to how many other activities they are engaged in. We split the sample according to high (above mean) vs. low (below or equal to mean) participation in other activities, such as going to the cinema, watching sport, or 'hanging out' with friends. There are more adverse effects for those with higher involvement in other activities, and at first this may appear contrary to the theoretical predictions, which suggest that time spent on social media encroaches on other activities known to be beneficial for wellbeing. However, looking at the results across the different domains we see that, for example, if children are engaged in lots of other activities, increased $netchat$ decreases their satisfaction with their *school work*; this could be a result of time pressures. While our instruments may be in doubt for the *friends* outcome, the IV results suggest that for those who have high engagement in other activities, social media use decreases satisfaction with *friends*, whereas the opposite is true for those with low engagement with other activities. This asymmetric effect may suggest that the latter group is relying more on online friends, and the former group is socialising more with 'real' friends via their other activities, and that increased time on social networks detracts from this. Finally, Panel C explores the cyberbullying theory. The UKHLS does not ask children separately about cyberbullying, so instead we split the sample according to whether or not children report general experience of being bullied, which will include cyberbullying. There are more adverse effects for those who report being bullied; those who are bullied feel worse about their *school work*, *family* and *life overall* if they spend more time on social networks and this provides some indirect support for the cyberbullying theory.

In one final piece of analysis in Table 8 we investigate gender differences in the relationship between social media use and wellbeing in the different domains. The results from four different specifications are presented, and the results vary across specifications. If $netchat$ is assumed to be exogenous, with FE (Panel C) or without (Panel A), then the majority of adverse effects are seen for girls, and there are no significant effects for boys, except for the *family* outcome in Panel A. However, once we instrument $netchat$ using *avsyncspeed*,[32] then without FE (Panel B) the ways that boys feel about their *school work*, *appearance*, *school attended* and *life overall* is adversely affected by the time they spend chatting on social networks. For girls adverse effects are seen for *school work*, *family*, *school attended* and *life overall*, but more time on social networks has a positive effect on how girls feel about their friends. When we include FE (Panel D), the adverse effects for girls are seen across all life domains, including *friends;* while for boys there are adverse effects for *family* and *friends*, but a positive effect on how they feel about their *school work.* Panel D is our preferred specification because it employs an instrument for $netchat$ to deal with endogeneity and controls for unobserved time invariant individual characteristics that might affect both $netchat$ and the wellbeing outcome in question.[33] These results suggest that girls are more adversely affected by time spent chatting on social networks than boys. For boys it makes them feel

[32] The results are similar regardless of which of our three instruments we use, so for conciseness we only report one set of results here.
[33] Caution should be taken when considering these results due to the small sample sizes.

less happy with their *friends*, but happier about their *school work*; whereas for girls it makes them feel less happy about all six domains, and in particular about their *appearance* and the *school* they attend.

5. CONCLUSION

Social media are a hugely important phenomenon of the past decade and children have been heavy adopters. Today's teenagers have grown up with online social networking; social media are a core part of their lives, providing their primary interface with the internet, and often used in an 'always on' state, via smartphones and tablets, permanently connecting them to their virtual social network. In this paper we have explored the effect of time spent on social networks on the wellbeing of children aged 10 to 15, measured by the way they feel about five different aspects of their life, plus life overall. We employ an IV strategy based on speed of access to the internet in local areas, in order to deal with the potential endogeneity of time spent on social networks in our model. In general, our instruments perform well statistically and seem valid intuitively, but there is some doubt on the instruments when looking at how children feel about their *friends*.

Overall we find that spending more time on social networks reduces the satisfaction that children feel with all aspects of their lives, except for their friendships. Spending one hour a day chatting on social networks reduces the probability of being completely satisfied with *life overall* by approximately 14 percentage points. This is not a trivial effect – being three times as large as the estimated adverse effect on wellbeing of being in a single parent household and is also larger than the effect of playing truant. Looking at the different aspects of life, the largest effects are for satisfaction with *family* and *school attended* and the smallest effects are for *appearance* and *school work*. We also explore three possible explanations for why social media use may have a negative effect on children's wellbeing. We find some support for all three explanations; 'social comparisons', 'finite resources' and 'cyberbullying', suggesting multiple channels through which these adverse effects may operate. Further, we find that girls suffer more adverse effects than boys and in particular feel less happy with their *appearance* and *school attended* the more time they spend chatting on social networks. One shortcoming of this work is that our data do not allow us to identify what children are doing when they are accessing social networks and given the multiplicity of uses of these sites it is possible that the effects on wellbeing will vary. Chatting online, for example, has been associated with increased empathic concern for others, while use of photographic media has been linked to narcissism and social comparisons (e.g., Alloway et al., 2014).

These are important findings given the central role of social media and social networking in children's lives, and the fact that childhood wellbeing has been shown in previous research to have persistent effects into adult life. Our results suggest that interventions to limit social media uses during childhood may help to improve wellbeing. As well as addressing policy makers' concerns about the effects of digital technology on children, we have also contributed to wider debates about the socioeconomic consequences of the internet and digital technologies more generally, a debate which to date has largely been based on evidence from outside of the UK.

