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The internet and children's psychological wellbeing

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A B S T R A C T

Late childhood and adolescence is a critical time for social and emotional development. Over the past two decades, this life stage has been hugely affected by the almost universal adoption of the internet as a source of information, communication, and entertainment. We use a large representative sample of over 6300 children in England over the period 2012–2017, to estimate the effect of neighbourhood broadband speed, as a proxy for internet use, on a number of wellbeing outcomes, which reflect how these children feel about different aspects of their life. We find that internet use is negatively associated with wellbeing across a number of domains. The strongest effect is for how children feel about their appearance, and the effects are worse for girls than boys. We test a number of potential causal mechanisms, and find support both for the 'crowding out' hypothesis, whereby internet use reduces the time spent on other beneficial activities, and for the adverse effect of social media use. Our evidence adds weight to the already strident calls for interventions that can reduce the adverse effects of internet use on children's emotional health.

1. Introduction

Late childhood and adolescence is a critical and potential vulnerable time for social and emotional development. One aspect of this life-stage that has changed dramatically in the past 20 years is the almost universal adoption of the internet as a source of information, communication, and entertainment. United Nations research has estimated that 3.5 billion people (47 per cent of the world population) use the internet globally; one third of these are under 18.[1] In the UK, today's teenagers have grown up with the internet and now spend more time online than they do watching television (Ofcom, 2015). Almost all 12–15 year olds (98 %) use the internet; with 96 % accessing it at home via a fixed broadband (BB) connection, and a large proportion also using a mobile network signal (Ofcom, 2015). "*The internet is not just something children access when they want certain bits of information; it is an essential and intrinsic part of the world they inhabit*" (House of Lords, 2017).

Internet use can have both beneficial and detrimental effects on children's wellbeing because of the wide range of activities that are undertaken online.[2] Jackson et al. (2008) describes a 'utopian' view, where the internet provides a chance to develop the skills needed for the modern workplace, as well as new opportunities for self-expression,

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[1] www.un.org/apps/news/story.asp?NewsID=54931#.WLlbn8pXUpE

[2] The same argument can be made for adults. Fujiwara et al. (2018), in their analysis of the wellbeing effects of the UK Superfast BB programme, find a negative association between BB speed and adult life satisfaction using Annual Population Survey data; although they find a positive association using UKHLS data.

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communication and access to information. However, she contrasts this with a 'dystopian' perspective where time online 'crowds out' other beneficial activities such as reading, playing sports and face-to-face interaction with friends and family, as well as exposing children to potentially inaccurate and harmful content, and sexual and commercial exploitation. Early empirical studies, largely based on cross section surveys of teenagers, lend support to an overall negative effect of internet use on wellbeing (Brenner, 1997; Kraut et al., 1998). However, more recent evidence is inconclusive, with, for example, Bauernschuster et al. (2014) finding a positive association between internet use and social capital, but Lohmann (2015) finding a negative influence of internet use of wellbeing, operating largely via relative income effects.

The potentially detrimental effects of online activity have prompted concern in the UK among a number of bodies responsible for the mental health and wellbeing of young people.[3] A recent enquiry on 'children and the internet' by the House of Lords (2017) concluded that the current regime of self-regulation very often put commercial considerations first, with scant regard for wellbeing.[4] The enquiry acknowledged the association between increasing numbers of unhappy and anxious children and the growth in internet use, but also called for more robust research into the possible causal relationships.[5] Our study is an attempt to respond to that call; we explore the association between children's emotional health and internet use, and also consider a number of potential causal channels, which we investigate empirically.

Children's use of the internet is an important topic for study because it is a significant component of time use, and its effects on wellbeing and mental health are ambiguous (Kalmus et al., 2014). Most of the existing evidence comes from samples of adults, or students in higher education (see for example Cotton, 2008; Bhuller et al., 2013). There is very little evidence for children, and that which does exist tends to come mainly from cross section data, and relatively small, bespoke samples (see for example Gross et al., 2002; Jackson et al., 2008).

In this study we use neighbourhood BB speed (as reported by Ofcom) as a proxy for internet access. There is increasing evidence to suggest that children do not regard the internet as a separate, distinct entity that they access; rather it is woven ubiquitously throughout all aspects of their life. For this reason, self-reported data on time spent on the internet may be misleading. In addition, children use the internet for a wide range of diverse activities, and it is likely that the impact on their wellbeing depends on the quality and type of activities they are engaged in. Our data contains only limited information on what children are doing online. Instead, we assume that faster BB speeds mean that children can access more content in a given amount of time. Hence, we might expect to observe an association between BB speed and child wellbeing because of the enhanced internet access enabled by faster BB speeds.

We improve on the majority of existing evidence on the effects of internet use, firstly, using a large nationally representative sample of children, rather than a small survey of a selective group. Secondly, we utilise measures of emotional health across different domains, which enable us to explore which aspects of children's lives are most affected. Thirdly, we explore a number of potential causal mechanisms that can help to explain why internet use affects emotional health. Fourthly, we use longitudinal data and fixed effects (FE) models, in order to eliminate endogenous selection bias arising from time-invariant unobserved variables, such as childhood circumstances or neighbourhood characteristics, which influence both wellbeing and BB speed. We also explore in detail the assumption of quasi-random assignment of BB speed, which is necessary for us to identify the effect of BB speed on psychological wellbeing. Finally, we also consider which groups of children are most affected by use of the internet.

Our results are worrying for anyone concerned with children's emotional health. We find a negative relationship between internet use and wellbeing domains. In our most stringent specification, children feel worse about their *schoolwork, appearance, friends* and the *school they attend,* as internet use increases. For example, a 1 % increase in BB speed reduces how children feel about their *appearance* by approximately 0.6 per cent. The adverse effects of the internet are worse for girls than boys, and the strongest effect (for both sexes) is for how they feel about their appearance. Our evidence also suggests that these results can be explained via the 'crowding out' hypothesis, whereby internet use reduces the time spent on other beneficial activities, and from the adverse effect of social media use.

2. Broadband speed and children's wellbeing

The potential influence of the internet on the emotional health and wellbeing of children is attracting increased attention across a range of disciplines. Castellacci and Tveito (2018) review this disparate literature and classify the relevant mechanisms through which the internet can affect wellbeing into four distinct channels. Their review does not consider children explicitly, but all of these channels have particular implications for children, which we attempt to draw out here; we also test a number of these causal channels in our empirical work. Children's wellbeing can be affected directly in the ways described below, but also indirectly via intergenerational effects; parents' behaviours and wellbeing can be shaped by internet use and this will in turn affect their children (see Pfeffer and

[3] The National Society for the Prevention of Cruelty to Children 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 (www.nspcc.org.uk/). An inquiry into cyberbullying by the charity Young Minds and The Children's Society was carried out in 2017 https://youngminds.org.uk/resources/policy/cyberbullying-inquiry/. Barnardo's, the children's charity, produced a 'youth and the internet' guide for policymakers in 2015 (Barnardo's, 2015).

[4] In 2019, the government published a White Paper setting out their recommendations for reducing online harms, particularly among children (HM Government, 2019).

[5] Recently, a cross-parliamentary enquiry on 'the impact of social media and screen-use on young people's health', again cited the lack of evidence of causal relationships: www.parliament.uk/business/committees/committees-a-z/commons-select/science-and-technology-committee/inquiries/parliament-2017/impact-of-social-media-young-people-17-19/

Schoeni, 2014). Further, there are reasons to expect that children may be particularly vulnerable to some of the mechanisms described below. As well as being at a critical stage of social and emotional development, children often adopt technological innovations before parents, schools or policy makers can consider the lasting implications of this technology. This problem is exacerbated by the fact that internet content is increasingly consumed via a tablet or phone, and this move to smaller, portable devices is making adult supervision much more difficult than when the internet was largely accessed via a single family computer.

The internet can influence wellbeing firstly because it changes time use patterns. On one hand, this can make existing tasks, like shopping, coursework and job search, more efficient, thus freeing up time for other activities. For example, by aiding job search the internet could improve parents' labour market outcomes, helping them to find jobs that better match their skills or exit unemployment spells more quickly, which in turn affects the child's wellbeing. Gürtzgen et al. (2018) found that, in Germany, digital technologies helped the unemployed find a job. On the other hand, there is evidence that the internet can crowd-out other activities known to be beneficial for wellbeing, such as playing sport and having face-to-face interactions with friends and family (Moreno et al., 2013; Wallsten, 2013). Further, in evidence given to the House of Lords (2017) enquiry, Barnardo's, the children's charity, warns that children are far from being fully informed, rational consumers when it comes to online commercial transactions. Ofcom research suggests that less than half of 12−15 year olds were aware of paid endorsements by vloggers or personalised advertising; they also could not spot advertising in online search results (Ofcom, 2015).

Secondly, the internet facilitates new activities, which can have positive or negative effects on wellbeing. The internet has enabled online gaming and digital social networks, which are now almost ubiquitous in their use among children; it also facilitates access to on demand entertainment via traditional media sites such as online television, as well as specialist online sites such as YouTube and music streaming apps like Spotify. While these activities can have important positive effects such as enabling children to develop creativity and social skills, and providing opportunities both for stimulation and relaxation, there is increasing concern about the potentially negative effects such as addiction, commercial exploitation and increased chances of exposure to inappropriate content (Kuss and Griffiths, 2012). In addition, there is some evidence that new activities such as gaming and streaming entertainment displace time spent on schoolwork (Kaiser Family Foundation, 2010).

Thirdly, the internet enables greater access to information; this can contribute to social and educational development. However, the proliferation of inaccurate content, 'fake news' and inappropriate sexual and/or violent content on the internet can be damaging to children's wellbeing. Further, while there is no conclusive evidence yet, there are suggestions that overwhelming exposure to information in itself may be affecting concentration and decreasing attention spans, in adults as well as children (Carr, 2010). Also, in common with many adults, children do not have an understanding of how search engines work and have limited knowledge to enable them to judge the accuracy or providence of online information (Ofcom, 2016). In a review of the effects of computers, software and the internet on education, Bulman and Fairlie (2016) argue that, while increased availability is associated with increased use, few studies find positive effects on educational outcomes. Faber et al. (2015) explore the effects of internet speed on test scores for English primary and secondary school students over the period 2002–2008, and find no significant effects on student time spent studying online or offline, or on their educational outcomes.

Much of the material that children are exposed to online can be classified as inappropriate (Martellozzo et al., 2016), and pornography has emerged as a particular concern. The British Board of Film Censors argue that "*This has led to the normalisation of largely unfettered access to the strongest, sometimes unlawful, pornography by children online*".[6] Young people themselves are also expressing their concerns about pornography on the internet; in a survey of 500 young people, 80 % said that it was too easy to access pornography online, and 72 % felt that this was leading to unrealistic views about sex, particularly among boys (Institute for Public Policy Research, 2014).[7]

Fourthly, the internet provides new communication tools, such as email, instant messaging, social media, Skype and Facetime. These tools have the potential to increase both the scope and intensity of social interactions, both of which are among the strongest predictors of wellbeing (Kahneman et al., 1999). Social media use has grown extremely rapidly, and is a core part of young people's lives. A survey in 2015 revealed that, in the UK, 92 % of 16–24 year olds had used social networks, such as Facebook, Snapchat, WhatsApp and Instagram, in the last three months.[8] 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 television channel found that more than three quarters of 10–12 year olds had social media accounts.[9] Social networks are children's 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). For this reason, we believe that social media use is potentially a very important mechanism through which internet use can influence children's emotional health. The results that we present in section 4 below lend support to this

[6] House of Lords (2017) para. 130.

[7] Online bullying (discussed below) is also intertwined with the normalisation of online sexual content. Almost half of 18 year-olds questioned in the same survey stated that sending naked pictures to each other (known as 'sexting') was part of everyday life; and that these pictures were often shared more widely in an attempt to bully and shame individuals.

