I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12834

Social Media Extensive Use and Emotional and Behavioural Outcomes in Adolescence: Evidence from British Longitudinal Data

Paul McNamee
Silvia Mendolia
Oleg Yerokhin

DECEMBER 2019

DISCUSSION PAPER SERIES

IZA DP No. 12834

Social Media Extensive Use and Emotional and Behavioural Outcomes in Adolescence: Evidence from British Longitudinal Data

Paul McNamee
University of Aberdeen

Silvia Mendolia
University of Wollongong and IZA

Oleg Yerokhin
University of Wollongong

DECEMBER 2019

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Social Media Extensive Use and Emotional and Behavioural Outcomes in Adolescence: Evidence from British Longitudinal Data

We investigate the relationship between social media use and emotional and behavioural outcomes in adolescence using data from a large and detailed longitudinal study of teenagers from the UK. To the best of our knowledge, this is the first study in economics to analyse the effect of social media use on adolescents' mental health. We use individual fixed effects, propensity score matching and treatment effects with Inverse Probability Weighted Regression Adjustment, controlling for a rich set of children's and family's characteristics and using comprehensive sensitivity analyses and tests to assess the potential role of unobserved variables. Our results show that prolonged use of social media (more than 4 hours per day) is significantly associated with poorer emotional health and more behavioural difficulties, and in particular decreased perception of self-value and increased incidence of hyperactivity, inattention and conduct problems. However, limited use of social media (less than 3 hours per day) has some positive effect on peer relationships.

JEL Classification: I10
Keywords: social media, mental health, fixed effects

Corresponding author:
Silvia Mendolia
School of Accounting, Economics and Finance
University of Wollongong
Northfields Avenue
North Wollongong, NSW 2522
Australia
E-mail: smendoli@uow.edu.au

1. Introduction

Poor mental health in adolescence has several long lasting consequences. Young people with mental health conditions are more likely to experience difficulties in their education (through increased chances of suspensions, exclusions, etc), poor engagement in the labour market (increases chances of unemployment and dependence on welfare), and are more likely to engage in criminal activities (see for example Currie and Stabile, 2006; Goodman et al., 2011; Lundborg et al, 2014, Anderson et al., 2015; Khan et al., 2015; Knapp et al., 2016; among many others, for a discussion of the impact of mental health conditions in childhood and adolescence on later life outcomes)

Social media are an important part of teenagers' lives throughout the world, with young people in the UK being extensive users of social media sites, such as Facebook, Instagram and Snapchat. Recent OECD data show that almost 95% of British 15 years old used social media outside school hours (OECD, 2016) and around 11% of girls and 5% of boys between 10 and 15 years old spent over three hours on social media on a normal school day in 2012 (ONS, 2013). Social media are an integral part of how young people interact with each other, and time spent on social media accounts for a substantial part of their communication time (Frith, 2017; Royal Sociey for Public Health, 2018). Further, children and young people are likely to access the internet and use social media privately, using mobile devices from their bedrooms, without any form of adult supervision (Frith, 2017).

The widespread use of internet and social media could constitute an opportunity for innovation, socialization and learning, but policy makers and researchers in public health have begun to raise concerns about the potential implications for young people's mental well-being (Royal Society for Public Health, 2018). Evidence of social media addiction affecting around 5% of young people is beginning to emerge (Centre for Mental Health, 2018), and concerns surrounding social media and young people have been debated in multiple domains (see for example, Parliamentary discussion in Britain in 2016, Adcok, 2016).

The evidence on the possible causal relationship between social media exposure and adolescents' well-being is scarce and most of the existing literature uses cross-sectional data, without considering the importance of unobserved individual characteristics. For this reason, several studies have pointed out that more research is needed, in order to fully understand the potential impact of social media use on young people's lives (see for example Adcok, 2016; Gunnell, 2018; Frith, 2017; Royal Society for Public Health, 2018; House of Commons, 2019; for a comprehensive review of existing descriptive evidence).

This study investigates the association between social media use and emotional and behavioural well-being for British adolescents, using data from *Understanding Society*, the UK Household Longitudinal Study. The economics literature on this issue is very limited. Our objective is to contribute to it by estimating the strength of the association between social media use and adolescents emotional and behavioural outcomes.

There are a variety of channels through which social media use can affect adolescents' well-being and mental health. On one hand, social media can promote interaction with peers with similar interests, facilitate communication and information on sensitive topics, and can be a vehicle of collaboration and involvement with the community. On the other hand, it can also facilitate the sourcing and transmission of harmful content, such as the spreading of cyber bullying and peer pressure, which can affect sleep patterns, perception of body image, and ultimately can result in increased stress and anxiety (see Adcok, 2016 for an interesting summary of recent evidence). For all these reasons, it is important to provide new evidence of the impact of social media exposure on teenagers, and focus special attention on the role of individual unobserved characteristics, as well as on the heterogeneity of the effects.

We contribute to the literature on social media and adolescents' well-being in several ways. First, we extend the existing literature from epidemiology, public health and social sciences by using longitudinal data and separately accounting for individual unobserved heterogeneity, and by analysing the relationship between social media use in adolescence and mental health in early adulthood years (16-20 years old). Existing studies analyse contemporaneous correlations between social media use and outcomes, and do not take into account the existence of unobserved time invariant characteristics (see for example Kelly et al., 2018, among many others). In other words, it is possible that unobserved characteristics such as personality traits, attitudes, or family values affect both social media use and outcomes. We explicitly consider this possibility and estimate models using individual fixed effects.

Second, we test our findings by using propensity score matching, which allows robust comparisons of individuals who are similar based on observable characteristics but differ in their social media use.

Third, we explore the effects of different level of exposure to social media using a treatment-effects inverse-probability-weighted regression-adjustment (IPWRA) framework developed by Imbens and Wooldridge (2009) and recently implemented by Cattaneo et al. (2013). Most of the existing evidence analyses social media activity without clearly distinguishing the level of exposure. Our results show that the association between social media use and mental health is particularly problematic only in the case of very long hours of exposure.

Fourth, we analyse the heterogeneity of the effect of social media, by studying the impact by gender, age, and socio-economic background of the child, and therefore we shed some light on the possible policy implications of our findings, by identifying the most vulnerable groups.

Lastly, we expand the analysis of the effect of social media, by considering different outcomes, and in particular focusing the attention on the relationship between social media use and behavioural difficulties.

The analysis of teenagers' mental well-being is especially relevant for the British population. Several studies in the UK have showed that mood disorders in young people have increased dramatically in the recent years, particularly among girls and young women (see Collishaw, 2015; Knapp et al, 2016; and Gunnell et al., 2018, among many others). Recent evidence has suggested that one in ten children and young people has some form of clinically diagnosable mental health disorder, including around 6% of British children having conduct disorder, over 3% having anxiety, 1% having depression, and between 1 and 3% with other disorders (UK Department of Health, 2017). Self-harm among adolescents has steadily increased over the last decade (see for example Morgan et al, 2017 describing a 68% increase in cases of hospital self-harm presentations in teenager girls between 2011 and 2014). Further, over three quarters of mental illness in adult life starts in adolescence (Knapp et al., 2016).

Our results show that long hours of social media activity are strongly associated with an increase of behavioural problems and lower mental health. The same association is not found when adolescents spend limited time on social media, which can have a mildly positive effect on peer relationships. There is, of course, the risk that potential confounders may affect our modeling, even when we use individual fixed effects estimation, since this approach addresses bias associated with time-invariant confounders. In our setting, we have extensive data on many of the determinants of social media use identified in the previous literature, and we build a credible case for a selection on observed variables assumption. However, we recognise that bias from unobserved variables may remain a concern. For these reasons, we also provide further tests of the results, using treatment effects and propensity score matching. Further, we perform tests that consider the possibility of selection on unobservables in the model (see Oster, 2019; Krauth, 2016), in order to examine the potential for these characteristics to affect the estimates. However, while the results can be taken as further evidence of a robust relationship between social media use and emotional and behavioural outcomes, caution must still be exercised when deriving causal inferences.

The rest of the paper is organised in the following sections. Section 2 provides a brief review of the most relevant work. Section 3 describes our data, Section 4 outlines our estimation methods, Section 5 presents results, and Section 6 discusses the results.

2. Review of existing literature

The role of technology in affecting human lives and well-being, and in particular the health and well-being of young people, is an issue that has attracted the attention of policy-makers and social scientists in recent years. The link between television and poor health and well-being outcomes (such as increased obesity, fast food consumption, sedentary lifestyle etc.) has now been established in many studies from various disciplines (see for example Department of Health, 2010 for a review of the existing evidence; and Hyll and Schneider, 2013).

However, technology has continued to change, and recent evidence shows that young people spend more time online than watching television (Ofcom, 2015). Recent studies in public health and epidemiology have analysed the relationship between social media use and several indicators of well-being and have produced mixed results (see for example Adcok, 2016; Royal Society for Public Health, 2018; Booker et al., 2018 for a review of the existing evidence). They concluded that more research is needed, especially using longitudinal data. Some recent evidence has shown that adolescents who spend long periods of time on social network websites show more body image concerns; lower levels of well-being, increased depressive symptoms, and poorer sleep quality (see for example Fardouly et al., 2015; Woods and Scott, 2016; Booker et al., 2018; Kelly et al., 2018; Viner et al., 2019). Recent studies have also documented the association between social media use and risky behaviours, lack of physical activity; and increased cyber bullying, (Nesi et al., 2017; Viner et al., 2019).

The main drawback of many of these studies is that they do not directly take into account the possibility that unobserved characteristics or other confounders (such as, for example, personality traits, ability, family values and beliefs, etc.) could explain the relationship between social media use and well-being. These characteristics could make, for example, an individual more likely to use social media and have poor mental well-being. Further, cross-sectional descriptive studies do not consider the risk of reverse causality (i.e. young people may be going online because they have low levels of well-being, and the relationship may run from well-being to social media use, rather than *viceversa*). This is a major limitation and substantially reduces the possibility to draw causal inferences from the existing literature.