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FIGURE 1: Distribution of dependent variables

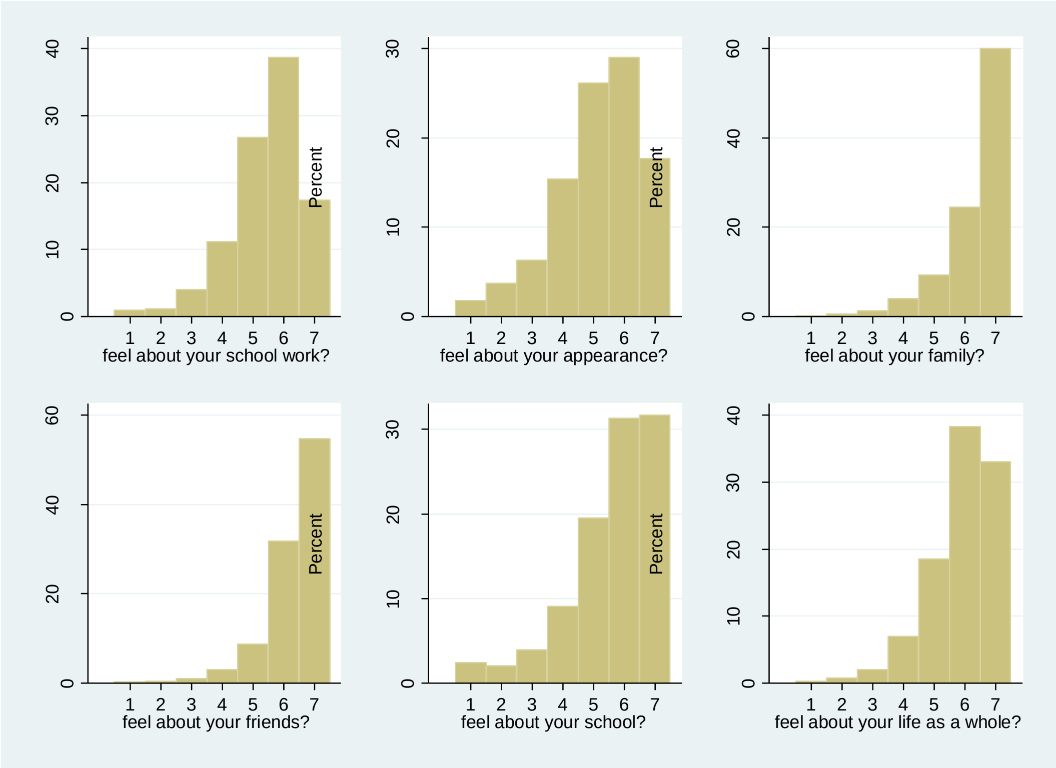


FIGURE 2: Distribution of hours spent chatting through social websites (*netchat*)