[8] www.ons.gov.uk/ons/guide-method/method-quality/specific/business-and-energy/e-commerce-and-ict-activity/social-networking/index.html

[9] www.bbc.co.uk/news/education-35524429

view. For this reason, we spend some time here considering this mechanism in more detail.

Digital social networks serve a multiplicity of functions. They are a tool for developing and maintaining interpersonal relationships, a real-time portal for accessing information, news, advice and social support, as well as a canvas for sketching a selective and idealised self-portrait. While it is generally acknowledged that social media can have a positive impact on social capital, for example by enhancing friendships and decreasing loneliness (Franzen, 2003; Antoci et al., 2012), 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 et al., 2013). Evidence is also emerging demonstrating a detrimental effect of social media use on sleep (Levenson et al., 2016).[10] There is also evidence that online communication substitutes for face-to-face interactions (Sabatini and Sarracino, 2017). Helliwell and Huang (2013) compare face-to-face 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 that only increases in the number of face-to-face friends are associated with improved wellbeing.

There are two additional complementary theories that can help to explain why extensive social media use may have a negative effect on children's emotional health, on top of the 'crowding out' hypothesis discussed above in relation to internet access in general. First, 'social comparison' theory, posits that increased social media use is linked to more frequent social comparisons, which are more likely to be 'upward' (negative) in direction. The material people choose to present online represents selectively idealised versions of their true lives (Mendelson and Papacharissi, 2010), and there is evidence that young social media users act naively, in that they fail to understand that the material is not representative (Royal Society for Public Health, 2017).[11] Sabatini and Sarracino (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 than those without, and Lohmann (2015) finds that people who regularly use the internet as a source of information derive less satisfaction from their income. 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. 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 et al., 2015; Verduyn et al., 2015). Issues of body image and self-esteem have been raised as a particularly negative aspect of greater social media use, especially among girls (Kleemans et al., 2016; Children's Society, 2018a). While, these concerns are not a new development (and have been linked in the past to women's magazines for example), the internet and social media increase the accessibility and immediacy of unrealistic body images, thus intensifying their effect.

Secondly, 'cyberbullying' theory, relates to the fact that children who spend more time on social networks have a greater chance of being the victim of direct attacks from others on their sense of self, wellbeing, and self-esteem (Cowie, 2013). Childline counselling services reported a 12 percent increase in the number of cases related to cyberbullying in 2016/17 compared to the previous year (Children's Society, 2018b). Sampasa-Kanyinga and Hamilton (2015) reported a significant increase in the odds of being victimised for every hour spent using social networking sites. While cyberbullying often overlaps with traditional 'offline' bullying, the former may be particularly pernicious because children's continual connectedness means they cannot escape (Slonje et al., 2012).[12] A recent study for the US using micro data from the *Youth Risk Behaviour Survey*, found that cyberbullying influences suicidal behaviour (Nikolaou, 2017), and 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).

3. Data and methodology

In this paper, we use data from *Understanding Society* – The UK Household Longitudinal Study (UKHLS), a representative sample of over 40,000 households across the UK (University of Essex, 2018). Eight waves are currently available, starting with wave 1 in 2009, which provided data on over 50,000 individuals, and the latest wave 8 (at the time of writing) where over 39,000 individuals were interviewed between 2016 and 2018. All adult members of each household are interviewed, along with children aged 10–15 years old. In this analysis, waves 3–8 are used; these provide data on just over 6300 children residing in England, who are the focus of the empirical analysis.[13]

Children's data comes from the Youth Self-completion Questionnaire, which is used alongside data from the adult surveys, giving information on household characteristics such as income, homeownership and parental education. The outcomes of interest are obtained by asking children how they feel about different aspects of their life, specifically: *school work*; *appearance*; *family*; *friends*; *school attended*; and *life as a whole* (see Appendix, Table A1 (In Supplementary material)). Internet use may affect these

[10] 'Fear of missing out' is linked to obsessive checking of social media feeds and sleep problems, with almost of half of pupils questioned in a survey admitting to checking their mobile devices after going to bed. www.hmc.org.uk/wp-content/uploads/2016/10/Mobile-Device-Media-Brief-FINAL.pdf

[11] Enke (2017) presents experimental evidence that this irrationality is also present in adult behaviour.

[12] A number of economic studies have illustrated the negative and persistent effects of being bullied in childhood. For example, Eriksen et al. (2014) find detrimental effects of being bullied on educational attainment in a large Danish sample. Brown and Taylor (2008) find that being bullied at school in the UK has an adverse effect on human capital accumulation both at and beyond school.

[13] We do not use UKHLS waves 1 and 2 because Ofcom data on BB speed are not available for those years at the level of disaggregation required. Similarly, the Ofcom data is available for LSOAs in England only.

domains of children's wellbeing differently, and perhaps even in opposing directions, hence it is useful to be able to disaggregate wellbeing in this way. We order the responses to range from "1=not happy at all" through to "7= completely happy". We interpret these measures as indicators of psychological wellbeing or emotional health (see Clark et al., 2018). After conditioning on missing values, we create an unbalanced panel of 6310 children for the period 2012 (wave 3) through to 2017 (wave 8). Out of this sample 36 % of children are observed once, 27 % twice, 17 % three times, 11 % four times, 6 % five times and 3 % in all waves, giving a total number of observations 13,938 across children and over time.

Data are available from Ofcom, the UK communications regulator, on the average synchronisation speed of existing BB connections, measured in megabits per second (mbps). This is defined at the neighbourhood level, where neighbourhoods are classified via Lower Layer Super Output Areas (LSOA).[14] LSOAs are very small areas; there are 32,844 LSOAs in England, with an average size of 650 households; and the children in our sample reside in 3765 LSOAs. The UKHLS provides LSOA identifiers for each household, enabling us to match neighbourhood BB speed to our sample of children. The BB speed data are available across all years 2012–2017 and are matched to the LSOA-year in which the child was interviewed. The sample of children we draw on live in households that do not change address during the period, which is important as the analysis is based upon location FE.

3.1. Reduced form approach

For ease of interpretation we standardize each outcome to have a mean of zero and standard deviation of unity,[15] and condition on a set of covariates and BB speed. The reduced form models we estimate are of the following form:

$$y_{ijw} = \boldsymbol{X}_{ijw}^{'}\boldsymbol{\beta} + \phi Z_{jw} + \alpha_i + \psi_j + \lambda_w + \varepsilon_{ijw} \quad (1)$$

where $i (= 1, .., 6310), j (= 1, .., 3765), w (= 3, .., 8)$ denote the child, the neighbourhood in which the child lives (LSOA), and wave of interview respectively; the outcome of interest is denoted by y_{ijw} and Z_{jw} is the average neighbourhood BB speed. The error term is normally distributed $\varepsilon_{ijw} \sim N(0, \Sigma)$ and α_i, ψ_j, λ_w denote child, neighbourhood and time specific FE, respectively. Eq. (1) is estimated using FE analysis, where the inclusion of FE eliminates endogenous selection bias arising from time-invariant unobserved variables, e.g. childhood circumstances or neighbourhood characteristics, which influence both wellbeing and BB speed. Our interest lies in the sign and statistical significance of the estimate $\hat{\phi}$, which, based upon the quasi-random assignment of BB (considered in detail below) gives the intention-to-treat (ITT) effect of BB speed on psychological wellbeing, capturing the causal effect of being assigned to treatment (see Angrist and Pischke, 2009).

The covariates in vector $\boldsymbol{X}_{ijw}$ control for individual child, parent, household and local area characteristics and comprise: age, specifically whether aged 10, 11, 12, 13 or 14 (with aged 15 as the omitted category); whether male; the number of children aged 0–2, 3–4, 5–11 or 12–15 in the household[16]; whether either of the child's parent(s) own their house, are employed, or have a degree or equivalent qualification; whether the child lives in a single parent household; the natural logarithm of real equivalized net household income; and local area characteristics (including the unemployment rate, gross value added (GVA) per capita, the share of females, the share of the population over 65, and the share of the population of working age) defined at the Local Authority District (LAD) level, to proxy for local economic conditions.[17]

Full variable definitions are given in the Appendix, Table A1. Summary statistics are shown in Table 1. Fig. 1 shows histograms of the distribution of each dependent variable prior to standardization. Clearly, across each of the psychological wellbeing outcomes, 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 higher in comparison to the other domains; approximately 20 % of respondents state that they are 'completely happy' with their *school work* and/or *appearance.*

Approximately 51 % of children are aged 13–15 and just under half are male. In terms of family background, 77 % of children have at least one parent who is either an employee or self-employed, 33 % of parents have a degree; 22 % of children live in a single parent household; the average real net equivalized household income is £1326 per month; and 67 % of parents own their home either outright or with a mortgage. Table 1 shows that the average BB speed over the period was just under 26 mbps. Fig. 2 provides kernel density plots of the neighbourhood average BB speeds for each year, where clearly the average speed, and also the variance, has increased over time. Fig. 3 shows the distribution in growth in BB at the LSOA level for each wave as a complement to Fig. 2, where growth occurred between all waves.

Fig. 4 shows a map of England split into LSOAs where white areas are not included in our sample. The map shows London along with the eight core cities of England with boundaries given in blue. By considering quartile ranges of average BB speed over time at the LSOA level, the map highlights where the variation in BB speed comes from. It would appear that BB speeds are highly dispersed, not concentrated in any one particular region, and not dominated by large cities, e.g. London (noticeably there is evidence of variation in BB speed across quartiles within London).

[14] The average synchronisation speed is the average speed at which the modem connects with the internet; it is a key BB performance metric used by Ofcom. The data are available from www.ofcom.org.uk

[15] Ferrer-i-Carbonell and Frijters (2004) show that assuming cardinality for ordinal measures of wellbeing is acceptable in models where individual effects are included, as is the case in our analysis.

[16] For the categories 5-11 and 12-15 the number of children excludes the respondent.

[17] In the UKHLS there are 330 LADs in England. The LAD variables are obtained from www.nomisweb.co.uk which is a service provided by the Office for National Statistics containing official labour market statistics.

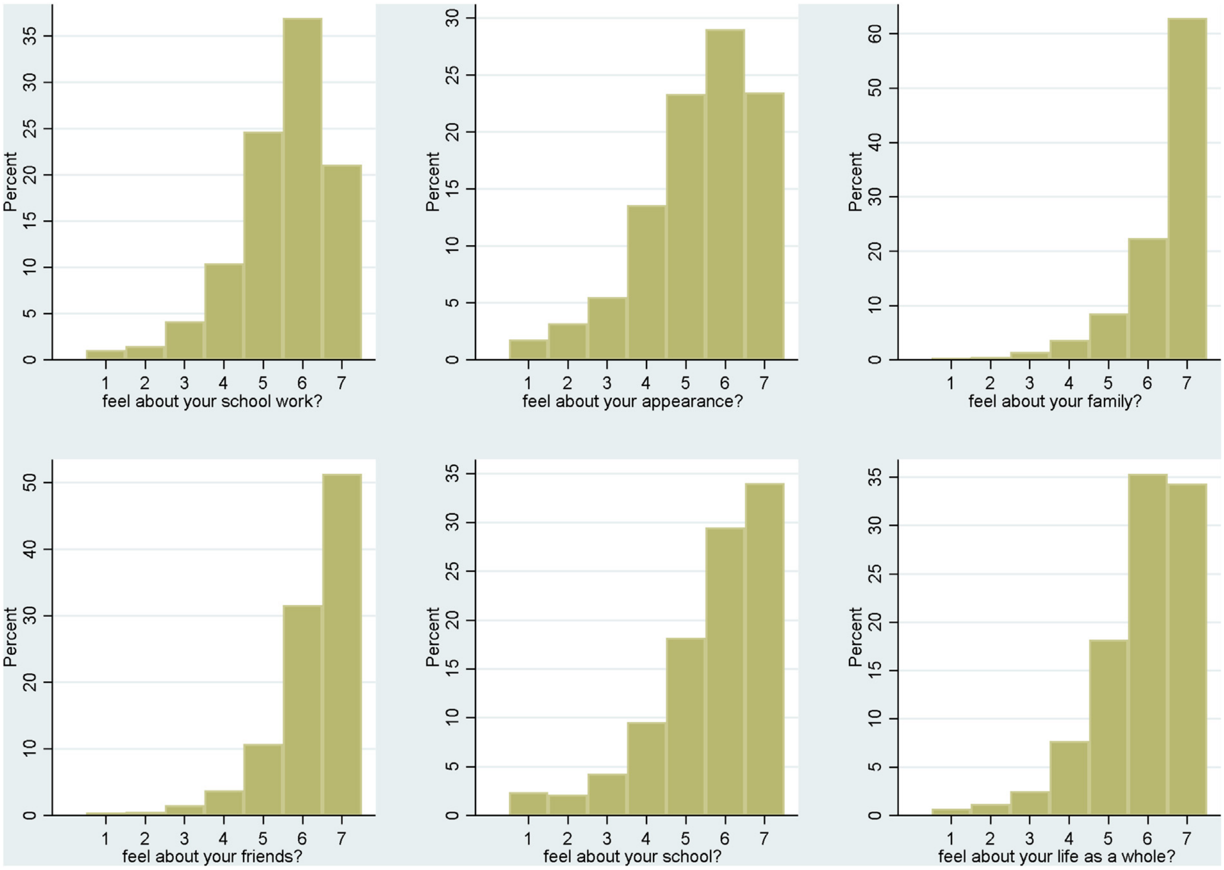

Fig. 1. Distribution of dependent (wellbeing) variables.