Some recent evidence from studies in experimental psychology has pointed out the importance of longitudinal data to analyse these issues, and has showed that results change substantially (more specifically, the relationship between technology use and well-being is lower) when longitudinal data are used (Orben et al, 2019). Further, some of the most recent studies show that little clear evidence can be derived from small exploratory studies, as these may suffer from several sources of bias.It is argued therefore that large scale data and more complex data analysis is needed to derive clearer results and conclusions (Orben and Przybylski, 2019).

Economists have recently began to engage with the analysis of the impact of social media on health, well-being and economic outcomes, and have analysed the relationship between internet use and income comparisons (Clark and Senik, 2010; Lohman, 2015), the impact of social image on economic behaviours (Holm and Samahita, 2018), or, more broadly, the impact of technology devices on young people's development (see for example Suziedelyte, 2015 for an analysis of the impact of videogames on teenagers' development). Lohman (2015) analyses the relationship between internet access and well-being, with specific attention to the way individuals position themselves in the society, and the well-being associated with these comparisons. Results from this study show that households with internet access have higher material aspirations, and in general lower satisfaction with their material possessions, and positionality concerns seem to play a very important role in this framework. Wallsten (2013) analyses the crowdout effect of time spent online and shows that increasing online leisure time decreases time for other activities, such as socialising, attending cultural events, working and sleeping. All of these factors may play a separate role in the analysis of the impact of social media use on young people's lives.

The economic literature on the effect of social media on health and well-being outcomes is extremely limited. McDool et al (2019) use the UK Household Longitudinal Study to analyse the relationship between internet use and life satisfaction for adolescents. They use quasi-random assignment of broadband speed (BB) to identify the effect; and show that an increase in BB speed reduces life satisfaction in several domains, including school work; appearance; family; and life as a whole. These results also suggest that the negative effect is driven by reduced time spent in other activities and by negative effect of social media use. The validity of these estimates relies on the assumption that BB speed was quasi-randomly assigned and not related to time-varying local area characteristics, which may also affect life satisfaction (see Department for Communities and Local Government, 2013, for a discussion of well-being by regional areas).

Our work complements and extends this very limited evidence by specifically analysing the association between social media use (rather than internet access) and new emotional and behavioural outcomes, by comparing the effect of different levels of engagement with social media (and in particular on the effect of prolonged exposure vs. limited number of hours online per day), and by extending the methodology used, including estimation with individual fixed effects, and matching methods and treatment effects to limit the risk of selection on the basis of observable characteristics. Further, we extend the limited existing evidence on the impact of social media use on contemporaneous mental health by analysing long lasting effects on mental well-being in late teenager years and early adulthood.

3. Data and descriptive statistics

We use data from the UK Household Longitudinal Study (UKHLS), known as *Understanding Society,* and in particular, from the youth questionnaire, including interviews with all children between 10 and 15 years old who belong to households in the survey.

UKHLS surveyed approximately 40,000 households living in the United Kingdom in wave 1, and included a wide range of questions on social, economic and behavioural issues. Data collection started in 2009-2010 for wave 1 and eight waves of data are currently available. All adult household members were interviewed at each successive wave, to verify how their personal and professional situation had changed. All household members aged 10-15 years completed a short self-completion youth questionnaire each year, until they were eligible to answer the adult survey at age 16. We use information about the children from the youth questionnaire and combine it with information about the parents derived from the adult survey. The final estimation sample includes over 23,000 observations from over 8,000 children.

The independent variable of interest is social media use and this information is derived from two questions asked at every wave. In the first question, the children are asked whether they belong to a social media website (such as Bebo, Facebook, Myspace, etc.) and, if they answer positively to this question, they are also asked how long they spend chatting or interacting with friends through a social web-site on a normal school day. The options to answer this question are: none, less than an hour, 1-3 hours, 4-6 hours, and 7 or more hours.

In the estimation, responders who say they do not belong to any social media website are grouped with those who say they do not spend any hours interacting with friends online.

3.1 Outcomes

We consider a variety of emotional and behavioural outcomes in order to draw a complete picture of the impact of social media use on teenagers' mental health.

We begin by analysing answers to eight questions included in the UKHLS youth survey covering mental well-being. These questions are very similar to the General Health Questionnaire items included in the adult survey. These questions are asked every second wave starting at wave 2 and are:

- I feel I have a number of good qualities
- I feel that I do not have much to be proud of
- I certainly feel useless at times
- I am able to do things as well as most other people
- I am a likeable person
- I can usually solve my own problems
- All in all, I am inclined to feel I am a failure
- At times, I feel I am no good at all

Children can answer these questions on a scale 1 to 4, with answers ranging from "Strongly agree" to "Strongly disagree". We follow the literature (see for example Ermisch et al., 2001) and construct a mental health indicator by summing up the number of times individuals place themselves in the most distressed category. The mental health index ranges from 0 to 8, where 0 indicates no problems at all and 8 indicates maximum mental distress.

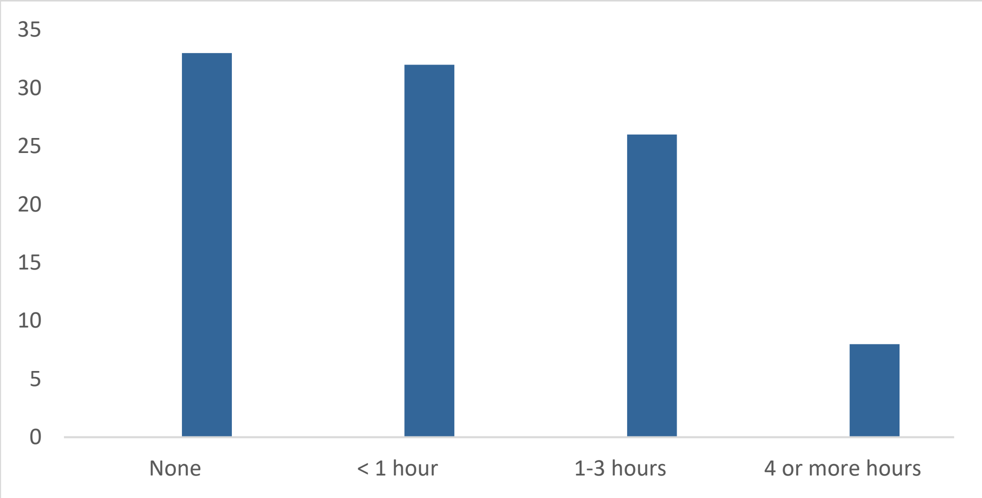
Second, we analyse the relationship between social media activity and the Strengths and Difficulties Questionnaire (SDQ), which is a behavioural screening questionnaire for children and young people. The SDQ includes 25 questions covering five areas, including hyperactivity/inattention, emotional symptoms, conduct problems, peer relationship, and pro-social behaviour. Children are presented with the 25 statements and can choose one option between: 'not true', 'somewhat true' and 'certainly true'. Twenty of these items (excluding the ones related to prosocial behaviour) are summed to create a total difficulties score which ranges from 0 to 40 (see Goodman, 1997 and Goodman, 1998 for a detailed analysis of SDQ). The UKHLS youth questionnaires includes SDQ every second wave (starting at wave 1).

Lastly, when young people turn 16, they are interviewed in the adult survey, which include the General Health Questionnaire (GHQ) Caseness score. Previous literature refers to the GHQ as one of the most reliable indicators of psychological distress or "disutility" (Argyle, 1989; Clark and Oswald, 1994). The GHQ Caseness score is constructed from the responses to 12 questions covering feelings of strain, depression, inability to cope, anxiety-based insomnia and lack of confidence. The twelve answers are combined into a total GHQ score that indicates the level of mental distress, giving a scale running from 0 (the least distressed) to 12 (the most distressed). Therefore, we are able to track children staying in the adult survey and observe the impact of social media use at age 14-15 on mental health at ages 16 to 20 years old.

3.2 Descriptive statistics

We begin by analysing social media use in the data and presenting a detailed analysis of the observable characteristics of children who use social media. Around a third of children in the estimation sample do not spend any time chatting and interacting with friends online (or do not have a social media profile), a similar proportion spends less than an hour online on a school day, just over a quarter of the sample is online between 1 and 3 hours per day, and around 8% of the interviewed children spend over 4 hours chatting online (see Figure 1).

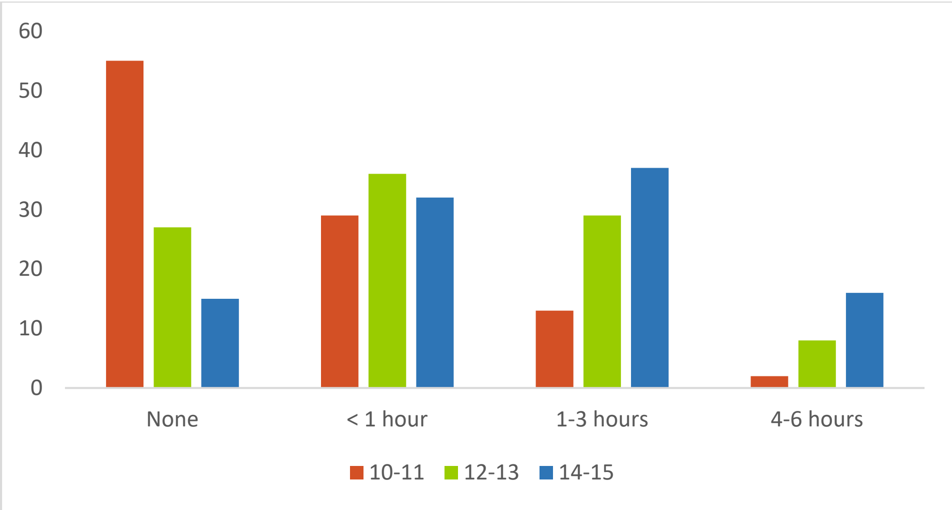
Figure 1 – Social media use in the estimation sample



N = 24,091 observations (NxT)