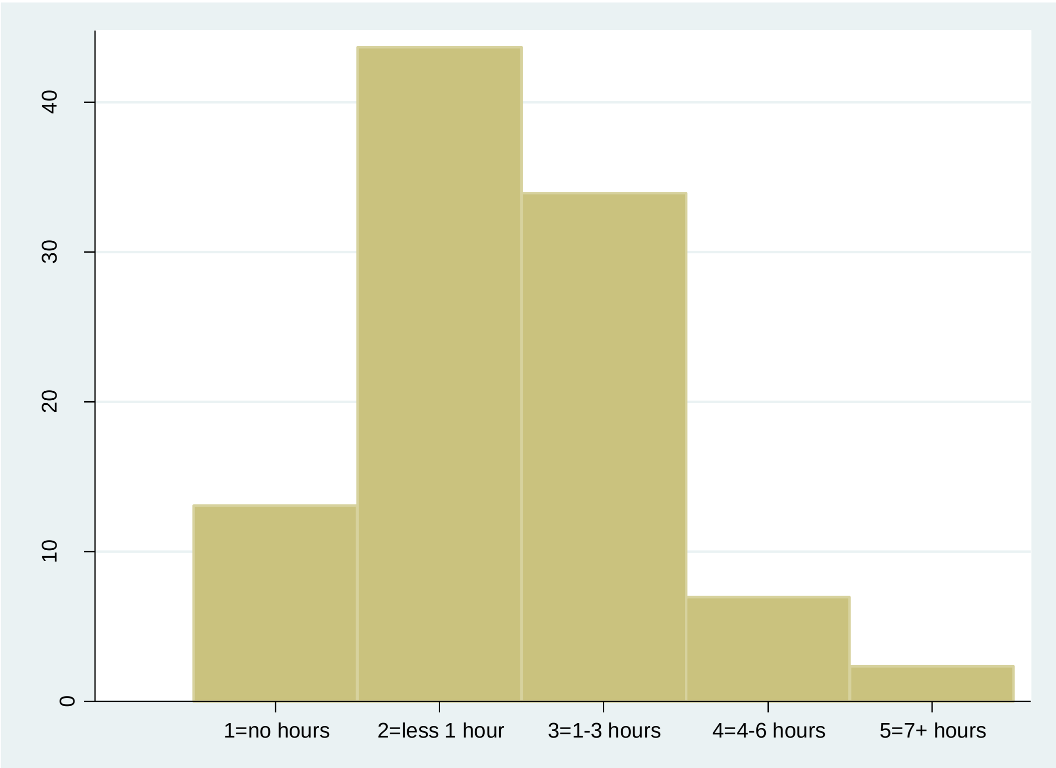


FIGURE 3: Distribution of instruments

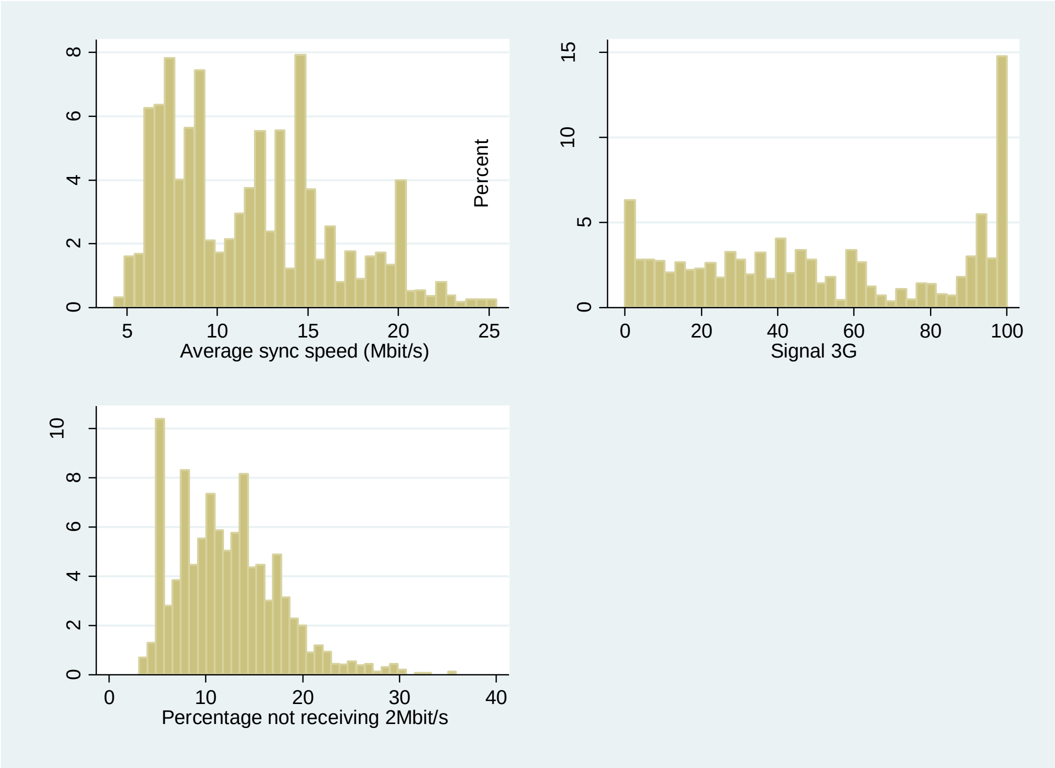


TABLE 1: Summary statistics – dependent variables, key explanatory variable and instruments

	MEAN	ST. DEV.	MIN	MAX
DEPENDENT VARIABLES, Level of Happiness with:				
School work	5.4689	1.181	1	7
Appearance	5.1796	1.413	1	7
Family	6.3528	0.995	1	7
Friends	6.3337	0.936	1	7
School	5.6196	1.418	1	7
Life	5.8934	1.088	1	7
EXPLANATORY VARIABLES, ***X***				
NETCHAT (time spent chatting on social media per school day) #	2.4182	0.887	1	5
Child Aged 10	0.0738	0.262	0	1
11	0.1294	0.336	0	1
12	0.1703	0.376	0	1
13	0.2094	0.407	0	1
14	0.2188	0.413	0	1
Child Male	0.4717	0.499	0	1
Child White	0.8217	0.383	0	1
No. close friends	5.7378	3.307	0	15
Time spent watching TV (on normal school day) #	2.9754	0.705	1	5
Parent employed	0.8388	0.368	0	1
Parent has degree	0.3200	0.467	0	1
Single parent household	0.2558	0.436	0	1
Real equivalised net household income (log per month)	6.3154	0.519	0	8.78
No. of other children in household aged 0-2	0.0780	0.295	0	3
3-4	0.0847	0.292	0	2
5-11	0.5359	0.726	0	6
12-15	0.5765	0.694	0	5
Home owners	0.6777	0.467	0	1
Eve. meal with family (No. in last 7 days) #	3.1260	0.965	1	4
Want to go to university	0.6999	0.458	0	1
Ever played truant	0.0886	0.284	0	1
Ever smoked	0.0968	0.296	0	1
Stayed out after 9pm (in last month)	0.1629	0.369	0	1
Urban area	0.2450	0.430	0	1
Local unemployment rate (log)	2.0235	0.387	0.47	3.11
INSTRUMENTAL VARIABLES, *Z*, (defined at local area level)				
avsyncspeed (Average synch speed of broadband connections)	11.8719	4.654	4.3	25.4
signal 3G (% of landmass with 3G outdoor coverage)	51.5065	33.916	0	100
notrec2mb (% of homes with broadband not at 2Mbits/second)	12.2081	5.285	3.1	35.9
Observations NT		6,788		
Children N		3,971		

These variables are categorical, see Appendix for full definitions.

TABLE 2a: Correlation between NETCHAT and instruments

INSTRUMENTAL VARIABLE	CORRELATION COEFFICIENT
AVSYNCSPEED	-0.0477 (p-value=0.001)
SIGNAL 3G	-0.0279 (p-value=0.002)
NOTREC2MB	0.0320 (p-value=0.008)

TABLE 2b: Average values of instrumental variables by category of NETCHAT

	NETCHAT =					Test of equality of IV means [1]	
INSTRUMENTAL VARIABLE	1=None	2=less 1 hour	3=1-3 hours	4=4-6 hours	5=7+ hours	Aggregate [2]	LAD [3]
AVSYNCSPEED (Mbits/second)	12.49	11.94	11.44	11.57	12.73	0.000	0.000
SIGNAL 3G (%)	56.06	51.19	49.99	50.16	58.02	0.000	0.000
NOTREC2MB (%)	11.48	12.23	12.56	12.25	11.29	0.000	0.000

[1] p-values for tests of null hypothesis of the equality of the IV means across NETCHAT. [2] Aggregate IV mean across NETCHAT. [3] LAD IV mean across NETCHAT.