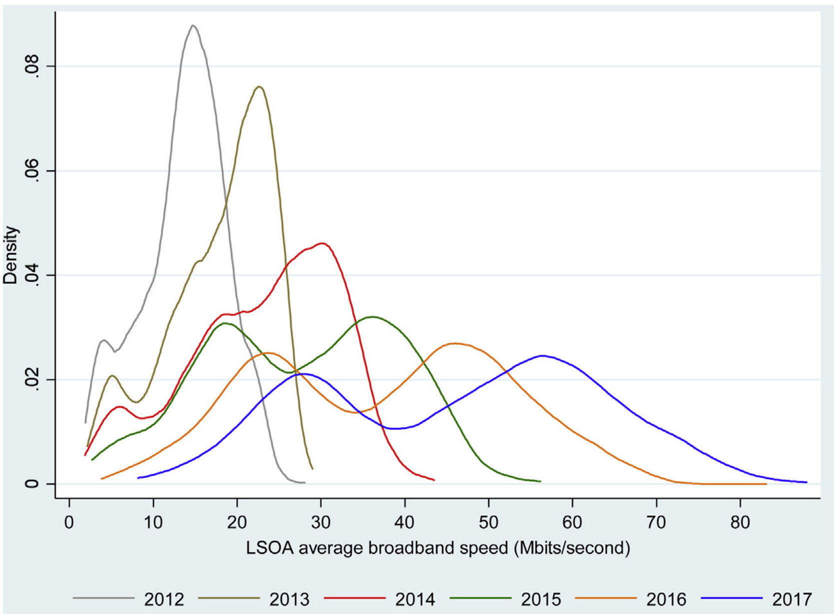

Fig. 2. Density plots of neighbourhood (LSOA) broadband speed (mbps) by wave, Z_{jw}.

Table 1
Summary statistics – dependent variables, key explanatory variables and broadband speed.

DEPENDENT VARIABLES, y, Level of Happiness with: @	MEAN	ST. DEV.	MIN	MAX
School work	5.5177	1.233	1	7
Appearance	5.3448	1.431	1	7
Family	6.3804	1.021	1	7
Friends	6.2409	1.026	1	7
School	5.6366	1.445	1	7
Life	5.8497	1.183	1	7
EXPLANATORY VARIABLES, ***X***				
Child Aged 10	0.1566	0.363	0	1
11	0.1653	0.371	0	1
12	0.1706	0.376	0	1
13	0.1732	0.378	0	1
14	0.1695	0.375	0	1
Child male	0.4999	0.500	0	1
Parent(s) employed	0.7726	0.419	0	1
Parent(s) has degree	0.3295	0.470	0	1
Single parent household	0.2233	0.417	0	1
Natural logarithm of real equivalized net monthly household income	7.0404	0.512	3.24	12.07
No. of other children in household aged 0–2	0.0761	0.289	0	3
3-4	0.0884	0.298	0	3
5–11	0.9310	0.880	0	5
12–15	1.0753	0.703	0	5
Parent(s) own home	0.6675	0.471	0	1
Natural logarithm of unemployment rate #	1.8261	0.444	0.26	2.80
Natural logarithm of GVA per capita #	10.0033	0.366	9.40	11.51
Natural logarithm of share of females #	3.9356	0.023	3.83	4.01
Natural logarithm of share of population 16–65 #	4.2903	0.084	4.06	4.51
Natural logarithm of share of population 65+ #	3.2378	0.382	1.92	4.24
Average synchronization speed (mbps), Z_{jw} $	25.6419	14.783	1.84	87.89
Number of children (N)	6310			
Observations (NT)	13,938			

@ Denotes variables that are categorical; in the empirical analysis these variables are standardized to have a mean zero and standard deviation of unity.
# Defined at the local authority district (LAD) level.
$ Defined at the neighbourhood (LSOA) level. See Appendix Table A1 for full definitions.

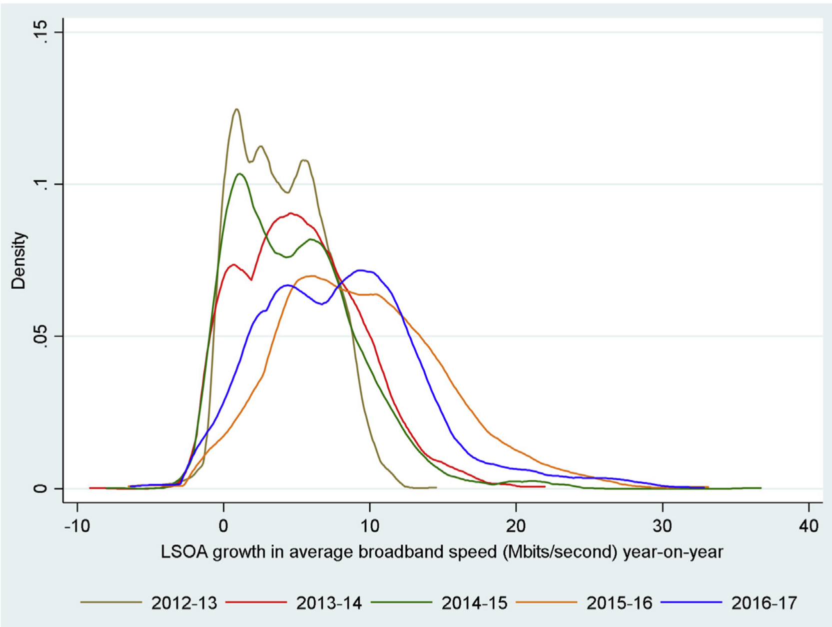

Fig. 3. Density plots of neighbourhood (LSOA) growth in broadband speed over time, ΔZ_{jw}.

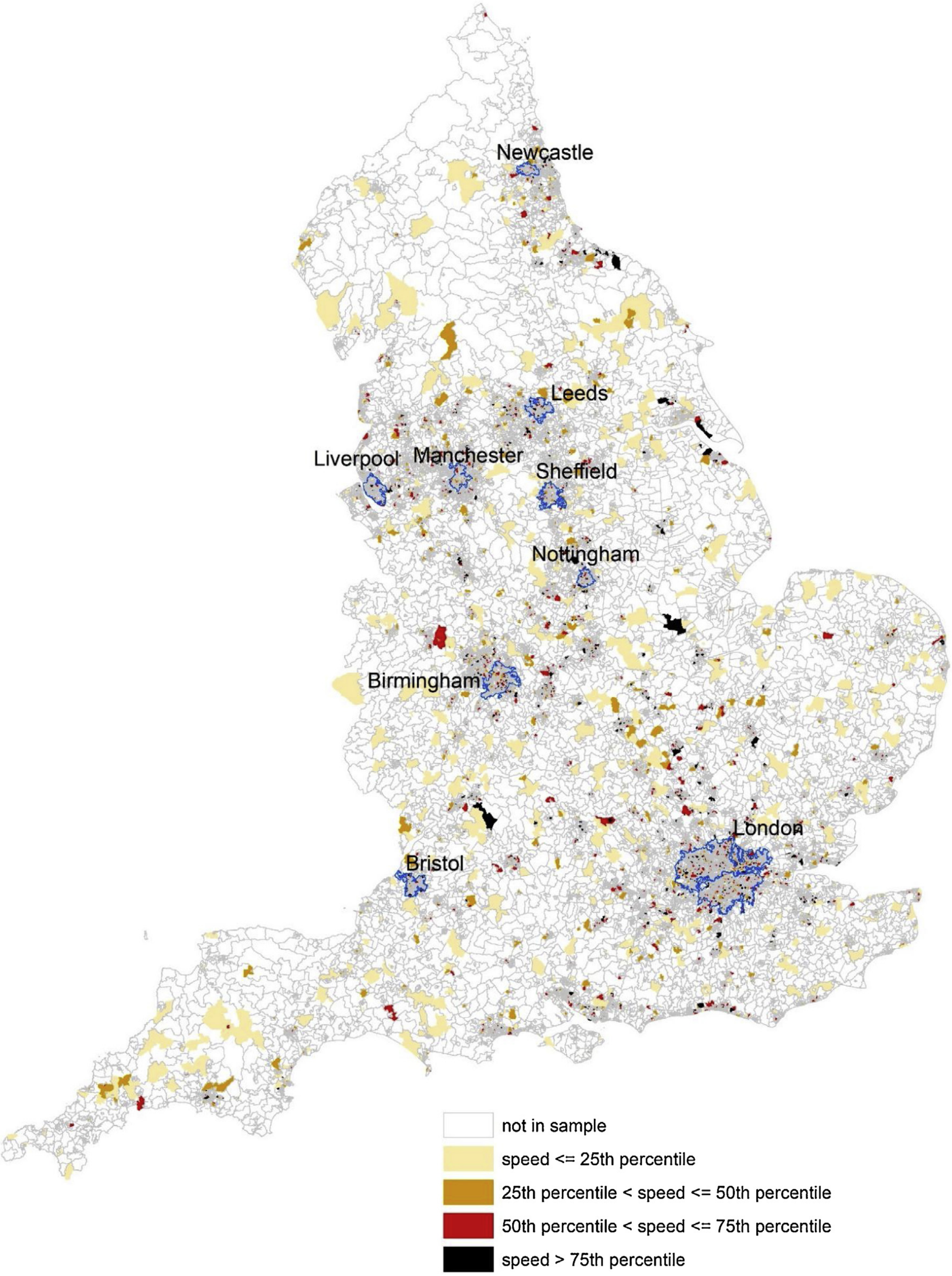

Fig. 4. Map showing the average broadband speed by quartile (produced in ArcGIS using Ofcom data).

3.2. Random allocation

The empirical approach adopted relies only on an assumption of quasi-random assignment of BB and does not require an exclusion restriction. BB rollout in England has been a complex mix of commercial and government initiatives. The bulk of commercial rollout, which was largely demand driven, was completed before our analysis period starts in 2012 (Department for Digital, Culture Media and Sport, 2018). Existing service quality was a result of a number of factors including poor home wiring, long telephone lines and random network effects (Department for Business Innovation and Skills and Department for Culture Media and Sport, 2009). The government subsidised superfast BB programme was announced in 2010 in response to concerns that commercial deployment would fail to reach many parts of the country where installation would not be profitable for a number of reasons (Department for Business Innovation and Skills and Department for Culture Media and Sport, 2010).[18] The government provided £780 m of public resources for a substantial programme developed in partnership with Local Authorities, who were expected to match central government funds on a one-to-one basis. Local Authorities were also responsible for procurement and management of contracts with local suppliers, resulting in a large amount of local variation (Department for Digital, Culture Media and Sport, 2018). Recently published evaluation evidence suggests that the areas that benefitted from this subsidised rollout had features that were expected to reduce the commercial viability of upgrading local infrastructure; these included, being further from the exchange, having a higher share of 'exchange only' lines and having a low density of premises (Department for Digital, Culture Media and Sport (2018).[19] The evaluation also reveals that schemes were primarily concentrated in rural areas with comparatively low population densities but any differences in economic performance were less apparent (Department for Digital, Culture Media and Sport (2018).