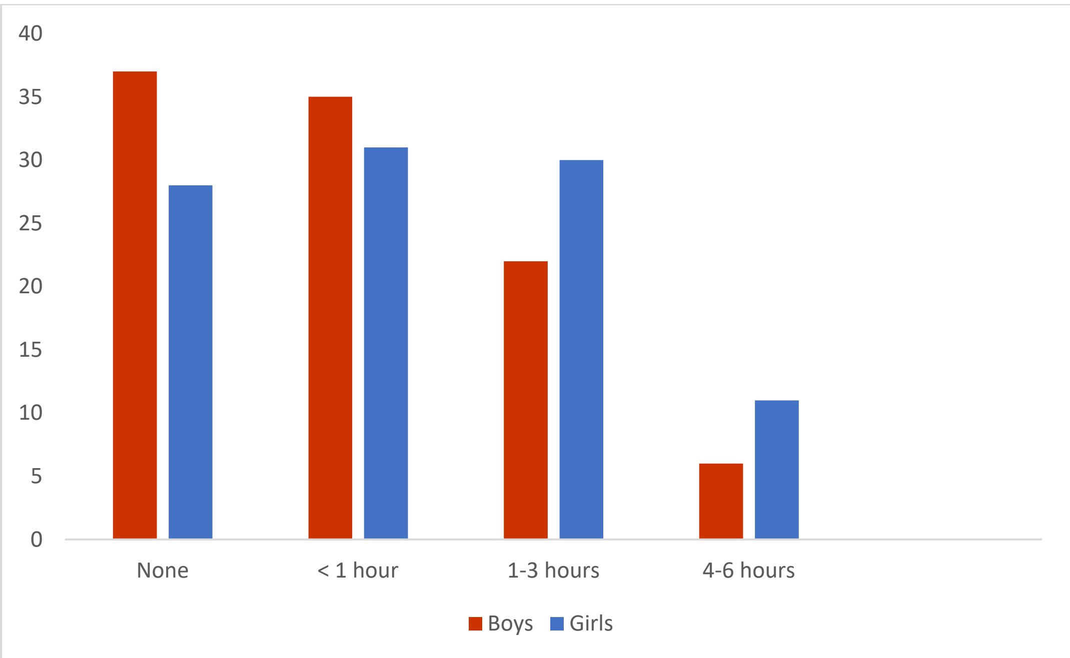
The average data includes important differences in the sample of social media users by age and gender. Figure 2 and 3 show that the number of children who spend very long hours on social media on a regular school day dramatically increases by age (only 2% of children age 10-11 are online for 4 or more hours, and this percentage increases to 16% for children age 14-15). Girls are also more likely to interact online for longer periods of time.

Figure 2 – Social media use by age



N = 24,091 observations (NxT)

Figure 3 – Social media use by gender



N = 24,091 observations (NxT)

Table 1 presents descriptive statistics of some relevant control variables by social media use, for the sample pooled across all waves and treated as a cross-section. The first column relates to all observations, while subsequent ones relate to subsets defined by various level of social media use (e.g., the sample includes 24,091 observations of individuals overall, 10,163 observations of individuals who spend less than 1 hour on social media, and so on). Children who use social media for 4 or more hours on a school day are less likely to have highly educated mothers, more likely to have mothers who are separated or single, and who work, and less likely to come from families with high monthly income. They are also less likely to come from ethnic minorities and more likely to live in urban areas, while there is no observable difference with their peers in terms of aspirations for future education. Descriptive statistics of emotional and behavioural outcomes are presented in Table 2.

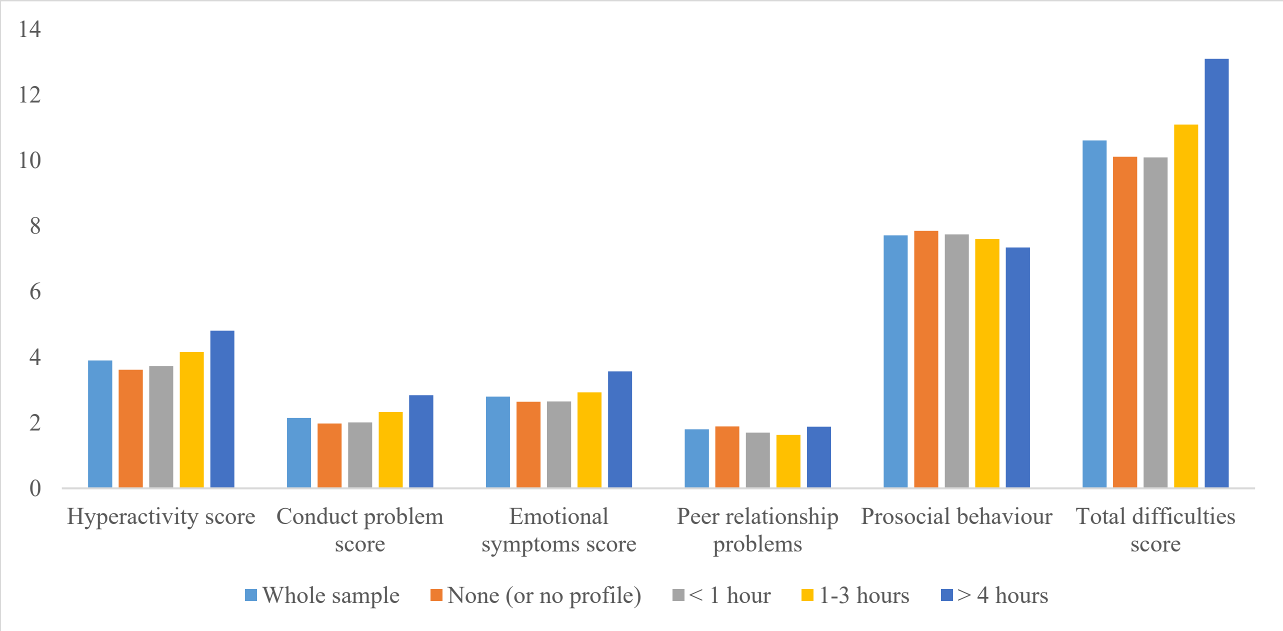
Table 1 and 2 here

Figure 4 reports outcomes by social media use. The number of observations is different from the one in Table 1 because questions about mental well-being and the SDQ are asked every second wave. There is a strong descriptive association between long hours spent on social media and worst outcomes in all the areas we consider. Children who spend 4 or more hours chatting with friends on social media on a school day have on average lower scores in most domains in the SDQ (excluding peer problems and prosocial behaviour). They are also more likely to experience negative feelings about themselves (e.g. feeling useless, not proud, not likeable, failure, etc.)

One natural concern in this analysis is that the unobservable characteristics of the youths who are more active on social media may be driving the results. For this reason, in our main estimation model, we continue to control for a variety of observable variables; we estimate models including individual fixed effects; we use estimation by propensity score matching and treatment effects to match individuals with different levels of social media use and similar observable characteristics; and we estimate the relevant models on a variety of subsamples (including, for example, children with different socio-economic backgrounds).

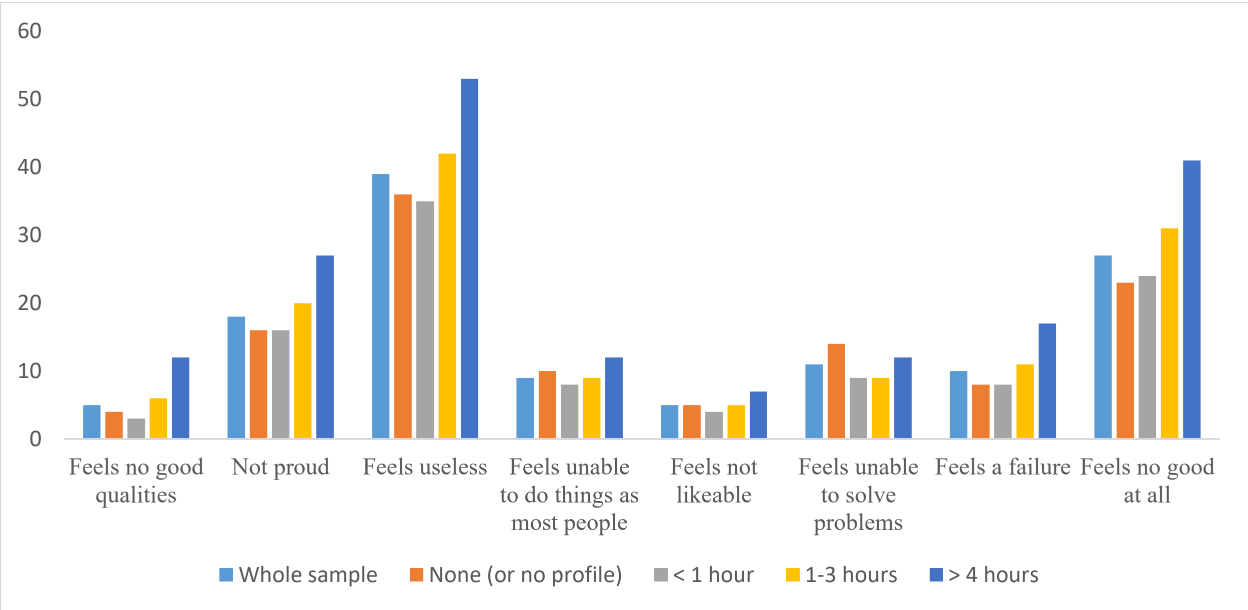
Figure 4 – Outcomes by social media use

Figure 4A - Strengths and Difficulties Questionnaire scores by social media use



N = 10,603 observations (NxT)

Figure 4B – Mental health by social media use (% in the most distressed category)



N = 13,488 observations (NxT)

4. Methodology

We begin by estimating an OLS model to control for observable confounders:

$$Y_{it} = \alpha + \beta sm_{ijt} + \boldsymbol{\delta}'\mathbf{x}_{ijt} + u_i + \varepsilon_{ijt},$$

where Y_{it} represents an outcome for individual i at time t; sm_{it} is an individual's reported social media activity; $\mathbf{x}_{it}$ is a vector of child and family characteristics; u_i is an individual fixed effect; and ε_{it} is the unobservable determinant of the outcomes that varies across *i* and *t.*

We take advantage of the richness of *Understanding Society* and we make some progress towards reducing the bias caused by unobserved heterogeneity, by including an extended list of control variables. The basic vector of covariates includes observables child's and family's characteristics such as: child's age, ethnic group, and gender, mother's mental health, education, labour market activity and marital status, family income, region of residence and urbanization.

