Internet Access and Youth's Mental Health and Well-being: Evidence from Ethiopia

Trang Thi Pham*[1,2] and Pui-Hang Wong[1,2]

[1]UNU-MERIT, Maastricht, the Netherlands

[2]School of Business and Economics, Maastricht University, Maastricht, the Netherlands

October 26, 2024

Abstract

In this paper, we provide one of the first robust evidence of the impact of internet access on adolescents' well-being and mental health in a low-income country context. We find reduced subjective well-being and increased measures of mental disorders indicators among young people in Ethiopia during 2020-2021 following internet diffusion. Our heterogeneity analysis reveals that the effects of internet access on mental health are unequal, with stronger negative impacts for adolescents from lower-wealth households. Additionally, our mechanism analysis suggests that passive internet use, particularly among youth from less advantaged socioeconomic backgrounds, might drive these negative outcomes. To address potential endogeneity issues by using observational data, we employ instrumental variable techniques combined with difference-in-difference estimations. The study highlights the significance of social causes in shaping mental health and offers policy implications regarding internet access and youth human capital development in the digital age.

Keywords: Internet, Youth, Mental health, Well-being, Inequality.

JEL Classifications: I14, O33, J13.

*We would like to thank Robin Cowan, Bruno Martorano, and Musa Hasen for enormously helpful comments and feedback; and the Young Lives team for data access.

Corresponding author: phamthi@merit.unu.edu

1 Introduction

The 21st century is the internet and mobile technology era (WEF, 2020). While first developed among academia in the US following WWII, then diffused in the Western World with predominantly anglophone content until the late 1990s (Goggin & McLelland, 2017); the internet has evolved from fixed broadband for desktop users to mobile broadband with smartphones being the first interface of digital access for a majority of people in many regions.[1] This has been driven by combinations of innovations in (mass-market) smartphones, cellular technologies, and satellite internet.[2]

For remote and underdeveloped regions in particular, the (potential) benefits of (mobile) internet diffusion have garnered significant enthusiasm, spurring global initiatives and investments for universal connectivity (Chiang, 2024; CORDIS, 2021; Duchamp & Congote, 2022; USAID, 2022). Many studies have analyzed the impacts on for example service sectors, such as retail sector for rural villages in Kazakhstan during 2006 to 2016 (Aldashev & Batkeyev, 2021);[3] financial inclusion in Africa (Evans, 2018); or promotion of self-organizing e-commerce ecosystem in Chinese remote villages (Leong et al., 2016); distance learning (Selim, 2020); and potential advantages of the internet of things (IoT) for agriculture and sustainable rural development in South Africa and Zambia (Dlodlo & Kalezhi, 2015). The outcomes of most of studies in the extant literature, however, are preliminary and/or evidently one-sided positive pieces of evidence, presenting 'at best, an incomplete picture' (Goggin & McLelland, 2017), or worse, 'optimistic simplism' discourse of internet connectivity (Friederici et al., 2017).

Simply bringing internet to remote, under-developed regions does not automatically lead to transformations in the economy and society, as it depends on innovation diffusion and utilization processes and market maturity conditions or inefficiencies;[4] or worse, it can result in negative development outcomes if distinct local socioeconomic characteristics and structures are not taken into account (Salemink et al., 2015). Recent anecdotal evidence

[1] With a technological trend toward delivering wireless broadband in rural areas as an alternative to wired broadband (European Commission, 2018; Mingliu & Wolff, 2004).

[2] The first smartphone with touch-screen and mobile apps is the iPhone which was launched in the US in 2007 (Woggon, 2022).
Cellular technology is a network technology offering wireless communications using radio frequencies over areas comprised of cells and transceivers, including base stations (BTS) or cell sites and terminal devices like smartphones; which have evolved from 1st generation (1G) to 5th generation (5G) and more (Arshad et al., 2019; Rouse, 2017).
Satellite internet is low earth orbit (LEO) satellite constellations providing high-speed broadband (Hanson, 2016). The first batch of satellite internet was launched by Starlink service in 2019 (Graydon & Parks, 2020; Stovall, 2024).

[3] While no impact on manufacturing and agriculture.

[4] In terms of input, output, land, credit, and risks markets (Bergquist, 2021; Jack, 2011), institutional quality or frameworks (Berdegué, 2005).

from the New York Times provides some of the earliest insights about the dangers caused by first-time wireless internet access to an isolated Amazonian tribe following Starlink's satellite coverage[5] (Nicas, 2024a, 2024b). While offering clear benefits, such as video chats with distant relatives, the ability to call for help in emergencies, and elevated aspirations among young people to travel the world and have professional careers; negative outcomes are also evident. In less than a year after gaining satellite coverage, teenagers have become increasingly attached to their phones and less motivated to work, with group chats filled with addictive social platforms, violent video games, scams, and age-inappropriate content. Evidence from more developed countries has shown that harms including misinformation, scams, digital addiction, and psychological or mental health disorders have arisen (Diomidous et al., 2016; Firth et al., 2019), possibly at a pace faster than individual awareness or societal understanding can keep up with (Firth et al., 2019; Loh & Kanai, 2016).