Overall, the subsidised programme, which was rolled out in the period coinciding with our analysis period, substantially distorted commercial demand driven BB installation. As a result, we do not expect BB speed in our analysis period to be systematically related to local socio-economic characteristics. We also explore this assumption empirically following Bhuller et al. (2013), who investigate whether increased internet access triggers sex crimes, and Akerman et al. (2015), who estimate whether or not the adoption of BB internet by firms enhances labour productivity. Firstly, we regress BB speed on neighbourhood (LSOA) and time FE, and area (LAD) level time varying characteristics (unemployment, population shares, education and GVA per head). We find that 83 percent of the variation in BB speed is attributable to time-invariant neighbourhood characteristics and common time effects, whilst less than 1 percent is due to time-varying covariates (which might pick up demand and supply effects associated with improving BB speeds). Secondly, we consider the timing of increasing BB speed, as revealed in Fig. 2, and baseline characteristics, which are evaluated at the start of the sample period, by estimating the following at the neighbourhood level:

$$\Delta Z_{jw} = \gamma_j + \left[\delta_w \times \bar{\boldsymbol{X}}_{j,2012}\right]' \psi_w + \varepsilon_{jw} \tag{2}$$

where ΔZ_{jw} is the first difference in average BB speed across waves, i.e. $\Delta Z_{jw} = Z_{jw} - Z_{jw-1}$, shown in Fig. 3, δ_w is a vector of time fixed effects and the vector $\bar{\boldsymbol{X}}_{j,2012}$ contains the 2012 mean of all child-family and area level covariates averaged at the neighbourhood level. Table 2 reports estimates of ψ_w and joint tests for each covariate of ψ_w across waves. It would appear that generally there is no systematic relationship between improving BB performance and the control variables. More importantly, there is little correlation with area-level background variables such as the unemployment rate, GVA per capita,[20] and population shares. This suggests that service expansion was not concentrated in those locations where the economy was growing fastest (or slowest). Moreover, the variation in the growth of BB speed shown in Fig. 3 did not just occur in years where the covariates predict the change in BB connection, see Table 2, and indeed perhaps not surprisingly the predictive power of the model is weak where the overall model F-statistic only has a p-value of 0.42.

Furthermore, we require that increasing BB speed is uncorrelated with the time-varying factors that influence psychological wellbeing. Following the approach of Altonji et al. (2005a, 2005b) we also test this by considering selection on observables as an indication of selection on unobservable effects. This is undertaken for the full sample of children and sub-samples of potential interest, e.g. males and females, since the effect of gender cannot be recovered in the FE framework of Eq. (1), where we explore the extent to which the BB speed is correlated with the part of the outcome explained by the covariates. Specifically we estimate the following for each outcome:

$$cov\left(\boldsymbol{X}'_{ijw}\boldsymbol{\beta},\, Z_{jw}\left|\alpha_i\right.\right)/var\left(Z_{jw}\left|\alpha_i\right.\right) \tag{3}$$

Table 3 shows the results of this where it is clear that for each domain across the full sample and the sub-groups, the correlation between $\boldsymbol{X}'_{ijw}\boldsymbol{\beta}$ and Z_{jw} is very low and practically indistinguishable from zero. This result is consistent with the assumption that increasing BB speed is uncorrelated with the time-varying factors that influence psychological wellbeing. To summarise we conclude that quasi-random assignment of BB in our data is a reasonable assumption, whereby the estimate of ϕ, from Eq. (1), provides the intention-to-treat (ITT) effect of BB speed on psychological wellbeing.

4. Results

In this section, we firstly estimate the reduced form model of Eq. (1) for the full sample of children, before

[18] Superfast BB is usually interpreted as meaning download speeds of at least 24 megabits per second.

[19] BB connections are made over a copper cable, which can either be connected to a roadside cabinet near the premises, or directly to the local telephone exchange. This latter type of 'exchange only' connection requires a more expensive upgrade procedure to enable the premises to access superfast BB.

[20] The only exception, albeit at the 10 per cent level, is for GVA per head, consistent with the finding of Bauernschuster et al. (2014) for Germany. Moreover, contrary to expectations, results show that where individually statistically significant the effect is associated with lower growth in internet speed, e.g. between 2012-13, $\hat{\psi}_3$, a 1% increase in GVA per head is associated with 0.086 per cent reduction in the growth of BB speed.

Table 2
Relationship between changing broadband speed and baseline average neighbourhood (LSOA) characteristics.

MEAN OF COVARIATE 2012	$\hat{\psi}_3$		$\hat{\psi}_4$		$\hat{\psi}_5$		$\hat{\psi}_6$		$\hat{\psi}_7$		$\hat{\psi}_8$		$H_0 : \psi_3 = \ldots = \psi_8 = 0$
Male	−2.05	*(1.80)*	−0.18	*(0.85)*	0.20	*(0.87)*	−0.01	*(0.02)*	−0.05	*(0.12)*	−0.44	*(0.71)*	0.93, *p=[0.475]*
Age10	3.02	*(1.35)*	0.19	(0.56)	−0.13	*(0.39)*	0.16	*(0.42)*	0.11	*(0.21)*	−0.64	*(0.72)*	0.53, *p=[0.790]*
Age 11	0.42	*(0.16)*	−0.18	*(0.56)*	−0.32	*(0.89)*	−0.16	*(0.43)*	0.19	*(0.35)*	−0.39	*(0.46)*	0.24, *p=[0.965]*
Age 12	0.78	*(0.37)*	0.17	*(0.56)*	0.25	*(0.79)*	−0.01	*(0.03)*	0.55	*(0.95)*	0.03	*(0.05)*	0.32, *p=[0.929]*
Age 13	−1.69	*(0.68)*	−0.29	*(1.01)*	−0.44	*(1.35)*	0.31	*(0.75)*	0.18	*(0.29)*	−0.44	*(0.59)*	0.70, *p=[0.651]*
Age 14	0.18	*(0.12)*	0.07	*(0.23)*	−0.33	*(0.95)*	−0.23	*(0.54)*	−0.12	*(0.19)*	−0.65	*(0.63)*	0.29, *p=[0.944]*
0-2 children	1.02	*(0.53)*	0.94	(1.71)	0.53	*(1.16)*	0.23	*(0.62)*	0.34	*(0.57)*	−0.75	*(1.06)*	1.69, *p=[0.121]*
3-4 children	0.35	*(0.13)*	−0.29	*(0.98)*	−0.04	*(0.11)*	−0.91	*(1.69)*	−0.84	*(1.68)*	−0.98	*(1.47)*	0.60, *p=[0.661]*
5–11 children	−0.29	*(0.26)*	−0.06	*(0.43)*	−0.15	*(0.94)*	−0.23	*(1.29)*	0.09	*(0.34)*	−0.34	*(0.94)*	0.56, *p=[0.759]*
12–15 children	0.44	*(0.30)*	−0.04	*(0.18)*	−0.22	*(0.88)*	0.13	*(0.47)*	−0.31	*(0.74)*	−1.07	*(1.87)*	0.78, *p=[0.587]*
Parent(s) own home	−1.08	*(0.49)*	0.28	*(1.11)*	−0.05	*(0.18)*	0.07	*(0.23)*	0.55	*(1.28)*	−0.21	*(0.34)*	0.59, *p=[0.741]*
Parent(s) employed	3.46	*(0.95)*	0.13	*(0.50)*	0.00	*(0.00)*	0.73	*(2.34)*	0.24	*(0.56)*	0.44	*(0.79)*	1.23, *p=[0.289]*
Parent(s) have degree	−1.72	*(1.38)*	−0.13	*(0.57)*	−0.22	*(0.90)*	−0.23	*(0.86)*	0.04	*(0.09)*	−0.03	*(0.05)*	0.58, *p=[0.745]*
Single parent household	2.04	*(2.49)*	0.21	*(0.87)*	0.32	*(1.17)*	−0.00	*(0.01)*	0.25	*(0.54)*	−0.69	*(1.11)*	1.60, *p=[0.143]*
Log real equiv. hh income	0.80	*(0.61)*	−0.36	*(1.49)*	−0.28	*(1.00)*	−0.09	*(0.31)*	−0.18	*(0.34)*	−1.21	*(1.94)*	1.11, *p=[0.356]*
Log unemployment rate	−1.99	*(0.70)*	−0.98	*(1.43)*	0.02	*(0.02)*	−0.83	*(1.41)*	−2.57	*(2.28)*	−1.06	*(1.05)*	1.13, *p=[0.341]*
Log GVA per capita	−8.60	*(1.99)*	−7.01	*(1.40)*	−5.87	*(1.01)*	−6.55	*(2.22)*	−7.62	*(1.56)*	−7.37	*(1.45)*	2.53, *p=[0.079]*
Log share of females	−3.61	*(1.09)*	−1.43	*(0.43)*	1.21	*(0.76)*	0.57	*(0.04)*	−3.66	*(0.93)*	−2.68	*(0.73)*	1.76, *p=[0.103]*
Log share of population 65+	−1.25	*(1.06)*	−6.15	*(1.54)*	−6.16	*(1.56)*	−7.41	*(1.93)*	−8.78	*(1.97)*	−8.52	*(1.63)*	0.95, *p=[0.461]*
Log share of population 16–65	2.00	*(0.71)*	1.72	*(1.20)*	2.36	*(1.66)*	2.39	*(1.70)*	2.55	*(1.81)*	0.28	*(0.19)*	1.43; *p=[0.200]*
F-statistic $H_0 : \delta_w = \psi_w = 0$	1.02; *p=0.4159*												
Number of LSOAs (N)	2,368												
Observations (NT)	4,766												

This table considers the relationship between improving BB performance and the control variables based upon their mean value in 2012, $\bar{\boldsymbol{X}}_{j,2012}$, including the area level controls to ascertain whether service expansion was concentrated in those locations where the economy was growing fastest. Figures reported are coefficients and those in parenthesis are t-statistics. The final column shows an F-statistic, which tests the null hypothesis that the parameters are jointly equal to zero across time for each covariate in turn.

Table 3
The role of selection on observables – full sample and heterogeneity.

	FULL SAMPLE	GENDER		AGE		URBAN-RURAL	
		Boys	Girls	Aged ≥13	Aged <13	Urban	Rural
SCHOOL WORK	−0.00095	−0.00188	−0.00136	−0.00089	−0.00117	−0.00017	−0.00050
APPEARANCE	0.00139	0.00275	−0.00073	0.00372	0.00038	0.00013	0.00018
FAMILY	−0.00097	−0.00057	−0.00152	−0.00748	0.00384	0.00005	−0.00015
FRIENDS	−0.00086	−0.00132	−0.00134	0.00016	0.00073	0.00013	0.00054
SCHOOL	−0.00171	−0.00031	−0.00362	0.00035	−0.00149	−0.00001	0.00041
LIFE OVERALL	−0.00093	−0.00119	−0.00160	0.00093	0.00055	0.00016	0.00017
Number of children (N)	6310	3,179	3,131	4,082	4,154	5,346	993
Observations (NT)	13,938	6964	6974	7073	6865	11,637	2,301

This table considers whether BB speed is uncorrelated with time-varying factors which are associated with psychological wellbeing, by considering selection on observables as an indication of selection on unobservable effects, where $cov\left(\boldsymbol{X}'_{ijw}\boldsymbol{\beta},\ Z_{jw}\,|\alpha_i\right)/var\left(Z_{jw}\,|\alpha_i\right)$ is shown for each outcome.

considering heterogeneity across a number of sub-groups. Finally, we explore potential mechanisms that may be capable of explaining the results.