We progressively extend the set of independent variables included in the model by also controlling for additional observable characteristics, including: child's risky behaviours (smoking and drinking), whether the child has at least five close friends, and number of children by age group in the family.

We use recently developed tests (see Oster, 2019, and Krauth, 2016, which have, in turn, been developed from Altonji *et al*, 2005) in order to investigate the stability of the coefficient(s) of interest when increasing the number of independent variables. In particular, we report estimates of the parameter δ, developed in Oster (2019), which indicates the level of selection on unobserved variables, proportional to the level of selection on observed variables, required to drive the treatment effect to zero.

The assumptions behind the calculation of δ can be varied. In particular, it is possible to vary the assumed value of *R-max,* defined as the *R*-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls. We follow Oster (2019) and set *R-max* equal to 1.3 times the *R*-squared from a regression of the outcome on the treatment and observed control variables. Results from this test are reported in the relevant section and confirm the credibility of our main estimates.

However, OLS estimates could still be biased because of unobserved characteristics that simultaneously affect social media use and mental health and behavioural outcomes and because of reverse causality (low mental well-being causing social media use, rather than *viceversa*). To address this issue, we use the "within" (i.e., person-specific) variation in the levels of social media use and within person variation of outcomes by estimating an individual fixed-effects model.

Unfortunately, fixed effects estimation is not a *panacea*. In this model, the causal interpretation of β relies on the assumption that the time-dependent error term ε_{it} is independent of changes in social media use and mental health, conditional on the regressors $\boldsymbol{x}_{it}$, and the individual fixed effect. This assumption fails if there are unobserved random shocks that affect both mental well-being and social media use. For this reason, we include several independent variables that may capture random shocks (such as maternal mental health, employment, marital status, and child's risky behaviours and friendships), and we use propensity score matching (PSM) and inverse probability weighted regression adjustment (IPWRA) treatment effects estimation to show the stability of the main results from the OLS fixed effects estimates.

PSM does not rely on the same functional form assumptions of OLS and restricts inference to samples where we can find overlap in the distribution of covariates across the treatment (i.e. children who spend long hours on social media are compared with children who have very similar observable characteristics but do not spend long hours on social media) (see Dehejia and Wahba 2002, Dehejia 2005, and Smith and Todd 2004 for a discussion of reduction of bias in PSM estimation). Matching attaches appropriate weights to the observations in the control group, so that the distribution of their observable characteristics is realigned to the treatment group (for relevant examples see Berger, Hill, & Waldfogel, 2005; Goodman & Sianesi, 2005; Ruhm, 2008; Caliendo et al., 2015).

More specifically, we first estimate the conditional probability of spending long hours on social media, called the propensity score, given our covariates. Then, estimated propensity scores are used to create a matched control group and for each treated child we find the comparison member with the closest propensity score. Non-matched individuals are dropped from the analysis[1].

We also examine the role of various levels of social media exposure and mental health using IPWRA treatment effects estimation based on the implementation in Cattaneo et al. (2013). This allows to compare outcomes for children with different levels of usage of social media with those of children who do not use social media at all (in this, IPWRA treatment effects is different from PSM, which only allows to examine the effect of a binary outcome).

Specifically, the probability of "treatment" (in this context, using social media for different number of hours) is estimated using a multinomial logit specification. The inverse of these predicted probabilities are used as weights in a second-stage regression (Wooldridge, 2007; Wooldridge, 2010; and Imbens and Wooldridge, 2009).

The IPWRA estimator has the "double robustness property" (Wooldridge, 2007 and 2010) in that only one of the two equations in the model must be correctly specified to consistently estimate the parameters of interest. In practice, estimates in the second stage (the mental health equation) are robust to misspecification of the first stage (the multinomial logit model of treatment propensities) provided that the second stage is correctly specified.

[1] Our analysis is performed using *teffects psmatch* and appropriate tests have been run, in order to compare covariate distributions across our matched groups to ensure that adequate balance has been obtained (results available in the Appendix Table)

Similarly, estimates from the first stage are robust to the second step, provided the weighting is correctly specified.

5. Results

In Table 3 shows the impact of social media use on mental well-being using individual-level fixed effects. The outcomes are binary variables representing increased distress for all outcomes.

There is a clear association between extended social media use and mental health. Children who spend very long hours on social media are more likely to experience several negative feelings about themselves, including feeling that they don't have any qualities or much to be proud of (+ 5-6 p.p), feeling useless (+ 12 p.p.), not likeable (+3 p.p.), not good at all (+12 p.p), and feeling a failure (+8 p.p.). In the model with individual fixed effects, all these effects are sizeable and higher than other important determinants of mental health, such as age, or maternal employment and marital status. Interestingly, short hours of interaction on social media (less than 1 hour per day or 1-3 hours per day) have a much smaller effect on mental well-being (+ 2 to 4 p.p and only for some indicators). The impact of extensive use of social media on the overall mental health score is also sizeable (+0.51 on a scale 0 to 8), equivalent to over 30% of a standard deviation.

In Table 4, results of the impact of social media use on mental health from the treatment effects model with IPWRA estimator are presented[2]. Results confirm findings from the estimation with individual fixed effects. The use of social media for prolonged periods has a detrimental effect on young people's mental well-being and the size of the effects is large.

[2] The number of observations in these tables is slightly lower than the one from the previous tables since individuals with low propensity scores are automatically eliminated from the sample by the estimation method to guarantee model convergence.

Interestingly, in this specification, short exposure to social media (less than 3 hours per day) seems to have some beneficial effects on individuals' perceptions of their own qualities and likeability. However, the effect of long hours of interactions with peers on social media website clearly have the opposite effect on the majority of mental health questions (6 out of 9 indicators) and the size of the effects is nontrivial.

Table 3 and 4 here

Results on the SDQ scores are presented in Tables 5 and 6 and confirm previous findings. Children who spend very long hours (4 or more per day) on social media have higher scores (more difficulties) in the areas of hyperactivity and attention deficit (+0.84 points or over 20% of a standard deviation); emotional symptoms (+0.40 points or 18% of a standard deviation); and conduct problems (+0.50 points or 27% of a standard deviation). However, limited or moderate use of social media (less than 1 hour or 1-3 hours per day), also presents an association with worse scores in the areas of hyperactivity and conduct problems (8 to 13% of standard deviation), but is also associated with a slight decrease in peer relationship problems (around 10% of a standard deviation).

The total difficulties score is significantly higher for children who spend very long hours on social media (+1.52 points or 27% of a standard deviation). Results from the treatment effects model with IPWRA estimator presented in Table 6 are higher in magnitude than the ones from the model including individual fixed effects, but confirm the overall associations. Long hours of social media are associated with worst scores in all areas (and the size of the effects ranges from 15% to 50% of a standard deviation) with the exception of a slight improvement in prosocial behaviours and peer relationships.

Table 5 and 6 here

Table 7 and 8 consider the relationship between long hours of interaction with peers on social media (4 hours or more per day) and mental well-being. In these tables, we also report the values of the parameter δ, proposed in Oster (2019). Almost all estimates of the δ parameter associated with Specification 1 and 2 are above 1, consistent with an 'acceptable' level of selection based on the rule-of-thumb suggested in Oster (2019).

We estimate these models using individual fixed effects and Propensity Score Matching. Appropriate tests have been run in order to ensure the balance in covariates between treatment and control group and results from these tests are available in the Appendix.

Results are very consistent with the previous ones and confirm the strong and negative effect on all components of mental well-being, with the only exception of prosocial behavior.

Table 7 and 8 here

All these results are very consistent with McDool et al (2019) showing that fast internet access increases the likelihood of long hours of social media use and this, in turn, decreases adolescents' life satisfaction with various domains by about 13%-16% of a standard deviation.

A natural concern in this analysis is that the results are driven by some random shocks, which affect both the child's emotional and behavioral outcomes and the use of social media. These may not be properly accounted for in the model including individual fixed effects and therefore different strategies and sensitivity tests are used to verify the stability of the main findings. As already shown, we have compared estimation with individual fixed effects and with propensity score matching and treatment effects. The results are robust to various specifications of the model and main findings are consistent across different estimation techniques.

Further, we progressively increased the set of independent variables in the regression, adding covariates that may capture such random shocks (e.g. maternal employment, marital status, mental health, etc) and including additional control variables, such as individual risky behaviours; whether the individual has at least five close friends; whether there are other children of different ages in the family (specification 2). We also run additional sensitivity tests including several variables which may capture time varying shocks, such as; individual and maternal health; individual religiosity; whether the individual is constantly trying to lose weight; whether the individual reports being the victim of bullying; parental involvement in the child's life (frequency of arguing with parents and parental involvement in school work). These results are consistent with the main findings, and are not reported for parsimony but are available on request.

In addition, we further explore the heterogeneity of the main results with a series of sub-group analyses, to explore the dynamics of these findings. For example, it is possible that the relationship is driven by peer effects and adolescence: children moving through the teenage years, they are more likely to use social media more frequently due to their friends also using it, as well as experience negative feelings about themselves. For this reason, in Table 9 and 10, we analyse the relationship between extended social media use (4 hours or more per day) and mental health on two subsamples of children, age 10-12 and age 13-15. Results are very stable and consistent for both subgroups of children, showing that high levels of exposure to social media significantly decrease mental well-being.

Similarly, it is possible that girls and boys use social media differently, and this is related to the association with their mental health. Therefore, we estimate the models separately by gender of the child. Results show that girls are more exposed to the negative effects of long hours on social media on self-esteem, but the overall effect on mental health is strong and significant for both groups (around +30% of a standard deviation in the overall mental health score for both boys and girls). Interestingly, boys show significantly stronger negative effects on hyperactivity and conduct scores (Table 10).