TABLE 3a: Coefficients from a random effects ordered probit model

	(1) School work	(2) Appearance	(3) Family	(4) Friends	(5) School	(6) Life
NETCHAT	-0.073***	-0.072***	-0.129***	0.025	-0.050**	-0.092***
	(0.020)	(0.021)	(0.026)	(0.022)	(0.021)	(0.022)
No. close friends	0.030***	0.030***	0.026***	0.088***	0.034***	0.045***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Age10	0.055	0.848***	1.190***	0.439***	0.660***	0.261***
	(0.081)	(0.089)	(0.118)	(0.091)	(0.089)	(0.089)
Age11	0.120*	0.627***	0.723***	0.346***	0.501***	0.282***
	(0.068)	(0.074)	(0.090)	(0.076)	(0.074)	(0.074)
Age12	0.020	0.332***	0.404***	0.201***	0.205***	0.086
	(0.064)	(0.069)	(0.082)	(0.071)	(0.068)	(0.069)
Age13	-0.029	0.086	0.131*	0.132**	0.019	-0.054
	(0.060)	(0.063)	(0.074)	(0.066)	(0.063)	(0.064)
Age14	-0.009	0.008	-0.011	0.100	-0.099	-0.132**
	(0.057)	(0.059)	(0.070)	(0.063)	(0.060)	(0.061)
Male	-0.195***	0.476***	-0.025	-0.027	-0.005	0.133***
	(0.039)	(0.044)	(0.051)	(0.042)	(0.043)	(0.043)
White	-0.162***	-0.325***	-0.035	0.023	-0.146**	-0.006
	(0.060)	(0.067)	(0.078)	(0.064)	(0.065)	(0.065)
Hrs. watching TV	-0.055**	-0.031	-0.006	-0.017	-0.041*	-0.034
	(0.024)	(0.025)	(0.030)	(0.026)	(0.024)	(0.026)
Parent employed	-0.088*	-0.050	-0.071	-0.033	-0.135**	-0.039
	(0.052)	(0.060)	(0.072)	(0.060)	(0.059)	(0.060)
Parent degree	0.113***	-0.113**	-0.280***	-0.047	0.140***	-0.050
	(0.044)	(0.049)	(0.058)	(0.048)	(0.048)	(0.048)
Single parent HH	-0.119***	-0.110**	-0.312***	-0.088*	-0.061	-0.168***
	(0.047)	(0.052)	(0.061)	(0.051)	(0.051)	(0.051)
Real equiv. income	0.022	-0.014	0.025	0.010	0.077	0.014
	(0.036)	(0.039)	(0.046)	(0.040)	(0.039)	(0.039)
HH child 0-2	0.141**	-0.090	-0.045	-0.078	-0.037	-0.002
	(0.061)	(0.066)	(0.079)	(0.066)	(0.065)	(0.066)
HH child 3-4	0.075	-0.003	-0.120	0.004	0.070	-0.148**
	(0.058)	(0.062)	(0.075)	(0.064)	(0.063)	(0.063)
HH child 5-11	-0.025	0.017	-0.066**	0.025	0.007	0.011
	(0.026)	(0.029)	(0.033)	(0.028)	(0.028)	(0.028)
HH child 12-15	-0.093***	0.017	-0.058	0.042	-0.073**	-0.080**
	(0.032)	(0.034)	(0.040)	(0.035)	(0.034)	(0.034)
Home owner	0.032	-0.011	-0.167***	-0.073	0.157***	0.070
	(0.047)	(0.052)	(0.062)	(0.051)	(0.051)	(0.052)
Eve. meal family	0.096***	0.122***	0.198***	0.080***	0.120***	0.161***
	(0.018)	(0.019)	(0.022)	(0.020)	(0.019)	(0.019)
Want to go university	0.326***	0.083**	0.138***	0.092**	0.197***	0.112***
	(0.037)	(0.39)	(0.047)	(0.041)	(0.040)	(0.040)
Ever played truant	-0.480***	-0.202***	-0.395***	-0.305***	-0.373***	-0.434***
	(0.060)	(0.063)	(0.072)	(0.065)	(0.063)	(0.063)
Ever smoked	-0.211***	-0.105	-0.195***	-0.113*	-0.282***	-0.205***
	(0.060)	(0.065)	(0.073)	(0.065)	(0.064)	(0.064)
Stayed out after 9pm	-0.217***	0.038	-0.182***	-0.054	-0.164***	-0.109**
	(0.046)	(0.049)	(0.056)	(0.051)	(0.048)	(0.049)
Urban	-0.087*	-0.018	-0.107*	0.005	-0.004	-0.031
	(0.048)	(0.054)	(0.064)	(0.053)	(0.053)	(0.053)
Unemployment rate	0.030	0.036	0.062	-0.126**	-0.094*	0.004
	(0.052)	(0.056)	(0.066)	(0.057)	(0.055)	(0.056)
$\chi^2(39)$; p-value	540.02; p=0.000	548.08; p=0.000	578.25; p=0.000	420.88; p=0.000	565.69; p=0.000	483.29; p=0.000
Observations NT	6,788	6,788	6,788	6,788	6,788	6,788
Children N	3,971	3,971	3,971	3,971	3,971	3,971

Notes: (i) standard errors are given in parentheses; (ii) *** p<0.01, ** p<0.05, * p<0.1; (iii) wave and regional dummies are also included.

TABLE 3b: Marginal effects for NETCHAT from a random effects ordered probit model

	(1) **School work**	(2) **Appearance**	(3) **Family**	(4) **Friends**	(5) **School**	(6) **Life**
Outcome=1 (not at all happy)	0.0004***	0.0004***	0.0000**	-0.0000	0.0006**	0.0001**
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0003)	(0.0000)
Outcome=2	0.0007***	0.0019***	0.0002***	-0.0000	0.0008**	0.0003***
	(0.0002)	(0.0006)	(0.0000)	(0.0000)	(0.0004)	(0.0001)
Outcome=3	0.0030***	0.0048***	0.0006***	-0.0000	0.0019**	0.0013***
	(0.0008)	(0.0014)	(0.0002)	(0.0001)	(0.0008)	(0.0003)
Outcome=4	0.0090***	0.0115***	0.0035***	-0.0002	0.0048**	0.0064***
	(0.0025)	(0.0034)	(0.0008)	(0.0006)	(0.0021)	(0.0015)
Outcome=5	0.0132***	0.0071***	0.0119***	-0.0002	0.0080**	0.0174***
	(0.0037)	(0.0021)	(0.0024)	(0.0006)	(0.0035)	(0.0041)
Outcome=6	-0.0128***	-0.0137***	0.0253***	-0.0001	-0.0013**	0.0036***
	(0.0036)	(0.0041)	(0.0050)	(0.0023)	(0.0007)	(0.0011)
Outcome=7 (completely happy)	-0.0136***	-0.0121***	-0.0415***	0.0015	-0.0148**	-0.0290***
	(0.0038)	(0.0036)	(0.0082)	(0.0051)	(0.0064)	(0.0068)
Observations NT	6,788	6,788	6,788	6,788	6,788	6,788
Children N	3,971	3,971	3,971	3,971	3,971	3,971

Notes: (i) standard errors are given in parentheses; (ii) *** p<0.01, ** p<0.05, * p<0.1; (iii) wave and regional dummies are also included.