4.1. Reduced form analysis

Table 4 presents the coefficients on Z_{jw}, i.e. $\hat{\phi}$ the ITT, showing the effect of BB speed on each of the wellbeing domains reported in each column. We report four different specifications of Eq. (1): (i) Panel A with no control variables, just child FE; (ii) Panel B incorporating covariates, $\boldsymbol{X}_{ijw}$, which include child and family characteristics as well as local economy controls (unemployment rate; GVA per head; share of females; share of population over 65; and the share of the population aged 16–65) and child FE; (iii) Panel C also incorporating time FE; and (iv) Panel D, incorporating the full set of covariates, time, area and child FE.

Focusing initially on the FE models in Panels A and B, across each domain there is a negative association with BB speed, i.e. $\hat{\phi} < 0$. The inclusion of covariates generally reduces the parameter estimate on Z_{jw} but the effect remains statistically significant. Looking at Panel B a 1 % increase in BB speed decreases happiness in each of the domains ranging from 0.008 standard deviations (around 0.8 per cent) for *appearance* to 0.005 standard deviations for *life overall*. In Panel D, which is the most stringent specification, BB speed remains statistically significant for four out of the six domains, where a 1 % increase in BB speed decreases happiness with *appearance* by 0.006 standard deviations (i.e. an ITT of around 0.6 per cent).

We compare the effect of BB speed to the other control variables in Table 5, which reports the full results from Panel C of Table 4. Interestingly, where statistically significant, younger children generally feel happier than those aged 15 (the omitted category) across each domain, whilst there are no effects stemming from household income. In related work, Anand and Roope (2016), who consider child wellbeing in Germany, also found no income effect, whilst, analysis from the US reveals that parental earnings are positively associated with a number of childhood health outcomes (Mazumder and Davis, 2013). Those children residing in a single parent household have lower psychological wellbeing for *appearance* and *life overall*. What is evident is that in a FE framework few child level and area level covariates are statistically significant, yet BB speed has a negative effect on four of the wellbeing domains. Focusing upon *appearance* the coefficient on Z_{jw} is on average approximately a tenth of the magnitude of the coefficient associated with whether the child lives in a single parent household, so arguably not a trivial effect. This is consistent with concerns about the negative influence of the internet on body image.

In Eq. (1) BB speed is assumed to have a linear effect on each domain. We now relax this by replacing Z_{jw} in Eq. (1) with a set of binary indicators for whether the BB speed is between: 10 and less than 20 megabits per second (mbps); 20 and less than 30 mbps; 30 and less than 40 mbps; 40 and less than 50 mbps; 50 and less than 60 mbps; and 60 mbps and above, respectively. The results of this analysis are shown in Table 6, which incorporates full controls, area, year and child FE. Clearly, there is evidence of linearity in that the higher BB speed is associated with worse wellbeing across all domains where statistically significant and the effect is monotonic, i.e. increasing in magnitude. For example, considering *appearance* having a BB speed between 20 and 30 mbps is associated with 0.11 lower standard deviations, but this rises in magnitude to a 0.36 standard deviation reduction in wellbeing for BB speeds at 60 mbps and above.

4.2. Sub-group analysis

By looking at the entire sample of children, we may be missing important differences across the distribution of children – i.e. the effects of BB speed may have heterogeneous impacts across different groups of children. Hence, we also consider the following sub-groups: male and females; children aged below 13 and those aged 13 and above; and urban and rural areas. Eq. (1) is re-estimated for each of these groups. Table 7 shows the results splitting the sample of 6310 children by gender (Panels A and B), age (Panels C and D), and urban-rural location (Panels E and F). All estimates incorporate controls as well as area, time and child FE. Considering gender differences, where statistically significant, the largest effects are apparent for girls, hence it would seem that BB speed is more detrimental for wellbeing across each domain for girls – with the largest effect stemming from how girls feel about

Table 4
Coefficients for the reduced form relationship between wellbeing domains and broadband speed.

PANEL A	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0095	*(9.70)*	−0.0156	*(15.80)*	−0.0162	*(15.84)*	−0.0114	*(10.11)*	−0.0174	*(16.37)*	−0.0139	*(13.76)*
Controls	×		×		×		×		×		×	
Area fixed effects	×		×		×		×		×		×	
Year fixed effects	×		×		×		×		×		×	
Child fixed effects	√		√		√		√		√		√	
R-squared	0.0140		0.0424		0.0417		0.0169		0.0446		0.0301	
PANEL B	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0061	*(4.07)*	−0.0080	*(5.50)*	−0.0076	*(5.04)*	−0.0059	*(3.54)*	−0.0073	*(4.61)*	−0.0054	*(3.57)*
Controls	√		√		√		√		√		√	
Area fixed effects	×		×		×		×		×		×	
Year fixed effects	×		×		×		×		×		×	
Child fixed effects	√		√		√		√		√		√	
R-squared	0.0180		0.0527		0.0518		0.0225		0.0586		0.0419	
PANEL C	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0045	*(2.70)*	−0.0061	*(3.53)*	−0.0026	*(1.50)*	−0.0037	*(2.92)*	−0.0037	*(2.93)*	−0.0025	*(1.50)*
Controls	√		√		√		√		√		√	
Area fixed effects	×		×		×		×		×		×	
Year fixed effects	√		√		√		√		√		√	
Child fixed effects	√		√		√		√		√		√	
R-squared	0.0191		0.0562		0.0582		0.0236		0.0623		0.0440	
PANEL D	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0041	*(2.40)*	−0.0062	*(3.60)*	−0.0024	*(1.36)*	−0.0037	*(2.91)*	−0.0035	*(2.89)*	−0.0024	*(1.43)*
Controls	√		√		√		√		√		√	
Area fixed effects	√		√		√		√		√		√	
Year fixed effects	√		√		√		√		√		√	
Child fixed effects	√		√		√		√		√		√	
R-squared	0.0283		0.0612		0.0609		0.0314		0.0659		0.0494	
Number of children (N)	6310											
Observations (NT)	13,938											

Controls include: age of child; number of children in household aged 0–2; number of children in household aged 3–4; number of children in household aged 5–11; number of children in household aged 12–15; whether live in a single parent household; whether parent(s) own home; whether either parent has a degree; log equivalized real household income and the following LAD level covariates, the natural logarithm of: the unemployment rate; GVA per capita; share of females; share of population over 65; and share of population aged 16–65. In Panel C we also include year fixed effects and in Panel D 320 Local Authority indicators, i.e. area fixed effects, are also included.

Table 5
Coefficients for all covariates (from Table 4 panel C).

	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0045	*(2.70)*	−0.0061	*(3.53)*	−0.0026	*(1.50)*	−0.0037	*(2.92)*	−0.0037	*(2.93)*	−0.0025	*(1.50)*
Age 10	0.1927	*(1.34)*	0.3014	*(2.17)*	0.4255	*(3.13)*	0.4556	*(2.99)*	0.4965	*(3.40)*	0.3111	*(2.17)*
Age 11	0.2237	*(1.92)*	0.2638	*(2.33)*	0.3618	*(3.31)*	0.3495	*(2.81)*	0.4205	*(3.52)*	0.3009	*(2.55)*
Age 12	0.1480	*(1.73)*	0.1116	*(1.36)*	0.2014	*(2.44)*	0.2985	*(3.29)*	0.2955	*(3.34)*	0.2034	*(2.37)*
Age 13	0.1198	*(1.99)*	0.0086	*(0.15)*	0.1234	*(2.14)*	0.1858	*(2.91)*	0.1417	*(2.27)*	0.1299	*(2.15)*
Age 14	0.0732	*(1.94)*	−0.0274	*(0.79)*	0.0351	*(0.93)*	0.1049	*(2.58)*	0.0354	*(0.92)*	0.0494	*(1.29)*
0-2 children	−0.0688	*(1.15)*	−0.0138	*(0.24)*	−0.0477	*(0.87)*	0.0279	*(0.42)*	−0.0161	*(0.25)*	−0.0874	*(1.57)*
3-4 children	0.0407	*(0.76)*	0.0131	*(0.24)*	−0.0589	*(0.99)*	0.0217	*(0.33)*	−0.0268	*(0.45)*	0.0038	*(0.07)*
5–11 children	−0.0477	*(1.13)*	−0.0155	*(0.39)*	−0.0885	*(1.94)*	−0.0305	*(0.65)*	−0.0236	*(0.55)*	−0.0262	*(0.62)*
12–15 children	−0.0283	*(0.95)*	0.0292	*(1.06)*	−0.0024	*(0.07)*	0.0195	*(0.60)*	−0.0117	*(0.39)*	0.0076	*(0.25)*
Parent(s) own home	0.1076	*(1.02)*	−0.0848	*(0.96)*	0.0433	*(0.44)*	0.0157	*(0.18)*	0.0458	*(0.49)*	0.0277	*(0.30)*
Parent(s) employed	−0.0729	*(1.59)*	−0.0456	*(1.20)*	−0.0699	*(1.72)*	−0.0274	*(0.64)*	−0.1028	*(2.17)*	−0.1042	*(2.54)*
Parent(s) have degree	−0.1787	*(1.97)*	−0.0512	*(0.46)*	−0.0222	*(0.21)*	0.1375	*(1.26)*	−0.0992	*(1.00)*	0.0520	*(0.45)*
Single parent household	−0.0790	*(0.91)*	−0.0606	*(2.04)*	−0.1039	*(1.03)*	0.1671	*(1.52)*	−0.1366	*(1.43)*	−0.2203	*(2.67)*
Log real equiv. hh income	0.0024	*(0.08)*	−0.0318	*(1.18)*	0.0288	*(0.93)*	−0.0513	*(1.52)*	−0.0200	*(0.68)*	−0.0285	*(0.95)*
Log unemp. rate	0.0529	*(1.46)*	0.0236	*(0.69)*	−0.0296	*(0.83)*	0.0537	*(1.31)*	0.0241	*(0.66)*	−0.0928	*(2.45)*
Log GVA per capita	−0.1815	*(0.55)*	0.1639	*(0.55)*	−0.4040	*(1.25)*	−0.4028	*(1.14)*	−0.0287	*(0.08)*	−0.2203	*(0.73)*
Log share females	0.4910	*(0.49)*	−0.1815	*(0.19)*	0.5060	*(0.49)*	−0.1570	*(0.14)*	1.6044	*(1.64)*	0.3306	*(0.34)*
Log share pop. 16–65	0.1618	*(0.59)*	0.4988	*(2.00)*	−0.2863	*(1.07)*	−0.0083	*(0.03)*	0.2458	*(0.90)*	0.0394	*(0.15)*
Log share pop. 65+	−0.0925	*(0.85)*	−0.2073	*(2.11)*	−0.0139	*(0.14)*	−0.0550	*(0.47)*	−0.1504	*(1.42)*	−0.0845	*(0.77)*
R-squared	0.0191		0.0562		0.0582		0.0236		0.0623		0.0440	
Number of children (N)	6310											
Observations (NT)	13,938											

Controls as per Table 4 Panel C.

Table 6
Coefficients for the reduced form relationship between wellbeing domains and broadband speed – non-linearity.