In Table 9 and 10, we also explore whether results are stable across various socio-economic groups and estimate the model for subsamples of children with different levels of maternal education. Results confirm the negative effect of long hours on social media, and the effect is slightly stronger for children with highly educated mothers (the impact on the mental health index is equivalent to 38% of a standard deviation while it is around 33% of a standard deviation for children whose mothers do not have a degree or equivalent).

Table 9 and 10 here

Finally, in Table 11, we estimate the relationship between extensive social media use at age 14 or 15 on mental health at age 16 to 20, using OLS and propensity score matching. At age 16, the children move to the adult survey and their mental health is analysed using the General Health Questionnaire, which has a score from zero (perfect mental health) to 12 (maximum distress). Interestingly, the negative effect of social media use is shown to persist for several years and is noticeable when the children move to the adult survey. This is an important result and substantially extends the existing evidence of the impact of social media on contemporaneous mental health.

Table 11 here

6. Conclusion

We estimate the relationship between social media use and mental health for children aged 10 to 15 years old. We use information from the Youth Survey in the longitudinal study Understanding Society, and we control for individual-level heterogeneity. Our results indicate a mixed picture, where limited time on social media has no effect on mental well-being (and can actually positively impact social relationships), while there are strong negative associations between very long hours on social media and increased emotional distress and worse behavioural outcomes. These relationships are robust to the inclusion of various independent variables, including child and family's characteristics, and to the use of different estimation techniques, including matching methods and the use of individual fixed effects.

The results suggest that high levels of exposure to social media have important negative effects on youths' mental well-being and behavioural difficulties, especially for girls and regardless of family's socio-economic status. This suggests that there is potentially a role for parents, teachers and educators to highlight the possible risks of prolonged social media use, compared to a more balanced approach, which includes some time on social media, as well as time in other socializing activities. The results clearly highlight that high intensity of use (rather than the use of social media *per se*) is strongly associated with adverse outcomes and therefore it seems important to address high levels of use, rather than stigmatise social media use as a completely negative phenomenon.

Identifying the causal pathways that make up the transmission mechanism through which high levels of social media use operate on mental well-being is beyond the scope of this paper. We cannot say any more than it appears that long hours on social media are strongly associated with poorer levels of mental health, but we cannot investigate why this relationship exists. A variety of factors is likely to contribute to these findings, including for example lack of sleep, and increased peer pressure.

One of the major limitations of the analysis is the difficulty to provide strong causal evidence on the relationship between social media use and mental health, in the absence of an exogenous variation in social media use. Time varying confounders could affect estimates including individual fixed effects, and PSM and treatment effects rely on selection on observables. Although every effort has been made to minimize these risks (including an extensive list of covariates, and running several sensitivity tests), caution is needed when interpreting these results as causal effects.

Future research could explore possible mediators and could try to use data that allow overcoming these limitations. In this context, it could be important to find exogenous variation in social media use, e.g. from cross-country estimates which exploit different mobile phone network speeds, which might then illuminate the existence of a causal relationship between social media use and mental health.

References

Adcock, A. Bate, A. Woodhouse, J. 2016. Effect of social media on the mental health of young people.Available from: https://researchbriefings.parliament.uk/ResearchBriefing/Summary/CDP-2016-0196

Anderson DM, Cesur R, Tekin E (2015) Youth depression and future criminal behaviour. Economic Inquiry 53: 294–317.

Berger, L. M., Hill, J., & Waldfogel, J. (2005). Maternity leave, early maternal employment and child health and development in the US. Economic Journal, 115, 29–47

Booker, C., Kelly, Y., Sacker, Am. (2018) Gender differences in the associations between age trends of social media interaction and well-being among 10-15 year olds in the UK. BMC Public Health 18:321 https://doi.org/10.1186/s12889-018-5220-4.

Caliendo, M., Cobb-Clark, D., & Uhlendorff, A. (2015). Locus of control and job search strategies. Review of Economics and Statistics, 97, 88-103.

Cattaneo, M. D., D. M. Drukker, and A. D. Holland. 2013. "Estimation of Multivalued Treatment Effects under Conditional Independence." Stata Journal 13: 407–50.

Centre for Mental Health (2018) Briefing 53: Social media, young people and mental health. Available online at: https://www.centreformentalhealth.org.uk/sites/default/files/2018-09/CentreforMentalHealth_Briefing_53_Social_Media.pdf

Clark, A. E., and Senik, C. (2010). Who compares to whom? The anatomy of income comparisons in Europe. The Economic Journal, 120, 573-94.

Currie, J., Stabile, M. (2006) Child mental health and human capital accumulation: The case of ADHD. Journal of Health Economics 25: 1094-1118.

Department of Health, Department for Education (2017) Transforming children and young people's mental health provision: a green paper. Available at https://www.gov.uk/government/consultations/transforming-children-and-young-peoples-mental-health-provision-a-green-paper

Department for Communities and Local Government (2013) Understanding differences in life satisfaction between local authority areas. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/252530/Understanding_differences_in_life_satisfaction_LA_areas.pdf

Ermisch J., Francesconi, M., & Pevalin, D. J. (2001). Outcomes for children of poverty. (Research Report 158). Leeds: Department for Work and Pensions.

Fardouly, J. Diedrichs, P. C. Vartanian, L. Halliwell, E. (2015) Social comparisons on social media: The impact of Facebook on young womens body image concerns and mood. Body Image, 13. pp. 38-45.

Frith E. Social media and children's mental health: a review of the evidence. Education Policy Institute.

Gerli, P., Matteucci, N., Whalley, J. (2019) Infrastructure Provision on the Margins: An Assessment of Broadband Delivery UK. International Journal of Public Administration. https://doi-org.ezproxy.uow.edu.au/10.1080/01900692.2019.1638932.

Goodman R. (1997) The strengths and difficulties questionnaire: a research note. Journal of Child Psychology and Psychiatry 38: 581–586.

Goodman R., Meltzer H., Bailey V. (1998) The strengths and difficulties questionnaire: a pilot study on the validity of the self-report version. European Child and Adolescent Psychiatry 7: 125–30.
Goodman. A, Joyce. R, Smith. J. (2011)The long shadow cast by childhood physical and mental problems on adult life. PNAS.. 108(15), 6032-6037.
Goodman, A., & Sianesi, B. (2005). Early education and children's outcomes: How long do the impacts last? Fiscal Studies, 26, 513–548.
Gunnell D (2018) Adolescent mental health in crisis. British Medical Journal. doi: 10.1136/bmj.k2608.
House of Commons- Science and Technology Committee (2019). Impact of social media and screen-use on young people's health. Fourteenth Report of Session 2017–19. Available online at:
https://publications.parliament.uk/pa/cm201719/cmselect/cmsctech/822/822.pdf
Hyll, W., and Schneider, L. (2013). The causal effect of watching TV on material aspirations: Evidence from the 'valley of the innocent'. Journal of Economic Behavior and Organization, 86, 37-51.
Kelly, Y, Zilanawala, A., Booker, C., Sacker, A. (2018) Social Media Use and Adolescent Mental Health: Findings From the UK Millennium Cohort Study. EClinical Medicine 6: 59-68.
Khan. L, Parsonage. M, Stubbs. J.(2015) Investing in children's mental health: A review of evidence on the costs and benefits of increased service provision. London: Centre for Mental Health. https://www.centreformentalhealth.org.uk/publications/investing-in-childrens-mental-health
Knapp. M, Ardino. V, Brimblecombe. N, Evans-Lacko. S, Iemmi. V, King. D, Wilson. J. (2016) Youth Mental Health: New Economic Evidence. London: London School of Economics. https://www.pssru.ac.uk/pub/5160.pdf
Krauth, B. (2016), "Bounding a linear causal model using relative correlation restrictions", Journal of Econometric Methods, 5, 117-141.
Lohmann, S. (2015) Information technologies and subjective well-being: does the Internet raise material aspirations? Oxford Economic Papers 67, 740-759.
Lundborg P, Nilsson A., Rooth D. (2014) Adolescent health and adult labor market outcomes. Journal of Health Economics 37, 25-40.
McDool, E., Power, P., Roberts, J., Taylor, K (2019) The internet and children psychological well-being. Journal of Health Economics (forthcoming).
Morgan C, Webb RT, Carr MJ, et al . (2017) Incidence, clinical management, and mortality risk following self harm among children and adolescents: cohort study in primary care. British Medical Journal 359:j4351. http://dx.doi.org/10.1136/bmj.j4351
Nesi J, Rothenberg W., Hussong A., Jackson K. (2017) Friends' Alcohol-Related Social Networking Site Activity Predicts Escalations in Adolescent Drinking: Mediation by Peer Norms. Journal of Adolescent Health 60, 641–647.
NHS (2016) Smoking, drinking and drug use among young people. England: 2016. https://files.digital.nhs.uk/47/829A59/sdd-2016-rep-cor-new.pdf
Orben, A., Dienlin, T., Przybylski, A. (2019) Social media's enduring effect on adolescent life satisfaction. PNAS 116: 10226-10228.
Orben, A., Przybylski, A. (2019) Screens, Teens, and Psychological Well-Being: Evidence From Three Time-Use-Diary Studies. Psychological Science 1-15. DOI: 10.1177/0956797619830329www.psychologicalscience.org/PS.

OECD (2016) PISA 2015 Results Students' well-being Volume III, OECD, April 2016: http://www.oecd.org/edu/pisa-2015-results-volume-iii-9789264273856-en.htm

ONS (2015) Measuring National Well-being: Insights into children's mental health and well-being, , using data from the Understanding Society survey 2012-13, ONS.

Department of Health. Schools and Families; Department for Children (2010). The Sedentary Behaviour and Obesity Expert Working Group. Sedentary behaviour and obesity: review of the current scientific evidence. London.

OfCom (2015) Children and parents: media use and attitudes report. London: Office of Communications.