TABLE 4a: Coefficients from an IV random effects ordered probit model

	(1) School work	(2) Appearance	(3) Family	(4) Friends	(5) School	(6) Life
PANEL A: IV=avsyncspeed						
NETCHAT	-0.384***	-0.405***	-0.402***	0.253**	-0.433***	-0.482***
	(0.068)	(0.071)	(0.074)	(0.065)	(0.093)	(0.145)
No. Close friends	0.034***	0.034***	0.030***	0.084***	0.038***	0.049***
	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)	(0.007)
Age 10	-0.177	0.593***	1.013***	0.727***	0.390***	-0.017
	(0.108)	(0.123)	(0.147)	(0.109)	(0.146)	(0.199)
Age 11	-0.022	0.479***	0.611***	0.520***	0.331***	0.113
	(0.089)	(0.100)	(0.113)	(0.089)	(0.116)	(0.155)
Age 12	-0.079	0.235***	0.332***	0.334***	0.096	-0.023
	(0.081)	(0.090)	(0.102)	(0.082)	(0.101)	(0.133)
Age 13	-0.076	0.046	0.099	0.208***	-0.026	-0.097
	(0.074)	(0.083)	(0.093)	(0.076)	(0.089)	(0.112)
Age 14	0.018	0.003	-0.012	0.129*	-0.100	-0.129
	(0.071)	(0.079)	(0.089)	(0.074)	(0.082)	(0.098)
Male	-0.283***	0.364***	-0.108*	0.040	-0.122**	0.010
	(0.044)	(0.050)	(0.055)	(0.046)	(0.053)	(0.071)
White	-0.087*	-0.306***	0.113	0.016	-0.030	0.132**
	(0.053)	(0.059)	(0.070)	(0.057)	(0.057)	(0.058)
Hrs. watching TV	-0.005	0.024	0.032	-0.064**	0.016	0.031
	(0.028)	(0.032)	(0.037)	(0.031)	(0.032)	(0.037)
Parent employed	-0.068	-0.043	-0.071	-0.053	-0.120*	-0.025
	(0.058)	(0.064)	(0.078)	(0.063)	(0.062)	(0.063)
Parent degree	0.074*	-0.140***	-0.307***	-0.020	0.085*	-0.094*
	(0.043)	(0.049)	(0.058)	(0.048)	(0.048)	(0.049)
Single parent HH	-0.097**	-0.087	-0.302***	-0.100*	-0.041	-0.144**
	(0.049)	(0.056)	(0.064)	(0.052)	(0.058)	(0.071)
Real equiv. income	0.008	-0.017	0.010	0.003	0.053	-0.007
	(0.062)	(0.073)	(0.063)	(0.049)	(0.106)	(0.179)
HH child 0-2	0.114*	-0.113	-0.079	-0.075	-0.074	-0.036
	(0.065)	(0.073)	(0.087)	(0.070)	(0.072)	(0.077)
HH child 3-4	0.087**	0.006	-0.099	0.001	0.080	-0.125*
	(0.064)	(0.072)	(0.087)	(0.071)	(0.071)	(0.070)
HH child 5-11	-0.035	0.005	-0.073**	0.033	-0.004	-0.002
	(0.027)	(0.030)	(0.035)	(0.029)	(0.031)	(0.036)
HH child 12-15	-0.086**	0.018	-0.053	0.046	-0.065	-0.071
	(0.035)	(0.041)	(0.046)	(0.038)	(0.044)	(0.055)
Home owner	0.017	-0.045	-0.179***	-0.054	0.140***	0.051
	(0.067)	(0.052)	(0.063)	(0.051)	(0.051)	(0.052)
Eve. meal family	0.082***	0.107***	0.188***	0.090***	0.104***	0.141***
	(0.021)	(0.024)	(0.027)	(0.022)	(0.026)	(0.035)
Want to go university	0.317***	0.084*	0.129**	0.090**	0.176***	0.105**
	(0.043)	(0.047)	(0.056)	(0.045)	(0.047)	(0.050)
Ever played truant	-0.384***	-0.103	-0.326***	-0.370***	-0.260***	-0.316***
	(0.071)	(0.079)	(0.089)	(0.074)	(0.077)	(0.81)
Ever smoked	-0.176***	-0.066	-0.162*	-0.119*	-0.221***	-0.153**
	(0.067)	(0.075)	(0.085)	(0.072)	(0.072)	(0.073)
Stayed out after 9pm	-0.148***	0.098*	-0.107	-0.068	-0.071	-0.015
	(0.053)	(0.059)	(0.069)	(0.058)	(0.058)	(0.059)
Urban	-0.103**	-0.039	-0.078	0.072	0.025	-0.015
	(0.049)	(0.055)	(0.062)	(0.051)	(0.062)	(0.082)
Unemployment rate	0.068	0.085	0.145**	-0.008	-0.013	0.080
	(0.063)	(0.072)	(0.073)	(0.059)	(0.091)	(0.142)
PANEL B: IV=Not rec 2mb	-0.554***	-0.400***	-0.432***	-0.085	-0.505***	-0.482***
NETCHAT	(0.050)	(0.071)	(0.075)	(0.064)	(0.052)	(0.145)
PANEL C: IV=Signal 3G	-0.699***	-0.461***	-0.519***	-0.156**	-0.539***	-0.546***
NETCHAT	(0.047)	(0.053)	(0.102)	(0.066)	(0.051)	(0.053)
Observations NT	6,788	6,788	6,788	6,788	6,788	6,788
Children N	3,971	3,971	3,971	3,971	3,971	3,971

Notes: (i) standard errors are given in parentheses; (ii) *** p<0.01, ** p<0.05, * p<0.1; (iii) wave and regional dummies are also included.