	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB ≥10 and <20 mbps	−0.0598	*(1.19)*	−0.0693	*(1.43)*	−0.0546	*(1.06)*	−0.0378	*(0.76)*	−0.0331	*(0.66)*	−0.0794	*(1.65)*
BB ≥20 and <30 mbps	−0.0961	*(1.56)*	−0.1135	*(1.95)*	−0.0388	*(0.63)*	−0.0318	*(0.50)*	−0.0335	*(0.06)*	−0.1091	*(1.80)*
BB ≥30 and <40 mbps	−0.1605	*(2.18)*	−0.1327	*(1.94)*	−0.0161	*(0.22)*	−0.0222	*(0.29)*	−0.0290	*(0.39)*	−0.1189	*(1.73)*
BB ≥40 and <50 mbps	−0.1906	*(2.28)*	−0.2238	*(2.87)*	−0.1136	*(1.36)*	−0.1261	*(1.46)*	−0.0705	*(0.84)*	−0.1876	*(2.28)*
BB ≥50 and <60 mbps	−0.2483	*(2.65)*	−0.2938	*(3.30)*	−0.0948	*(1.02)*	−0.1327	*(1.34)*	−0.1029	*(1.08)*	−0.2240	*(2.44)*
BB ≥60 mbps	−0.2635	*(2.41)*	−0.3671	*(3.35)*	−0.0562	*(0.50)*	−0.2103	*(1.76)*	−0.2033	*(1.78)*	−0.2300	*(2.18)*
Controls	✓		✓		✓		✓		✓		✓	
Area fixed effects	✓		✓		✓		✓		✓		✓	
Wave fixed effects	✓		✓		✓		✓		✓		✓	
Child fixed effects	✓		✓		✓		✓		✓		✓	
R-squared	0.0288		0.0619		0.0618		0.0323		0.0667		0.0503	
Number of children (N)	6310											
Observations (NT)	13,938											

Notes: [1] BB refers to broadband speed which is defined as a set of binary indicators for whether the average synchronization speed is between: ≥10 and <20 megabits per second (mbps); ≥20 and <30 mbps; ≥30 and <40 mbps; ≥40 and <50 mbps; ≥50 and <60 mbps; and ≥60 mbps, respectively. [2] Controls include: age; number of children in household aged 0–2; number of children in household aged 3–4; number of children in household aged 5–11; number of children in household aged 12–15; whether live in a single parent household; whether parent(s) own home; whether either parent has a degree; log equivalized real household income; and year of interview. We also include 320 Local Authority indicators, i.e. area fixed effects, and the following LAD level covariates, the natural logarithm of: the unemployment rate; GVA per capita; share of population over 65; and share of population aged 16–65.

their *appearance*; again consistent with body image concerns. In Panels C and D, the sample of children is split by age, specifically whether aged below 13 or aged 13 and above.[21] The largest effects are all for those children aged 13 and over. The only significant effects of BB speed for those children under the age of 13 are on *appearance* and *family*, where a 1 % increase in BB speed reduces happiness in these domains by around 0.007 and 0.006 standard deviations respectively.

Although we have controlled for area (LAD) level covariates and area FE, it is possible that children in more geographically isolated localities have worse internet access, and also fewer opportunities to engage in activities (such as sports, or interacting with friends) that could affect their psychological well-being. To investigate this, in Table 7 Panels E and F we split the sample according to whether the child lives in an urban or rural location.[22] No significant effects are found for children in rural households, but the negative effect of BB speed holds across each domain, for those children living in urban areas.

4.3. Potential mechanisms

This section explores the potential mechanisms that may explain the negative association between BB speed and wellbeing domains, discussed in Section 2. Firstly, for children living in a household with unemployed parent(s) a faster internet connection may help parents find jobs that better match their skills or exit unemployment spells more quickly. Secondly, a faster internet connection may affect the happiness of the parents, which in turn may influence the happiness of their children. Thirdly, an improved internet connection may be associated with children's academic outcomes. Fourthly, the internet may crowd-out other activities that the child would otherwise have undertaken which in turn reduces wellbeing. Finally, we consider whether BB speed is associated with children's use of social media.

To investigate each of the above channels we take a two-step approach. Firstly, we explore whether each of the mechanisms has a direct influence on each domain of children's wellbeing, to do this we estimate the following:

$$y_{ijw} = \boldsymbol{X}'_{ijw}\boldsymbol{\gamma}_1 + \theta mechanism_{ijw} + \alpha_{1i} + \psi_{1j} + \lambda_{1w} + \nu_{1ijw} \tag{4a}$$

where the results are shown in Table 8, which, for brevity, only report $\hat{\theta}$. Then in the next stage we investigate whether BB speed (Z_{jw}) is associated with the mechanism in question, by estimating:

$$mechanism_{ijw} = \boldsymbol{X}'_{ijw}\boldsymbol{\gamma}_2 + \pi Z_{jw} + \alpha_{2i} + \psi_{2j} + \lambda_{2w} + \nu_{2ijw} \tag{4b}$$

[21] Given that BB deployment increases over time (see Fig. 2) as does age of the children, splitting into age categories may help to disentangle these two effects.

[22] Urban areas are defined as settlements with a population of 10,000 or more according to Department for Environment, Food and Rural Affairs www.gov.uk/government/collections/rural-urban-classification.

Table 7
Coefficients for the reduced form relationship between wellbeing domains and broadband speed – heterogeneity.

PANEL A: Males	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0017	*(0.74)*	−0.0051	*(2.29)*	−0.0013	*(0.53)*	−0.0015	*(0.60)*	−0.0041	*(1.63)*	−0.0001	*(0.05)*
R-squared	0.0185		0.0339		0.0446		0.0247		0.0428		0.0241	
Observations (NT)	6964											
PANEL B: Females	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0057	*(2.27)*	−0.0063	*(2.43)*	−0.0031	*(1.19)*	−0.0052	*(1.90)*	−0.0024	*(0.87)*	−0.0040	*(1.50)*
R-squared	0.0514		0.1047		0.0890		0.0503		0.0966		0.0941	
Observations (NT)	6974											
PANEL C: Aged <13	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0026	*(0.75)*	−0.0068	*(2.02)*	−0.0060	*(1.96)*	−0.0060	*(1.53)*	−0.0006	*(0.20)*	−0.0020	*(0.58)*
R-squared	0.0164		0.0494		0.0533		0.0196		0.0344		0.0293	
Observations (NT)	6865											
PANEL D: Aged ≥13	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0137	*(4.26)*	−0.0090	*(3.10)*	−0.0029	*(0.89)*	−0.0072	*(2.86)*	−0.0006	*(0.17)*	−0.0061	*(1.92)*
R-squared	0.0292		0.0183		0.0281		0.0226		0.0294		0.0307	
Observations (NT)	7073											
PANEL E: Rural	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0052	*(1.12)*	−0.0017	*(0.35)*	0.0042	*(0.94)*	−0.0047	*(0.83)*	0.0006	*(0.15)*	−0.0011	*(0.21)*
R-squared	0.0244		0.0813		0.0581		0.0350		0.0802		0.0603	
Observations (NT)	2,301											
PANEL F: Urban	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
BB speed	−0.0039	*(2.06)*	−0.0085	*(4.41)*	−0.0040	*(2.69)*	−0.0039	*(1.72)*	−0.0052	*(2.41)*	−0.0036	*(1.95)*
R-squared	0.0274		0.0580		0.0637		0.0318		0.0634		0.0471	
Observations (NT)	11,637											

Controls include: age of child; number of children in household aged 0–2; number of children in household aged 3–4; number of children in household aged 5–11; number of children in household aged 12–15; whether live in a single parent household; whether parent(s) own home; whether either parent has a degree; log equivalized real household income; and year of interview. We also include 320 Local Authority indicators, i.e. area fixed effects, and the following LAD level covariates, the natural logarithm of: the unemployment rate; GVA per capita; share of females; share of population over 65; and share of population aged 16–65.

The results of this analysis are shown in Table 9, where for brevity we only report $\hat{\pi}$. From an empirical perspective, for a mechanism to be capable of explaining the link between BB speed and children's wellbeing one would expect the estimates of both θ and π to be statistically significant.

Initially, focusing upon on transitions in labour market state, we consider transitions of either parent from unemployment in the previous time-period into employment in the current year, giving a sample size of 5668 based on 2987 children. Table 8 Panel A shows that there is no association between parental transition into employment and any child wellbeing domain, and in Table 9 Panel A clearly BB speed has no significant effect on this potential mechanism (where Eq. 4b is estimated as a linear probability model). Next turning to the duration of the parents unemployment spell, based upon a sample of 5047 covering 2716 children who currently have an unemployed parent, there is some evidence of an inverse relationship between the length of time that the parent has been unemployed and their child's feelings about *school work* and *school* (Table 8 Panel B). However, it would appear that parental labour market experience is not a potential mechanism as BB speed has no significant effect on the duration of parental unemployment. Moreover, the coefficient is positive where a priori we would expect it to be negative, with faster internet connection allowing parents to exit unemployment quicker, perhaps due to enabling a better job match (maybe due to improved job search through online resources or through being able to obtain additional formal job interviews, e.g. see Gürtzgen et al., 2018).

We now consider the wellbeing of the parent as a potential mechanism for the effect on child wellbeing. We measure parental psychological wellbeing using the General Health Questionnaire (GHQ-12), which covers various dimensions, including: depression; anxiety; somatic symptoms; feelings of incompetence; difficulty in coping; and sleep disturbance (Goldberg and Williams, 1988).[23] The GHQ-12 score is on the scale 0 (the least distressed) through to 12 (the most distressed). After removing missing values on parental GHQ-12 the focus is upon a sample of 13,227 observations comprising 6069 children. The results shown in Table 8 Panel C reveal an inverse relationship between the parents GHQ-12 score and children's wellbeing across the domains *school work*, *appearance* and *life overall*, i.e. parents in more distressed states have children with lower wellbeing in these domains, $\hat{\theta} < 0$. This is consistent with an intergenerational correlation in wellbeing. However, whether this is the mechanism through which BB speed is operating is doubtful given the estimate of the

[23] The GHQ-12 is a widely used screening instrument for common mental disorders, in addition to being a general measure of psychiatric wellbeing.

Table 8
Potential mechanisms and children's wellbeing.

PANEL A: Transitions [1]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
UE to employed	−0.0374	*(0.82)*	0.0130	*(0.31)*	−0.0580	*(1.20)*	−0.0214	*(0.41)*	−0.0194	*(0.40)*	0.0092	*(0.21)*
R-squared	0.0335		0.0510		0.0461		0.0405		0.0561		0.0454	
Observations (NT)	5668											
PANEL B: Duration of UE spell [1]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
UE duration	−0.0459	*(2.63)*	−0.0234	*(1.49)*	−0.0270	*(1.52)*	−0.0189	*(1.09)*	−0.0452	*(2.61)*	−0.0326	*(0.68)*
R-squared	0.0365		0.0479		0.0520		0.0448		0.0661		0.0513	
Observations (NT)	5047											
PANEL C: Parental wellbeing [1]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
GHQ12	−0.0110	*(2.32)*	−0.0110	*(2.35)*	−0.0067	*(1.41)*	0.0032	*(0.58)*	−0.0042	*(0.91)*	−0.0120	*(2.54)*
R-squared	0.0302		0.0613		0.0646		0.0319		0.0677		0.0519	
Observations (NT)	13,227											
PANEL D: Key stage 2 [2]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
GCSE attainment	0.0100	*(0.38)*	0.0227	*(0.78)*	−0.0097	*(0.32)*	−0.0103	*(0.39)*	−0.0062	*(0.22)*	−0.0035	*(0.13)*
R-squared	0.5285		0.5281		0.4879		0.5186		0.4881		0.5221	
Observations (NT)	778											
PANEL E: Key stage 4 [2]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Hours spent online	−0.0001	*(0.01)*	0.0043	*(0.32)*	0.0026	*(0.20)*	−0.0016	*(0.13)*	0.0002	*(0.02)*	0.0107	*(0.79)*
R-squared	0.3376		0.3484		0.3497		0.3269		0.3210		0.3379	
Observations (NT)	1096											
PANEL F: Activities [3]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Number of activities	0.0542	*(3.58)*	0.0447	*(3.26)*	0.0036	*(0.25)*	0.0557	*(3.58)*	0.0221	*(1.48)*	0.0229	*(1.79)*
R-squared	0.0426		0.0979		0.0632		0.0513		0.0928		0.0754	
Observations (NT)	7389											
PANEL G: Social media [3]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Hours spent online	−0.0331	*(3.95)*	−0.0284	*(3.77)*	−0.0232	*(2.87)*	−0.0038	*(0.42)*	−0.0368	*(3.94)*	−0.0374	*(4.54)*
R-squared	0.0372		0.0586		0.0620		0.0386		0.0733		0.0624	
Observations (NT)	9948											
PANEL H: Social media [3]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
≥5 hours spent online	−0.1646	*(4.24)*	−0.1348	*(3.81)*	−0.1310	*(3.59)*	−0.0343	*(0.84)*	−0.1697	*(4.07)*	−0.1593	*(4.31)*
R-squared	0.0302		0.0607		0.0624		0.0309		0.0679		0.0517	
Observations (NT)	9948											
PANEL I: Social media [3]	SCHOOL WORK		APPEARANCE		FAMILY		FRIENDS		SCHOOL		LIFE	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Belong to social media site	−0.0812	*(3.29)*	−0.0653	*(2.90)*	−0.0386	*(1.65)*	0.0538	*(2.10)*	−0.0131	*(0.54)*	−0.0163	*(0.66)*
R-squared	0.0288		0.0596		0.0609		0.0313		0.0650		0.0491	
Observations (NT)	13,938											