Royal Society for Public Health (2018) Status Of Mind - Social media and young people's mental health and wellbeing. London, 2018.

Ruhm, C. J. (2008). Maternal employment and adolescent development. Labour Economics, 15, 958–983.

Viner, R.; Giresh, A.; Stiglic, N.; Hudson, L.; Goddings, A.; Ward, J.; Nicholls, D. (2019). Roles of cyberbullying, sleep, and physical activity in mediating the effects of social media use on mental health and wellbeing among young people in England: a secondary analysis of longitudinal data. The Lancet Child and Adolescent Health, 3, 685-696.

Wallsten, S. (2013). What we are not doing when we're online. NBER Working Paper 19549.

Woods, H. C. and Scott, H. (2016) #Sleepyteens: social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem. Journal of Adolescence, 51, 41-49.

Tables

Table 1 Means (Std Devs) of independent variables for sub-groups of estimation sample, by social media use

	Whole sample	Does not belong to a social media website or spends no time online	Spends less than 1 hour online	Spends 1-3 hours online	Spends 4 hours or more online
Mother has a degree (%)	25	30	26	20	19
Mother has other HE (%)	15	14	16	16	16
Mother senior high school – Age 18 (%)	19	18	19	19	18
Mother junior high school – Age 16 (%)	26	24	26	28	27
Mother has other qual. (%)	8	7	7	9	10
Mother has no education (%)	7	7	7	8	11
Mother is married (%)	67	72	68	63	55
Single mother (%)	16	13	16	18	21
Mother is divorced or separated (%)	17	14	16	19	23
Mother is employed (%)	70	67	70	72	70
Mother is unemployed (%)	4	4	4	5	5
Mother is out of labour force (%)	26	29	26	24	25
Family Monthly Income < £ 2,272 (%)	24	23	23	26	28
Family Monthly Income £ 2,272- £ 3,439 (%)	25	25	24	26	25
Family Monthly Income £ 3,439-£ 5,114 (%)	25	26	26	24	26
Family Monthly Income > £ 5,114 (%)	26	26	28	25	20
Living in an urban area (%)	76	76	75	77	80
Living in a rural area (%)	24	24	25	23	20
White (%)	80	76	80	84	83
Black (%)	4	5	4	4	5
Other ethnic group (%)	5	5	5	5	5
Asian (%)	10	14	11	7	7
Would like to go to university (%)	93	93	94	94	93
N	24,091	7,921	7,891	6,270	2,009

Table 2 – Means (Std Devs) of SDQ Scores and Mental Health components

SDQ SCORES	MEAN (SD)
Emotional Symptoms (0-10)	2.77 (2.20)
Conduct Problems (0-10)	2.18 (1.80)
Hyperactivity/Inattention (0-10)	3.94 (2.30)
Peer Relationship Problems (0-10)	1.73 (1.63)
Prosocial (0-10)	7.73 (1.82)
Total Difficulties (0-35)	10.63 (5.63)
Mental health index (0-8)	1.23 (1.52)
Mental health Index components (=1 if in the most distressed group)	%
SA=Strongly Agree; A=Agree; D=Disagree; SD=Strongly Disagree	
I feel I have a number of good qualities (D or SD)	5
I don't have much to be proud of (A or SA)	18
I certainly feel useless at times (A or SA	39
I am able to do things as well as most other people (D or SD)	9
I am a likeable person (D or SD)	5
I can usually solve my own problems (D or SD)	11
All in all, I am inclined to feel I am a failure (A or SA)	10
At times, I feel I am no good at all (A or SA)	27

Table 3 – Impact of various level of exposure to social media on mental health. Estimation by OLS FE

Mental health components	No good qualities (0-1)	Not proud (0-1)	Feels useless (0-1)	Feels unable (0-1)	Feels not likeable (0-1)	Unable to solve problems (0-1)	Feels a failure (0-1)	Feels no good at all (0-1)	Mental health score (0-8)
Specification 1									
Less than 1 hour	-0.011	0.005	-0.024	0.007	0.003	-0.017	-0.001	0.005	-0.025
	(0.008)	(0.014)	(0.017)	(0.011)	(0.008)	(0.012)	(0.011)	(0.016)	(0.052)
1-3 hours	0.009	-0.000	0.035	0.018	0.004	-0.008	0.028	0.035	0.119
	(0.010)	(0.016)	(0.020)*	(0.013)	(0.009)	(0.014)	(0.013)**	(0.019)*	(0.061)*
4 or more hours	0.055	0.074	0.127	0.031	0.031	-0.003	0.084	0.135	0.550
	(0.013)***	(0.023)***	(0.028)***	(0.018)*	(0.013)**	(0.019)	(0.018)***	(0.026)***	(0.085)***
N	13,488	13,502	13,496	13,496	13,485	13,485	13,338	13,474	12,968
Specification 2									
Less than 1 hour	-0.010	0.010	-0.015	0.012	0.005	-0.017	-0.000	0.011	0.005
	(0.008)	(0.014)	(0.017)	(0.011)	(0.008)	(0.012)	(0.011)	(0.016)	(0.053)
1-3 hours	0.009	0.001	0.041	0.022	0.006	-0.006	0.027	0.040	0.148
	(0.010)	(0.017)	(0.020)**	(0.013)*	(0.010)	(0.014)	(0.013)**	(0.019)**	(0.062)**
4 or more hours	0.054	0.065	0.120	0.024	0.028	-0.010	0.081	0.123	0.515
	(0.014)***	(0.023)***	(0.028)***	(0.018)	(0.014)**	(0.019)	(0.018)***	(0.026)***	(0.086)***
N	13,115	13,126	13,119	13,122	13,111	13,110	12,978	13,107	12,635

Note: Specification 1 includes child's age binary variables, ethnicity and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Specification 2 includes all the variables in Specification 1 and risky behaviours (ever drunk or smoked); n. of children in various age groups in the family; and a binary variable equal to 1 if the child has at least 5 close friends (50^{th} percentile and above). The outcomes are binary variables equal to 1 if the child has placed herself/himself in the most distressed category (e.g. has answered "agree" or "strongly agree" to the statement "I am inclined to feel I am a failure"; or has answered "disagree" or "strongly disagree" to the statement "I feel like I have a number of good qualities", and so on). Therefore, a positive sign of the estimate represents increased distress. Highest mental health score represents worst mental health. * indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Table 4– Impact of various level of exposure to social media on mental health. Estimation by Treatment effects IPWRA (Spec. 1)

Mental health components	No good qualities (0-1)	Not proud (0-1)	Feels useless (0-1)	Feels unable (0-1)	Feels not likeable (0-1)	Unable to solve problems (0-1)	Feels a failure (0-1)	Feels no good at all (0-1)	Mental health score (0-8)
Less than 1 hour	-0.016 (0.005)***	0.002 (0.009)	-0.007 (0.012)	-0.013 (0.007)	-0.021 (0.006)**	-0.033 (0.007)**	-0.006 (0.007)	-0.004 (0.011)	-0.120 (0.038)***
1-3 hours	-0.004 (0.006)	0.028 (0.011)***	0.051 (0.013)***	-0.001 (0.008)	-0.019 (0.006)***	-0.022 (0.009)**	0.021 (0.008)***	0.045 (0.012)***	0.081 (0.044)*
4 or more hours	0.025 (0.009)***	0.082 (0.018)***	0.127 (0.022)***	0.007 (0.013)	0.007 (0.0122)	0.003 (0.016)	0.056 (0.014)***	0.104 (0.020***	0.406 (0.073)***
N	13,320	13,332	13,328	13,327	13,318	13,315	13,170	13,305	12,805

Note: Specification 1 includes child's age binary variables, ethnicity and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence.). Highest mental health score represents worst mental health. * indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Table 5 – Impact of various level of exposure to social media on Strengths and Difficulties Questionnaire (SDQ) Scores. Estimation by OLS FE

SDQ Items	Emotional Symptoms (0-10)	Conduct Problems (0-10)	Hyperactivity/ Inattention (0-10)	Peer Relationship Problems (0-10)	Prosocial (0-10)	Total Difficulties (0-35)
Specification 1						
Less than 1 hour	-0.027 (0.085)	0.029 (0.065)	0.195 (0.083)**	-0.065 (0.062)	0.067 (0.070)	0.127 (0.195)
1-3 hours	0.098 (0.098)	0.232 (0.075)***	0.298 (0.095)***	-0.153 (0.072)**	0.029 (0.081)	0.465 (0.225)**
4 or more hours	0.396 (0.145)***	0.497 (0.112)***	0.841 (0.141)***	-0.186 (0.107)*	-0.171 (0.121)	1.541 (0.333)***
N	10,603	10,600	10,600	10,602	10,610	10,593
Specification 2						
Less than 1 hour	-0.022 (0.089)	0.032 (0.067)	0.188 (0.086)**	-0.062 (0.065)	0.055 (0.072)	0.127 (0.203)
1-3 hours	0.070 (0.103)	0.238 (0.078)***	0.269 (0.100)***	-0.179 (0.076)**	0.015 (0.084)	0.384 (0.236)
4 or more hours	0.354 (0.153)**	0.496 (0.116)***	0.844 (0.148)***	-0.162 (0.113)	-0.159 (0.125)	1.523 (0.349)***
N	10,034	10,031	10,032	10,033	10,037	10,028

Note: Specification 1 includes child's age binary variables, ethnicity, and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Specification 2 includes all the variables in Specification 1 and risky behaviours (ever drunk or smoked); n. of children in various age groups in the family; and a binary variable equal to 1 if the child has at least 5 close friends (50th percentile and above).* indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Table 6– Impact of various level of exposure to social media on Strengths and Difficulties Questionnaire (SDQ) Scores. Estimation by Treatment effects IPWRA (Spec. 1)