TABLE 4b: Marginal effects for NETCHAT from an IV random effects ordered probit model

	(1) School work	(2) Appearance	(3) Family	(4) Friends	(5) School	(6) Life
PANEL A: IV=Avsyncspeed						
Outcome=1 (not at all happy)	0.003***	0.004***	-0.000*	-0.000*	0.009***	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.003)	(0.000)
Outcome=2	0.005***	0.013***	0.001**	-0.000*	0.009***	0.002**
	(0.001)	(0.003)	(0.000)	(0.000)	(0.003)	(0.001)
Outcome=3	0.017***	0.028***	0.003**	-0.002***	0.018***	0.008***
	(0.004)	(0.005)	(0.001)	(0.000)	(0.004)	(0.002)
Outcome=4	0.047***	0.060***	0.012***	-0.008***	0.041***	0.032***
	(0.008)	(0.009)	(0.003)	(0.002)	(0.008)	(0.006)
Outcome=5	0.063***	0.036***	0.037***	-0.026***	0.062***	0.076***
	(0.009)	(0.005)	(0.007)	(0.007)	(0.010)	(0.010)
Outcome=6	-0.061***	-0.069***	0.075***	-0.055***	-0.009***	0.016***
	(0.009)	(0.010)	(0.012)	(0.013)	(0.003)	(0.004)
Outcome=7 (completely happy)	-0.074***	-0.072***	-0.128***	0.092***	-0.129***	-0.135***
	(0.014)	(0.014)	(0.022)	(0.023)	(0.027)	(0.021)
PANEL B: IV=Notrec2mb						
Outcome=1 (not at all happy)	0.007***	0.004***	0.000*	-0.000	0.012***	0.001
	(0.002)	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)
Outcome=7 (completely happy)	-0.111***	-0.071***	-0.137***	0.031	-0.151***	-0.149***
	(0.011)	(0.013)	(0.022)	(0.023)	(0.015)	(0.043)
PANEL C: IV=Signal 3G						
Outcome=1 (not at all happy)	0.014***	0.005***	0.000	0.000	0.014***	0.002**
	(0.003)	(0.002)	(0.000)	(0.000)	(0.003)	(0.001)
Outcome=7 (completely happy)	-0.148***	-0.084***	-0.162***	-0.057**	-0.161***	-0.168***
	(0.012)	(0.012)	(0.029)	(0.024)	(0.014)	(0.015)
Observations NT	6,788	6,788	6,788	6,788	6,788	6,788
Children N	3,971	3,971	3,971	3,971	3,971	3,971

Notes: (i) standard errors are given in parentheses; (ii) *** $p<0.01$, ** $p<0.05$, * $p<0.1$; (iii) wave and regional dummies are also included.

TABLE 5: Model diagnostics for IV random effects ordered probit models

	(1) School work	(2) Appearance	(3) Family	(4) Friends	(5) School	(6) Life
PANEL A: IV=Avsyncspeed						
Cross-equation correlation	0.252***	0.253***	0.186***	-0.185	0.311***	0.281***
	(0.032)	(0.029)	(0.035)	(0.136)	(0.036)	(0.032)
Instrument in outcome equation						
Avsyncspeed	0.005	0.003	0.001	-0.011***	0.002	0.001
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
NETCHAT	-0.074***	-0.072***	-0.134***	0.022	-0.053**	-0.094***
	(0.020)	(0.021)	(0.026)	(0.022)	(0.021)	(0.022)
PANEL B: IV=Notrec2mb						
Cross-equation correlation	0.278***	0.248***	0.209***	0.057	0.366***	0.315***
	(0.027)	(0.029)	(0.035)	(0.035)	(0.027)	(0.051)
Instrument in outcome equation						
Notrec2mb	-0.001	-0.003	0.004	0.011***	0.002	0.003
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
NETCHAT	-0.075***	-0.072***	-0.135***	0.023	-0.054**	-0.095***
	(0.020)	(0.021)	(0.026)	(0.022)	(0.021)	(0.022)
PANEL C: IV=Signal 3G						
Cross-equation correlation	0.491***	0.296***	0.276***	0.126***	0.392***	0.365***
	(0.026)	(0.026)	(0.041)	(0.036)	(0.026)	(0.028)
Instrument in outcome equation						
Signal 3G	0.001	0.001	0.001	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NETCHAT	-0.075***	-0.072***	-0.134***	0.025	-0.054**	-0.094***
	(0.020)	(0.021)	(0.026)	(0.022)	(0.021)	(0.022)
PANEL D: Sargan tests						
Avsyncspeed & Signal 3G $\chi^2(1)$; p-value	3.305; p=0.581	3.343; p=0.168	0.027; p=0.868	0.198; p=0.657	0.441; p=0.507	0.067; p=0.796
Notrec2mb & Signal 3G $\chi^2(1)$; p-value	0.891; p=0.345	0.962; p=0.327	2.259; p=0.133	1.436; p=0.231	0.310; p=0.578	1.388; p=0.239

Notes: (i) standard errors are given in parentheses; (ii) *** p<0.01, ** p<0.05, * p<0.1; (iii) Sargan χ^2 tests are based upon linear 2SLS specifications.