Notes: [1] controls include: age of parent(s); age of child; number of children in household aged 0–2; 3–4; 5–11; 12–15; whether live in a single parent household; whether parent(s) own home; whether either parent has a degree; log equivalized real household income; and year of interview. Local Authority indicators, i.e. area fixed effects, are also included as well as the following LAD level covariates, the natural logarithm of: the unemployment rate; GVA per capita; share of females; share of population over 65; and share of population aged 16–65. [2] Regressions are at LAD level based on mean characteristics including area fixed effects, but excluding the age of the child and parent(s). Key Stage 2 tests are taken when children are aged 10–11, where the measure is the percentage of children obtaining level 4 or more in reading, writing and mathematics SATs (test score ranges from 1–100). Key Stage 4 (GCSE) tests are usually taken when children are aged 15/16, where the measure is the percentage of children who achieve five or more A* to C grades, including Mathematics and English. [3] Controls include: age of child; number of children in household aged 0–2; 3–4; 5–11; 12–15; whether live in a single parent household; whether parent(s) own home; whether either parent has a degree; log equivalized real household income; and year of interview. Local Authority indicators, i.e. area fixed effects, are also included as well as the following LAD level covariates, the natural logarithm of: the unemployment rate; GVA per capita; share of females; share of population over 65; and share of population aged 16–65. Each model includes child fixed effects, with the exception of Panels D and E.

Table 9
How broadband influences potential mechanisms.

	EFFECT OF BROADBAND SPEED ON POTENTIAL MECHANISMS			
	Coef	t-stat	R-squared	Observations (NT)
PANEL A: Transitions [1]	−0.0011	*(0.83)*	0.0875	5668
PANEL B: Duration of UE spell [1]	0.0091	*(1.60)*	0.2400	5047
PANEL C: Parental wellbeing [1]	−0.0044	*(0.99)*	0.0191	13,227
PANEL D: Key stage 2 – SATs [2]	0.1832	*(9.52)*	0.8742	778
PANEL E: Key stage 4 – GCSEs [2]	−0.3761	*(8.25)*	0.5534	1096
PANEL F: Number of activities	−0.0100	*(3.01)*	0.0810	7389
PANEL G: Social media – hours spent online [3]	0.0088	*(2.73)*	0.1298	9948
PANEL H: Social media – ≥5 hours spent online [3]	0.0016	*(2.42)*	0.0650	9948
PANEL I: Social media – Belong to social media site [3]	0.0045	*(5.37)*	0.0184	13,938

Each row represents a separate regression model; notes as per Table 8.

association of the speed of the internet connection with GHQ-12; $\hat{\pi}$, is statistically insignificant, as can be seen from Table 9 Panel C.[24]

A key potential mechanism through which BB speed may be operating is that of the child's educational progress. As part of the National Curriculum assessment in England, statutory Standard Attainment Tests (SATs) are undertaken throughout a child's school years. We explore attainment via two alternative outcome measures relevant for children of different ages. Key Stage 2 tests are taken when children are aged 10–11, and Key Stage 4 (GCSE) tests are usually taken when children are aged 15/16.[25] For Key Stage 2 our outcome is the percentage of children obtaining level 4 or more in reading, writing and mathematics SATs where the test score ranges from 1 to 100.[26] For Key Stage 4 our outcome is the percentage of children who achieve five or more A* to C grades, including Mathematics and English.[27] Unfortunately, these educational outcome measures are not available at the child level. Instead, we use LAD area level outcomes (for the LAD of pupil residence), which are defined consistently over the period 2013–2015 for Key Stage 2 and 2012-17 for Key Stage 4.[28] For this area level analysis we average child wellbeing scores (for the appropriately aged children) for each domain at the LAD-year level and all other covariates are also averaged accordingly. These data are then matched at the LAD-year level to the Key Stage test results. For the Key Stage 2 results we focus on children aged 10 and 11, yielding a sample of 778 observations. For the Key Stage 4 results we focus on children aged 15 giving a sample of 1096 observations. For this analysis, the regressions in Eqs. (4a) and (4b) are based at the LAD level conditional on annual mean characteristics incorporating area FE.

The results are shown in Table 8 Panels D (Key Stage 2) and E (Key Stage 4); these reveal no relationship between test scores in reading, writing and mathematics (Key Stage 2 performance), or GCSE attainment (Key Stage 4 performance) and any of the child wellbeing domains. However, interestingly BB speed is strongly positively associated with Key Stage 2 attainment, and negatively associated with Key Stage 4 attainment, as can be seen from Table 9 Panel D (E). This evidence suggests that the effect of faster internet speeds on child wellbeing domains is not operating through educational attainment. This is consistent with the findings of Faber et al. (2015) who report that even very large changes in available internet speeds have an estimated zero effect on educational attainment (i.e. when summed across different Key Stages).

Next, we consider whether a faster internet connection potentially crowds out beneficial activities that the child might otherwise engage in. In waves 4, 6 and 8 of the UKHLS children were asked a series questions regarding the activities that they undertake, including: playing sports; face-to-face interaction with friends and family; going to youth clubs or other organised events; undertaking voluntary or community work; and attending out of school classes such as art, music etc. Focusing upon a subsample of 5150 children (7389 observations) present in these waves, we sum the number of activities that the child undertakes at least once per week. The number of activities ranges from zero (13.5 %) to six or more (2.5 %) where on average children undertake two activities at least once a week. Table 8 Panel F shows that the number of activities that the child undertakes is positively associated with wellbeing, and significantly so for four out of six domains. In Table 9 Panel F, we explore whether BB speed is potentially crowding out face-to-face interaction. The estimate on BB speed is negative and statistically significant, which is consistent with the crowding out hypothesis whereby the internet reduces the number of activities the child undertakes, which ultimately results in lower wellbeing (Moreno et al., 2013; Wallsten, 2013).

[24] In terms of the mechanisms considered so far: labour market transitions are based upon either the mother or father exiting unemployment into a state of employment; the duration of the unemployment spell is the average across both parents; and the GHQ-12 score is also averaged across both parents, where applicable (i.e. couple households). The same results hold if we consider the father only, the mother only, or single parent households. Results are available upon request.

[25] Note that information on Key Stage 3, SATs taken between ages 11 and 14, stopped being collected in 2011 with information from 2009 based solely upon on-going teacher assessment.

[26] https://www.gov.uk/government/collections/statistics-key-stage-2. The national expectation for children in English schools is that children reach a level 2/3 by the end of Year 2 (Key Stage 1 SATs) and a level 4/5 by the end of Year 6 (Key Stage 2 SATs).

[27] https://www.gov.uk/government/collections/statistics-gcses-key-stage-4

[28] Ideally, the analysis would be at the child level. However, currently this is not possible by matching in the National Pupil Database (NPD) to the UKHLS as the matched NPD data is only available for those children interviewed in UKHLS wave 1, and the NPD data for these children is only available up to 2012/13.

The final mechanism we explore is the role of social media. Given that social media sites are children's primary interface with the internet, we believe that they may represent a key channel for the effects of internet use on wellbeing. In the Youth Self-completion Questionnaire of the UKHLS children are asked: *Do you belong to a social website such as Bebo, Facebook or Myspace?* 65 % 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 website like that on a normal school day?* The responses to this question are coded into the variable range from "1=none", "2=less than an hour", "3 = 1–3 h", "4 = 4–6 h", and "5 = 7 or more hours". We replace the 1–5 scale with "midpoints" of the ranges (i.e. 0, 0.5, 2, 5, and 8) since arguably this is a better approximation of the linear effect and also enables interpretation of the impact an additional hour spent online.[29] In Tables 8 and 9 Panels G to I we consider: the number of hours spent online; non-linearity by exploring whether children spend 5 or more hours online; and then whether the child is a member of a social media site, respectively. For hours spent online and intense time spent using social media (i.e. 5 h or above), the sample size is 9948 comprising 5235 children; whilst for membership of a social network the corresponding observations are 13,938 and 6310 respectively (the sample size for time spent online is slightly lower due to missing values on hours).

Focusing on hours spent online and the association with children's wellbeing, Table 8 Panel G reveals that time spent online is inversely related to each domain and statistically significant, with the exception of *friends*. For example, an extra hour spent online decreases the wellbeing score of *appearance* and *school work* by around 0.03 standard deviations (i.e. approximately 3 per cent). Similarly, spending a large amount of time online (5 h or more), has a large inverse association with all wellbeing domains apart from *friends*, see Table 8 Panel H; thus it appears that the negative effects of social media use are intensified with high use.

Another aspect which we investigate is the decision to use social media, where again there is an inverse relationship across three of the six domains, see Table 8 Panel I, although perhaps not surprisingly, the magnitude of the effect is not as large as that seen in Panel G from extremely high daily time spent online. It would appear that time spent online using social media sites is a plausible mechanism, but empirically this rests upon $\pi > 0$, i.e. faster internet speed should a priori result in more time spent using online sites, and moreover whether the estimate is statistically significant. This is investigated by estimating Eq. (4b), with the results reported in Table 9 Panels G to I, where greater internet speed is associated with more time spent online, intense usage (five or more hours) and membership of social media sites. This is evidence in favour of social media being a key mechanism that could link BB speed to child wellbeing;[30] in contrast, evidence of other mechanisms possibly operating through parental outcomes, e.g. in the labour market or intergenerational transmission of wellbeing, or the child's educational progress, are not evident in the data.

5. Conclusion

In this paper we have explored the effect of internet use on the psychological wellbeing of children aged 10–15, measured by the way they feel about five different aspects of their life, and their life overall. Internet use is proxied by the BB speed available in the neighbourhood. We employ a FE framework where, based upon the quasi-random allocation of BB speed, we recover the ITT effect, which shows that even in the most stringent specifications estimated there is evidence of a negative causal relationship between faster BB speed and domains of children's wellbeing. The largest effect from a 1 % increase in BB speed is for how children feel about their *appearance*, decreasing the score by approximately 0.6 per cent on average. A number of potential channels are investigated as possible mechanisms capable of explaining this phenomenon. The empirical analysis provides support for both the 'crowding out' hypothesis (whereby beneficial activities are sacrificed for more time spent on the internet) and also for the adverse effect of increased social media use.

The internet, and social media in particular, are hugely important phenomena of the past decade. Given the extent of use among children and adolescents, concern with the potential adverse (and long-term) effects on children's emotional health is increasing. The results of our analysis are important given the central role of these platforms in children's lives, and the fact that childhood wellbeing has been shown in previous research to have persistent effects into adult life (e.g. Lindeboom et al. (2010); Conti and Heckman (2014) and Bertoni (2015)). Our results suggest that interventions to appropriately limit internet and social media use during childhood may help to improve emotional health.

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[29] We are grateful to an anonymous referee for this suggestion.

[30] These results might also explain why in the sub-group analysis the effects of BB speed were only observed for older children, given the minimum age stipulation on social media use; and similarly, when we considered gender differences the wellbeing of girls was more adversely affected by BB speed (consistent with Booker et al., 2018), see Table 7.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jhealeco.2019.102274.