SDQ Items	Emotional Symptoms (0-10)	Conduct Problems (0-10)	Hyperactivity/ Inattention (0-10)	Peer Relationship Problems (0-10)	Prosocial (0-10)	Total Difficulties (0-35)
Less than 1 hour	0.022 (0.058)	0.144 (0.045)***	0.242 (0.059***	-0.227 (0.047)***	-0.025 (0.046)	0.131 (0.148)
1-3 hours	0.062 (0.067)	0.579 (0.056)***	0.660 (0.070)***	-0.330 (0.052)***	-0.131 (0.054)**	0.968 (0.178)***
4 or more hours	0.325 (0.111)***	0.835 (0.097)***	1.129 (0.122)***	-0.191 (0.011)*	-0.348 (0.0107)***	2.095 (0.303)***
N	10,594	10,591	10,591	10,593	10,601	10,584

Note: Specification 1 includes child's age binary variables, ethnicity, and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. * indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Table 7 – Impact of *long hours (4 or more hours per day)* on social media on mental health. Estimation by OLS FE and PSM

Mental health components	No good qualities (0-1)	Not proud (0-1)	Feels useless (0-1)	Feels unable (0-1)	Feels not likeable (0-1)	Unable to solve problems (0-1)	Feels a failure (0-1)	Feels no good at all (0-1)	Mental health score (0-8)
Specification 1									
OLS FE	0.055	0.072	0.119	0.019	0.028	0.008	0.071	0.115	0.502
	(0.011)***	(0.019)***	(0.023)***	(0.015)	(0.011)**	(0.016)	(0.015)***	(0.022)***	(0.071)***
δ	2.96	3.13	3.83	15.52	2.74	-0.67	4.19	3.39	3.56
PSM	0.053	0.062	0.125	0.023	0.015	0.014	0.067	0.125	0.488
	(0.012)***	(0.018)***	(0.021)***	(0.013)	(0.011)	(0.013)	(0.014)***	(0.020)	(0.072)***
N	13,488	13,502	13,496	13,496	13,485	13,485	13,338	13,474	12,968
Specification 2									
OLS FE	0.053	0.060	0.105	0.008	0.023	0.001	0.068	0.098	0.438
	(0.011)***	(0.019)***	(0.024)***	(0.015)	(0.011)**	(0.016)	(0.015)***	(0.022)***	(0.072)***
δ	2.57	2.36	3.05	2.43	1.93	-0.03	3.46	2.64	2.90
PSM	0.050	0.054	0.108	0.005	0.021	0.025	0.047	0.090	0.451
	(0.013)***	(0.019)	(0.022)***	(0.014)	(0.011)***	(0.013)*	(0.016)***	(0.021)***	(0.073)***
N	13,115	13,126	13,119	13,122	13,111	13,110	12,978	13,107	12,635

Note: Specification 1 includes child's age binary variables, ethnicity, and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Specification 2 includes all the variables in Specification 1 and risky behaviours (ever drunk or smoked); n. of children in various age groups in the family; and a binary variable equal to 1 if the child has at least 5 close friends (50th percentile and above).). Highest mental health score represents worst mental health. * indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Table 8 – Impact of *long hours (4 or more hours per day)* on social media on Strengths and Difficulties Questionnaire (SDQ) Scores. Estimation by OLS FE and PSM

SDQ Items	Emotional Symptoms (0-10)	Conduct Problems (0-10)	Hyperactivity/ Inattention (0-10)	Peer Relationship Problems (0-10)	Prosocial (0-10)	Total Difficulties (0-35)
Specification 1						
OLS FE	0.354	0.364	0.611	-0.081	-0.211	1.247
	(0.124)***	(0.096)***	(0.121)***	(0.091)	(0.103)**	(0.285)***
δ	6.19	-8.46	-27.13	-13.77	2.47	264.03
PSM	0.330	0.708	0.910	0.043	-0.390	2.825
	(0.127)***	(0.094)***	(0.0121)***	(0.090)	(0.094)**	(0.291)***
N	10,603	10,600	10,600	10,602	10,610	10,593
Specification 2						
OLS FE	0.326	0.360	0.633	-0.046	-0.188	1.275
	(0.131)**	(0.100)***	(0.127)***	(0.097)	(0.107)*	(0.299)***
δ	4.11	-16.17	64.93	-7.98	1.86	15.30
PSM	0.464	0.798	0.787	0.151	-0.251	2.164
	(0.124)***	(0.094)***	(0.126)***	(0.090)	(0.098)***	(0.301)***
N	10,034	10,031	10,032	10,033	10,037	10,028

Note: Specification 1 includes child's age binary variables, ethnicity and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. Specification 2 includes all the variables in Specification 1 and risky behaviours (ever drunk or smoked) ; n. of children in various age groups in the family; and a binary variable equal to 1 if the child has at least 5 close friends (50th percentile and above).* indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Table 9 – Impact of *long hours* on social media on mental health– By gender; age; and maternal education (Estimation by PSM, Specification 1)

Mental health components	No good qualities (0-1)	Not proud (0-1)	Feels useless (0-1)	Feels unable (0-1)	Feels not likeable (0-1)	Unable to solve problems (0-1)	Feels a failure (0-1)	Feels no good at all (0-1)	Mental health score (0-8)
Girls	0.0831 (0.015)***	0.054 (0.022)***	0.110 (0.026)***	0.034 (0.017)**	0.016 (0.013)	0.009 (0.018)	0.079 (0.019)***	0.146 (0.026)***	0.513 (0.098)***
Boys	0.017 (0.014)	0.051 (0.027)*	0.061 (0.034)*	-0.025 (0.020)	0.031 (0.015)**	0.029 (0.020)	0.043 (0.023)**	0.067 (0.031)***	0.336 (0.109)***
Age 10-12	0.008 (0.019)	0.024 (0.034)	0.087 (0.043)**	0.004 (0.024)	-0.008 (0.017)	0.054 (0.027)**	0.053 (0.028)*	0.091 (0.042)***	0.495 (0.131)***
Age 13-15	0.059 (0.014)***	0.059 (0.021)***	0.078 (0.025)***	0.0005 (0.017)	0.029 (0.012)	0.005 (0.016)	0.079 (0.017)***	0.115 (0.024)***	0.544 (0.085)***
Mother has degree or equivalent	0.075 (0.019)***	0.052 (0.031)*	0.127 (0.035)***	0.041 (0.022)*	0.013 (0.020)	0.033 (0.019)*	0.127 (0.023)***	0.110 (0.035)***	0.578 (0.123)***
Mother has no degree or equivalent	0.047 (0.016)***	0.043 (0.022)*	0.127 (0.025)***	-0.014 (0.016)	0.006 (0.014)	0.033 (0.017)*	0.050 (0.019)***	0.088 (0.025)***	0.416 (0.091)***

Note: Specification 1 includes child's age binary variables, ethnicity and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence.). Highest mental health score represents worst mental health. * indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Table 10 – Impact of *long* hours on social media on Strengths and Difficulties Questionnaire (SDQ) Scores – By gender; age; and maternal education (Estimation by PSM, Specification 1)

SDQ Items	Emotional Symptoms (0-10)	Conduct Problems (0-10)	Hyperactivity/ Inattention (0-10)	Peer Relationship Problems (0-10)	Prosocial (0-10)	Total Difficulties (0-35)
Girls	0.730 (0.154)***	0.885 (0.116)***	1.175 (0.151)***	0.261 (0.104)***	-0.351 (0.109)***	2.758 (0.38)***
Boys	0.127 (0.173)	0.488 (0.183)***	0.627 (0.194)***	-0.032 (0.150)	-0.288 (0.17)*	1.15 (0.483)***
Age 10-12	0.213 (0.250)	0.782 (0.214)***	1.311 (0.273)***	0.051 (0.193)	-0.688 (0.206)***	2.01 (0.661)***
Age 13-15	0.444 (0.137)***	0.749 (.112)***	0.931 (0.132)***	0.069 (0.093)	-0.216 (0.109)**	2.381 (0.313)***
Mother has degree or equivalent	0.426 (0.222)*	1.152 (0.148)***	1.301 (0.212)***	0.209 (0.151)	-0.237 (0.147)	2.685 (0.491)***
Mother has no degree or equivalent	0.404 (0.153)***	0.610 (0.121)***	0.860 (0.155)***	-0.082 (0.109)	-0.490 (0.128)***	2.400 (0.388)***

Note: Specification 1 includes child's age binary variable, ethnicitys and gender; mother's mental health, employment, education, marital status, family income, GOR, urban/rural region of residence. * indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Table 11 - Impact of long hours on social media at age 14-15 on mental health at age 16-20 (Estimation by OLS and PSM)

	OLS			PSM		
	Whole sample	Age 16-17	Age 18-20	Whole sample	Age 16-17	Age 18-20
Mental health score from adult survey	0.423	0.441	0.387	0.475	0.500	0.415
(0-12)	(0.102)***	(0.110)***	(0.149)**	(0.081)***	(0.104)***	(0.137)***
N	10,690	6,057	4,633	10,690	6,057	4,633

Note: Independent variables: gender; age binary variables; labour force status binary variables (employed, unemployed, out of the labour force; student-omitted group); GOR; higher educational qualification; * indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave). OLS standard errors are clustered at individual level.

Appendix

Strengths and Difficulties Questionnaire – List of Items

"Now for some questions about how you see yourself as a person. For each item, please tick the box for Not True, Somewhat True or Certainly True. It would help us if you answered all items as best you can even if you aren't absolutely certain. Please give your answers on the basis of how things have been for you over the last six months."