TABLE 6: Coefficients for NETCHAT from fixed effect (difference) models

	(1) School work	(2) Appearance	(3) Family	(4) Friends	(5) School	(6) Life
<u>PANEL A:</u> <u>Exogenous</u>						
NETCHAT	-0.051	-0.096**	-0.089**	-0.011	-0.079***	-0.087**
	(0.045)	(0.046)	(0.036)	(0.040)	(0.005)	(0.041)
$\alpha_i = 0$; p-value	p=0.000	p=0.000	p=0.000	p=0.428	p=0.000	p=0.000
<u>PANEL B:</u> <u>IV=Avsyncspeed</u>						
NETCHAT	-0.255	-1.559***	-1.035***	-0.955***	-1.469***	-0.949***
	(0.204)	(0.309)	(0.209)	(0.228)	(0.307)	(0.225)
$\alpha_i = 0$; p-value	p=0.000	p=0.000	p=0.000	p=0.373	p=0.000	p=0.000
<u>PANEL C:</u> <u>IV=Notrec2mb</u>						
NETCHAT	-0.572**	-1.798***	-1.059***	-1.119***	-1.536***	-1.038***
	(0.235)	(0.363)	(0.230)	(0.264)	(0.339)	(0.253)
$\alpha_i = 0$; p-value	p=0.000	p=0.000	p=0.000	p=0.950	p=0.000	p=0.001
<u>PANEL D:</u> <u>IV=Signal 3G</u>						
NETCHAT	-0.399	-1.775***	-1.059***	-1.021***	-1.532***	-1.068***
	(0.250)	(0.397)	(0.254)	(0.279)	(0.374)	(0.281)
$\alpha_i = 0$; p-value	p=0.000	p=0.000	p=0.000	p=0.677	p=0.000	p=0.004
Children N	1,010	1,010	1,010	1,010	1,010	1,010

Notes: (i) controls include all time varying covariates from Table 3A; (ii) standard errors are given in parentheses; (iii) *** p<0.01, ** p<0.05, * p<0.1; (iv) regional dummies are also included; (v) results in Panel A are from a fixed effects (FE) regression treating NETCHAT as exogenous; (vi) in Panels B-D results are based upon an instrumental variables FE model using a different instrument in each panel; (vii) $\alpha_i = 0$ tests the null hypothesis that the child fixed effects are jointly equal to zero.

TABLE 7: Sub-group analysis – coefficients reported on NETCHAT

	EXOGENOUS		IV ANALYSIS	
PANEL A: Self Esteem	BELOW MEAN	ABOVE MEAN	BELOW MEAN	ABOVE MEAN
School Work	-0.087** (0.038)	-0.103*** (0.037)	-0.446*** (0.119)	-0.020 (0.272)
Appearance	-0.079** (0.036)	-0.014 (0.037)	-0.806*** (0.099)	0.045 (0.158)
Family	-0.093** (0.041)	-0.084 (0.056)	-0.903*** (0.115)	0.092 (0.313)
Friends	-0.075** (0.036)	0.005 (0.040)	0.041 (0.169)	-0.732*** (0.123)
School	-0.093** (0.039)	-0.055 (0.047)	-0.923*** (0.101)	-0.828*** (0.124)
Life	-0.094*** (0.035)	-0.058 (0.040)	-0.479*** (0.110)	-0.062 (0.169)
Observations NT (Children N)	NT_{below}=1,920; NT_{above}=2,126 (N_{below}=1,679; N_{above}=1,852)			
PANEL B: Number of activities	EXOGENOUS		IV ANALYSIS	
	BELOW MEAN	ABOVE MEAN	BELOW MEAN	ABOVE MEAN
School Work	-0.068** (0.034)	-0.137*** (0.041)	-0.089 (0.148)	-0.437*** (0.128)
Appearance	-0.065* (0.037)	-0.069* (0.039)	-0.283* (0.155)	-0.532*** (0.118)
Family	-0.087** (0.038)	-0.152** (0.063)	-0.545*** (0.118)	-0.540*** (0.201)
Friends	0.009 (0.040)	0.062 (0.044)	0.282** (0.128)	-0.902*** (0.118)
School	-0.038 (0.037)	-0.123*** (0.042)	-0.012 (0.148)	-0.808*** (0.109)
Life	-0.066** (0.031)	-0.143*** (0.042)	-0.411*** (0.107)	-0.616*** (0.131)
Observations NT (Children N)	NT_{below}=2,163; NT_{above}=1,883 (N_{below}=1,892; N_{above}=1,658)			
PANEL C: Ever bullied by other children	EXOGENOUS		IV ANALYSIS	
	NEVER	SOMETIMES	NEVER	SOMETIMES
School Work	-0.064** (0.031)	0.066** (0.032)	-0.005 (0.039)	-0.665*** (0.208)
Appearance	-0.021 (0.031)	-0.081** (0.040)	-0.356 (0.266)	-0.210 (0.432)
Family	-0.065* (0.037)	-0.112** (0.047)	0.379 (0.372)	-0.595** (0.287)
Friends	0.043 (0.036)	0.022 (0.045)	0.064 (0.342)	0.558* (0.309)
School	-0.041 (0.032)	0.053 (0.043)	-0.509* (0.269)	0.550 (0.349)
Life	-0.061* (0.032)	-0.147** (0.062)	0.127 (0.372)	-0.787*** (0.142)
Children N	$N_{never\ bullied}$=1,819; $N_{sometimes\ bullied}$=923			

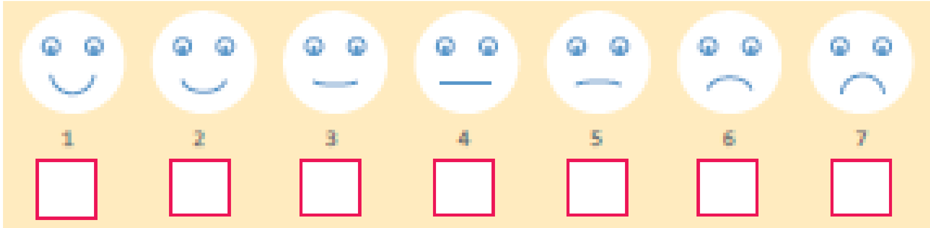
Notes: (i) each row is a different model, i.e. wellbeing outcome; (ii) standard errors are given in parentheses; (iii) *** p<0.01, ** p<0.05, * p<0.1; (iv) controls as in Tables 3A and 4A; (v) due to data availability Panels A and B are based on waves 2 and 4 only and Panel C is based upon the wave 3 cross section only; (vi) for the IV analysis the instrument used is the average synchronisation speed.