References

Akerman, A., Gaarder, I., Mogstad, M., 2015. The skill complementarity of broadband internet. Q. J. Econ. 130, 1781–1824.
Altonji, J.G., Elder, T.E., Taber, C.R., 2005a. An evaluation of instrumental variable strategies for estimating the effects of Catholic schooling. J. Hum. Resour. 40, 791–821.
Altonji, J.G., Elder, T.E., Taber, C.R., 2005b. Selection on observed and unobserved variables: assessing the effectiveness of Catholic schools. J. Polit. Econ. 113, 151–184.
Anand, P., Roope, L., 2016. The development and happiness of very young children. Soc. Choice Welfare 47, 825–851.
Angrist, J., Pischke, J.-S., 2009. Mostly Harmless Econometrics: An Empiricists Companion. Princeton University Press.
Antoci, A., Sabatini, F., Sodini, M., 2012. See you on Facebook! A framework for analyzing the role of computer-mediated interaction in the evolution of social capital. J. Socio- Econ. 41, 541–547.
Barnardo's, 2015. Youth and the Internet: A Guide for Policy Makers. www.barnardos.org.uk/youth_and_the_internet_report.pdf.
Bauernschuster, S., Falck, O., Woessmann, L., 2014. Surfing alone? The internet and social capital: evidence from an unforeseeable technology mistake. J. Public Econ. 117, 73–89.
Bertoni, M., 2015. Hungry today, unhappy tomorrow? Childhood hunger and subjective wellbeing later in life. J. Health Econ. 40, 40–53.
Beardsmore, R., 2015. Measuring National Well-being: Insights Into Children's Mental Health and Well-being. Office for National Statistics, London.
Bhuller, M., Havnes, T., Leuven, E., Mogstad, M., 2013. Broadband internet: An information superhighway to sex crime? Rev. Econ. Stud. 80, 1237–1266.
Booker, C., Kelly, Y., Sacker, A., 2018. Gender differences in the associations between age trends of social media interaction and well-being among 10-15 years olds in the UK. BMC Public Health 18 (321).
Boyd, D., 2014. It's Complicated: The Social Lives of Networked Teens. Yale University Press.
Brenner, V., 1997. Psychology of computer use: XLVII. Parameters of internet use, abuse, and addiction: the first 90 days of the internet usage survey. Psychol. Rep. 80, 878–882.
Brown, S., Taylor, K., 2008. Bullying, education and earnings: evidence from the national child development study. Econ. Educ. Rev. 27, 387–401.
Bulman, G., Fairlie, R.W., 2016. Technology and education: computers, software, and the internet. In: Hanushek, E.A., Machin, S., Woessmann, L. (Eds.), Handbook of the Economics of Education, vol. 5. Elsevier, pp. 239–280.
Carr, N., 2010. The Shallows: How the Internet Is Changing the Way We Think, Read and Remember. Atlantic Books.
Castellacci, F., Tveito, V., 2018. Internet use and well-being: a survey and a theoretical framework. Res. Policy 47, 308–325.
Children's Society, www.childrenssociety.org.uk/ 2018a. Safety Net: Cyberbullying's Impact on Young People's Mental Health: Inquiry Report.
Children's Society, www.childrenssociety.org.uk 2018b. The Good Childhood Report.
Chou, H.G., Edge, N., 2012. "They are happier and having better lives than I am": the impact of using Facebook on perceptions of others' lives. Cyberpsychol. Behav. Soc. Netw. 15, 117–121.
Clark, A.E., Flèche, S., Layard, R., Powdthavee, N., Ward, G., 2018. The Origins of Happiness: The Science of Well-being Over the Life Course. Princeton University Press.
Clark, A.E., Senik, C., 2010. Who compares to whom? The anatomy of income comparisons in Europe. Econ. J. 120, 573–594.
Conti, G., Heckman, J.J., 2014. Economics of child well-being. In: Ben-Arieh, A., Casas, F., Frones, I., Korbin, J.E. (Eds.), Handbook of Child Well-Being: Theories, Methods and Policies in Global Perspective. Springer, pp. 363–401.
Cotton, S.R., 2008. Students' technology use and the impacts on well-being. New Dir. Stud. Serv. 124, 55–70.
Cowie, H., 2013. Cyberbullying and its impact on young people's emotional health and well-being. Psychiatrist 37, 167–170.
Department for Business Innovation and Skills and Department for Culture Media and Sport, 2009. Digital Britain: Final report. Cm7650.
Department for Business Innovation and Skills and Department for Culture Media and Sport, 2010. Britain's Superfast Broadband Future.
Department for Digital, Culture Media and Sport, 2018. Evaluation of the Economic Impact and Public Value of the Superfast Broadband Programme.
Enke, B., 2017. What You See Is All There Is. Harvard University, Mimeo.
Eriksen, T., Nielsen, H., Simonsen, M., 2014. Bullying in elementary school. J. Hum. Resour. 49, 839–871.
Faber, B., Sanchis-Guarner, R., Weinhardt, F., 2015. ICT And Education: Evidence From Student Home Addresses. CEP Discussion Paper No. 1359.
Ferrer-i-Carbonell, A., Frijters, P., 2004. How important is methodology for the estimate of the determinants of happiness? Econ. J. 114, 641–659.
Franzen, A., 2003. Social capital and the Internet: evidence from Swiss panel data. Kyklos 56, 341–360.
Fujiwara, D., Houston, R., Keohane, K., Gramatki, I., Maxwell, C., 2018. Subjective Wellbeing Analysis of the Superfast Broadband Programme. Simetrica.
Goldberg, D.P., Williams, P., 1988. A User's Guide to the GHQ. NFER-Nelson, Windsor.
Gross, E.F., Juvonen, J., Gable, S.L., 2002. Internet use and well-being in adolescence. J. Soc. Issues 58, 75–90.
Gürtzgen, N., Nolte, A., Pohlan, L., van den Berg, G., 2018. Do Digital Information Technologies Help Unemployed Job Seekers Find a Job? Evidence From the Broadband Internet Expansion in Germany. IZA Discussion Paper No. 11555.
Helliwell, J., Huang, H., 2013. Comparing the happiness effects of real and on-line friends. PLoS One 8, 1–17.
Hinduja, S., Patchin, J.W., 2010. Bullying, cyberbullying, and suicide. Arch. Suicide Res. 14, 206–221.
HM Government, 2019. Online Harms White Paper. CP57.
House of Lords, 2017. Growing up With the Internet. HL 130.
Institute for Public Policy Research, 2014. Young People, Sex and Relationships: The New Norms. IPPR, London.
Jackson, L.A., Fitzgerald, H.E., Zhao, Y., Kolenic, A., von Eye, A., Harold, R., 2008. Information Technology (IT) use and children's psychological well-being. Cyberpsychology Behav. 11, 755–758.
Kahneman, D., Diener, E., Schwarz, N., 1999. Well-being: The Foundations of Hedonic Psychology. Russell Sage Foundation.
Kaiser Family Foundation, 2010. Generation M2: Media in the Lives of 8- to 18-Year Olds. Kaiser Family Foundation Study.
Kalmus, V., Siibak, A., Blinka, L., 2014. Internet and child well-being. In: Ben-Arieh, A., Casas, F., Frones, I., Korbin, J.E. (Eds.), Handbook of Child Well-Being: Theories, Methods and Policies in Global Perspective. Springer, pp. 2093–2133.
Kleemans, M., Daalmans, S., Carbaat, I., Anshutz, D., 2016. Picture perfect: the direct effect of manipulated Instagram photos on body image in adolescent girls. Media Psychol. 21, 93–110.
Kraut, R., Patterson, M., Lundmark, V., Kiesler, S., Mukopadhyay, T., Scherlis, W., 1998. A social technology that reduces social involvement and psychological wellbeing? Am. Psychol. 53, 1017–1031.
Kross, E., Verduyn, P., Demiralp, E., Park, J., Lee, D.S., Lin, N., 2013. Facebook use predicts declines in subjective well-being in young adults. PLoS One 8, 1–6.
Kuss, D.J., Griffiths, M.D., 2012. Online gaming addiction in children and adolescents: a review of empirical research. J. Behav. Addict. 1, 3–22.
Levenson, J.C., Shensa, A., Sidani, J.E., Colditz, J.B., Primack, B.A., 2016. The association between social media use and sleep disturbance among young adults. Prev. Med. 85, 36–41.
Lindeboom, M., Portrait, F., van den Berg, G.J., 2010. Long-run effects on longevity of a nutritional shock early in life: the Dutch potato famine of 1846-1847. J. Health Econ. 29, 617–629.

Lohmann, S., 2015. Information technologies and subjective well-being: Does the internet raise material aspirations? Oxf. Econ. Pap. 67, 740–759.

Martellozzo, E., Monaghan, A., Adler, J.R., Davidson, J., Leyva, R., Horvath, M.A.H., 2016. I Wasn't Sure It Was Normal to Watch It. . . NSPCC. Middlesex University, London.

Mazumder, B., Davis, J.M.V., 2013. Parental earnings and children's well-being: An analysis of the Survey of Income and Programme Participation matched to social security administrative earnings data. Econ. Inq. 51, 1795–1808.

Mendelson, A.L., Papacharissi, Z., 2010. Look at us: collective narcissism in college student facebook photo galleries. In: Papacharissi, Z. (Ed.), The Networked Self: Identity, Community and Culture on Social Network Sites. Oxford University Press, New York, pp. 251–273.

Moreno, M.A., Jelenchick, L.A., Koff, R., Eickhoff, J.C., Goniu, N., Davis, A., Young, H.N., Cox, E.D., Christakis, D.A., 2013. Associations between internet use and fitness among college students: an experience sampling approach. J. Interact. Sci. 1, 4.

Nikolaou, D., 2017. Does cyberbullying impact youth suicidal behaviors? J. Health Econ. 56, 30–46.

Ofcom, www.ofcom.org.uk/ 2015. Children and Parents: Media Use and Attitudes Report.

Ofcom, www.ofcom.org.uk/ 2016. Children and Parents: Media Use and Attitudes Report.

Pfeffer, F., Schoeni, R., 2014. Intergenerational transmission of well-being. Focus 31, 39–43.

Royal Society for Public Health, London 2017. #StatusofMind: Social Media and Young People's Mental Health and Wellbeing.

Sabatini, F., Sarracino, F., 2016. Keeping up With the e-Joneses: Do Online Social Networks Raise Social Comparisons? Munich Personal RePEc Archive, pp. 69201.

Sabatini, F., Sarracino, F., 2017. Online social networks and subjective wellbeing. Kyklos 70, 456–480.

Sampasa-Kanyinga, H., Hamilton, H.A., 2015. Use of social networking sites and risk of cyberbullying victimization: a population-level study of adolescents. Cyberpsychol. Behav. Soc. Netw. 18, 704–710.

Slonje, R., Smith, P.K., Frisén, A., 2012. The nature of cyberbullying, and strategies for prevention. Comput. Human Behav. 29, 26–32.

Tandoc Jr., E.C., Ferrucci, P., Duffy, M., 2015. Facebook use, envy, and depression among college students: Is Facebook depressing? Comput. Human Behav. 43, 139–146.

University of Essex, 2018. Institute for Social and Economic Research, NatCen Social Research, Kantar Public. Understanding Society: Waves 1-8, 2009-2017 and Harmonised BHPS: Waves 1-18, 1991-2009. [data collection], 11th edition., pp. 6614, UK Data Service. SN.

Verduyn, P., Lee, D.S., Park, J., Shablack, H., Orvell, A., Bayer, J., Ybarra, O., Jonides, J., Kross, E., 2015. Passive Facebook usage undermines affective well-being: experimental and longitudinal evidence. J. Exp. Psychol. Gen. 144, 480–488.

Wallsten, S., 2013. What Are We Not Doing When We're Online? NBER Working Paper No. 19549.