- I try to be nice to other people. I care about their feelings
- I am restless, I cannot stay still for long
- I get a lot of headaches, stomach-aches or sickness
- I usually share with others (food, games, pens, etc.)
- I get very angry and often lose my temper
- I am usually on my own. I generally play alone or keep to myself
- I usually do as I am told
- I worry a lot
- I am helpful if someone is hurt, upset or feeling ill
- I am constantly fidgeting or squirming
- I have one good friend or more
- I fight a lot. I can make other people do what I want
- I am often unhappy, down-hearted or tearful
- Other people my age generally like me
- I am easily distracted, I find it difficult to concentrate
- I am nervous in new situations. I easily lose confidence
- I am kind to young children
- I am often accused of lying or cheating
- Other children or young people pick on me or bully me
- I often volunteer to help others (parents, teachers, children)
- I think before I do things
- I take things that are not mine from home, school or elsewhere
- I get on better with adults than with people my own age
- I have many fears, I am easily scared
- I finish the work I'm doing

Table A1 – Impact of other independent variables on youth mental health index (Specification 1 and 2 – See Table 3)

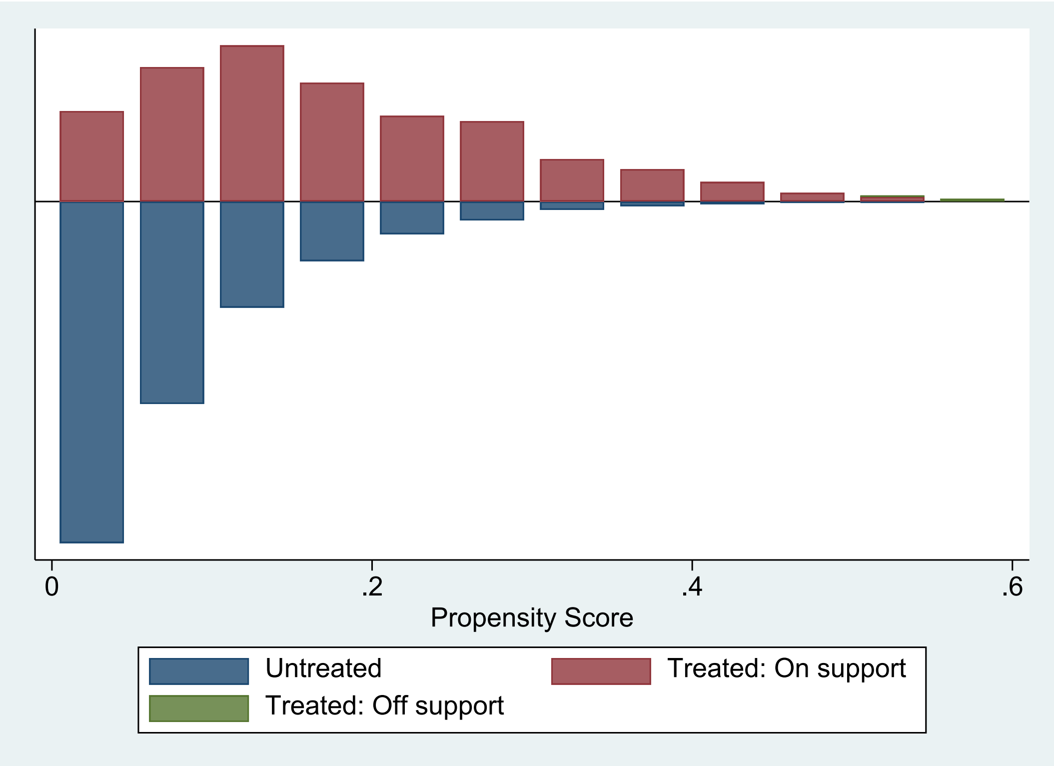
	Spec. 1	Spec.2
Mother's mental health	0.013 (0.008)*	0.014 (0.008)*
Age 11	0.019 (0.099)	0.018 (0.100)
Age 12	-0.064 (0.057)	-0.012 (0.077)
Age 13	0.168 (0.099)*	0.171 (0.113)
Age 14	0.049 (0.068)	0.001 (0.090)
Age 15	0.377 (0.103)***	0.243 (0.125)*
Age 16	0.606 (0.677)	0.653 (0.675)
Mother unemployed	0.167 (0.124)	0.103 (0.127)
Mother Out of the labour force	-0.031 (0.079)	-0.084 (0.081)
Single mother	-0.176 (0.159)	-0.161 (0.159)
Mother is separated	0.043 (0.120)	0.023 (0.123)
Log (Household Income)	0.003 (0.058)	-0.005 (0.059)
Mother has other HE	-0.062 (0.326)	0.054 (0.330)
Mother senior high school	0.117 (0.325)	0.109 (0.332)
Mother junior high school	0.363 (0.367)	0.400 (0.372)
Mother has other qual	0.332 (0.462)	0.326 (0.467)
Mother has no education	0.532 (0.489)	0.521 (0.498)
Living in urban area	-0.179 (0.238)	-0.171 (0.241)
Ever smoked		0.220 (0.093)**
Ever drank alcohol		0.388 (0.057)***
N. children 0-2 y.o.		0.087 (0.078)
N. children 3-4 y.o.		0.053 (0.069)
N. children 5-11 y.o.		0.109 (0.053)**

N. children 12-15 y.o.		0.047
		(0.043)
Has at least 5 friends		-0.171
		(0.042)***
Constant	0.053	0.042
	(0.938)	(0.947)
R^2	0.04	0.06
N	12,968	12,635

Note: GOR FE are omitted. Highest mental health score represents worst mental health. * indicates significant at 10% level, ** at 5% and ***1% . N represents number of observations (person × wave).

Balance Tests – Estimation of the impact of long hours on social media on the mental health index with PSM

Web Appendix Figure 1: *Histogram showing common support and balance of the matched sample. All observations are on the common support.*



Web Appendix Figure 2: *Plot summarizing the balance statistics comparing the unmatched and matched sample (from –psgraph-)*

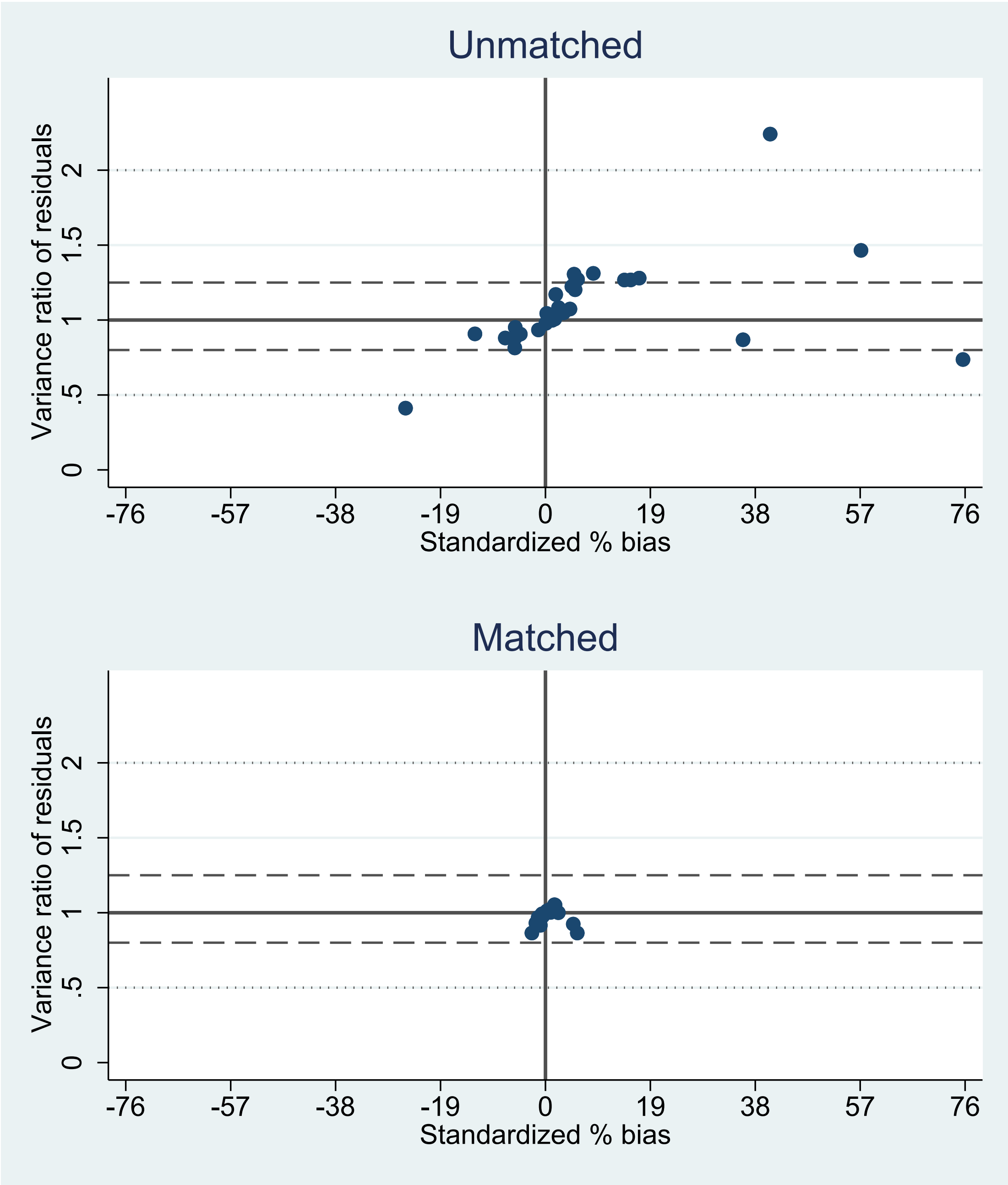


Table A2 Means and T test for treated and control group

	Treated	Control	T test (p value)
Age	13.575	13.603	0.634
Female	0.677	0.658	0.337
Mother's mental health (0-12)	2.62	2.70	0.447
Mother has other HE	0.157	0.183	0.101
Mother senior high school – Age 18	0.183	0.183	1.000
Mother junior high school – Age 16	0.286	0.265	0.250
Mother has other qual.	0.098	0.100	0.837
Mother has no education	0.088	0.088	0.942
Single mother	0.228	0.210	0.297
Mother is divorced or separated	0.211	0.218	0.689
Mother is unemployed	0.052	0.059	0.529
Mother is out of labour force	0.248	0.230	0.289
Log (Household income)	8.080	8.090	0.710
Living in an urban area	0.791	0.798	0.684
Black	0.054	0.061	0.480
Other ethnic group	0.059	0.058	0.930
Asian	0.046	0.051	0.568