TABLE 8: Sub-group analysis by gender – Coefficients reported on NETCHAT

	(1) School work	(2) Appearance	(3) Family	(4) Friends	(5) School	(6) Life
PANEL A: Exogenous random effects ordered probit						
BOYS (NT = 3,202)	-0.030	-0.039	-0.076**	0.023	-0.009	-0.005
	(0.030)	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)
GIRLS (NT=3,586)	-0.092***	-0.084**	-0.158***	0.026	-0.068**	-0.149***
	(0.028)	(0.029)	(0.034)	(0.032)	(0.029)	(0.029)
PANEL B: IV random effects ordered probit						
BOYS (NT = 3,202)	-0.791***	-0.565***	-0.156	-0.088	-0.181**	-0.258***
	(0.062)	(0.075)	(0.106)	(0.091)	(0.089)	(0.09)
GIRLS (NT=3,586)	-0.617***	-0.049	-0.342***	0.799***	-0.541**	-0.392***
	(0.072)	(0.086)	(0.095)	(0.076)	(0.082)	(0.082)
PANEL C: Exogenous fixed effect (difference) models						
BOYS (N = 462)	0.095	-0.070	-0.026	-0.033	0.030	-0.035
	(0.068)	(0.068)	(0.049)	(0.053)	(0.069)	(0.057)
GIRLS (N=548)	-0.082	-0.141**	-0.133***	0.057	-0.056	-0.117**
	(0.060)	(0.058)	(0.052)	(0.059)	(0.072)	(0.059)
PANEL D: IV fixed effect (difference) models						
BOYS (N = 462)	1.724**	-0.561	-1.114**	-0.941*	-0.384	-0.260
	(0.816)	(0.578)	(0.563)	(0.548)	(0.565)	(0.465)
GIRLS (N=548)	-1.039***	-2.117***	-1.126***	-0.869***	-2.044***	-1.235***
	(0.326)	(0.414)	(0.303)	(0.323)	(0.510)	(0.346)

Notes: (i) controls include all covariates from Table 3A (time varying only in the case of Panels C and D); (ii) standard errors are given in parentheses; (iii) *** p<0.01, ** p<0.05, * p<0.1; (iv) regional dummies are also included; (v) for the IV analysis in Panels B and D the instrument used is the average synchronisation speed.

APPENDIX: Variable definitions

VARIABLE NAME	DEFINITION
<u>DEPENDENT VARIABLES</u>	The next few questions are about how you feel about different aspects of your life. The faces express various types of feelings. Below each face is a number where '1' is completely happy and '7' is not at all happy. Please tick the box which comes closest to expressing how you feel about each of the following things...  We reorder this variable so that it is increasing in happiness, i.e. '1=not at all happy' and '7=completely happy'
YPHSW (School)	Your school work?
YPHAP (Appearance)	Your appearance?
YPHFM (Family)	Your family?
YPHFR (Friends)	Your friends?
YPHSC (School)	The school you go to?
YPHLF (Life)	Which best describes how you feel about your life as a whole?
<u>KEY INDEPENDENT VARIABLE</u>	
NETCHAT	Do you belong to a social web-site such as Bebo, Facebook or MySpace? How many hours do you spend chatting or interacting with friends through a social web-site like that on a normal school day? 1=none, 2=less than an hour, 3=1-3 hours, 4=4-6 hours, and 5=7 or more hours.
<u>INSTRUMENTAL VARIABLES, *Z*</u>	Defined at the local area district
AVSYNCSPEED	Average synchronisation speed of existing broadband connections
SIGNAL 3G	The percentage of landmass with 3G outdoor coverage from all operators
NOTREC2MB	The percentage of homes with broadband currently not achieving 2 megabits per second (Mbit/s)

APPENDIX: Variable definitions – cont.

VARIABLE NAME	DEFINITION
EXPLANATORY VARIABLES IN ***X***	
No. close friends	Number of close friends
Age10	1=child aged 10; 0=otherwise
Age 11	1=child aged 11; 0=otherwise
Age 12	1=child aged 12; 0=otherwise
Age 13	1=child aged 13; 0=otherwise
Age 14	1=child aged 14; 0=otherwise
Male	1=child is male; 0=female
White	1=child is white; 0=other ethnicity
Hrs. watching TV	How hours do you spend watching TV, including video and DVDs, on a normal school day? 1=none; 2=less than an hour; 3=1-3 hours; 4=4-6 hours; and 5=7 or more hours
Parent employ	1= mother and/or father in paid employment or self-employed; 0=other labour market state
Parent degree	1= mother or father has a degree qualification or equivalent; 0=other qualification or none.
Single parent HH	1=child is in a single parent household; 0=otherwise
Real equiv. income	Natural logarithm of real equivalised net household monthly income in 2009 prices
HH child 0-2	Number of children in household aged 0-2
HH child 3-4	Number of children in household aged 3-4
HH child 5-11	Number of children in household aged 5-11 (excluding respondent)
HH child 12-15	Number of children in household aged 12-15 (excluding respondent)
Home own	1=parent owns home outright or on a mortgage; 0=other housing tenure state
Eve. meal family	In the past 7 days how many times have you eaten an evening meal together with the rest of your family who live with you? 1=none; 2=1-2 times; 3=3-5 times; and 4=6-7 times.
Want to go university	1=whether child would like to go to college or university; 0=otherwise
Ever played truant	1=whether in the last 12 months child has ever played truant from school; 0=otherwise
Ever smoked	1=whether child has ever smoked cigarettes; 0=otherwise
Stayed out after 9pm	1=whether in the past month the child has stayed out after 9pm without their parent(s) knowing their whereabouts; 0=otherwise
Urban	1=family live in an urban area; 0=family live in a rural area
UE rate	Natural logarithm of the local area district unemployment rate