Despite such significant negative effects on livelihoods and human capital development variables, particularly for young people, the primary focus in current literature remains on addressing barriers to internet access in remote areas and promoting greater usage (Friederici et al., 2017; Park, 2017; Smart et al., 2016). This emphasis overlooks the rural socioeconomic and geographical contexts, or in other words, 'acontextual modernism' discourse (Friederici et al., 2017), and potentially profound adverse effects on socioeconomic and human development outcomes (Hosman, 2024; Salemink et al., 2015). These negative sides have been considerably less stressed, possibly leading to underestimated or biased evaluations of (future) interventions.

As such, there is an urgent need to conduct more timely studies on remote, less developed areas, where reported lifestyle changes and under-developed socioeconomic conditions create new forms of stratification and increased exposure to harmful content (Cénat, 2020; Hosman, 2024). Youth and adolescents, in particular, face heightened negative effects on well-being and other human capital variables by being both a tech-savvy group, who adopts digital technologies and social media more than any other groups (ITU, 2020, 2023), and a vulnerable demographic (Patel et al., 2016; Twenge & Campbell, 2019). Mental health disorders at young ages can accumulate and carry over beyond adolescence (UN, 2023) and constrain human development by reducing individuals' capacity and working ability, contributing to intergenerational and within-generation social immobility (Golberstein et al., 2019; Goodman et al., 2011; Ridley et al., 2020; UNDP, 2022). Hence, this necessitates more timely research on the well-being and mental health impacts of internet diffusion for youth in less-developed contexts.

[5] Starting from mid-2023. Despite lacking electricity, phone screens light up at night, using battery power from solar panels.

Furthermore, within remote, under-developed communities, additional socioeconomic stratification can produce exacerbated negative effects on adolescents' well-being and mental health, due to differences in internet use types. It has been shown that inequalities in educational levels, wealth, and socioeconomic status shape internet use patterns (C. Harris et al., 2017; Martínez-Domínguez & Mora-Rivera, 2020; OECD, 2017). These patterns then affect youth's mental health through mechanisms such as social comparison (Braghieri et al., 2022), or 'crowding out' hypothesis, whereby internet use lessens the time spent on other beneficial activities (McDool et al., 2020). These scant pieces of evidence so far, again pertain to developed countries' context only. As such, it is essential to investigate the heterogeneous impacts of internet's mental health outcomes even within less developed communities.

Set against this backdrop, this study is carried out to provide one of the early evidence of internet access's mental health impacts among young people in a low-income context. We make some important contributions. First, our study is among the first papers analyzing the negative outcomes of internet access on adolescents' well-being for the Global South context, adding to literature the nuanced effects of internet diffusion in low-income countries. Second, we contribute to the still largely underexplored literature on the unequal impacts of internet use on mental health and well-being in terms of socioeconomic status, e.g., for adolescents from different household wealth levels – a notable finding for least developed countries context.[6] Third, our mechanism analysis shows that disadvantaged youth appear to engage in more passive internet activities, which are likely caused by the addictive design of the technology algorithm in the attention economy (Acemoglu & Johnson, 2023; Costello et al., 2023), and reinforced by the systematic inequality regarding the lack of alternative healthy activities and less support in confronting with negative effects for youth from less advantaged backgrounds (Firth et al., 2024; Scheerder et al., 2017).

For empirical analysis, to alleviate a number of endogeneity concerns by using observational data, we employ combined instrumental variable and difference-in-difference for our estimations. Analyzing longitudinal data from the Young Lives Survey for Ethiopia during 2020-2021, we found strong evidence of the detrimental effect of internet access on subjective well-being and mental health among young people. Additional results on effect heterogeneities are robust following multiple robustness tests and after addressing the possible differential impacts of COVID-19 on different socioeconomic groups. Our overall findings highlight noteworthy implications regarding health and human capital development policies for developing countries in the mobile digital age, and illuminate the exacerbation of the Matthew effects in the digital era (Kümpel, 2020; Trucano, 2013).

[6] According to UN's countries classification (OHRLLS, 2024).

In the next content, related literature will be presented in Section 2; Section 3 describes the data sources and descriptive analysis, and Section 4 states our empirical strategy. Our research results, including main results, robustness tests, and mechanisms analyses, are shown in Section 5. Section 6 concludes and provides discussion and policy implications.

2 Extant literature and background

Here we synthesize extant literature on internet use and youth mental health, highlight key mechanisms behind the unequal effects on youth from different socioeconomic backgrounds, and briefly describe the COVID-19 context in which our empirical data was collected.

2.1 Youth's mental health and the role of internet use

Mental health among youths has worsened in the past two decades (Patel et al., 2016), with depression, generalized anxiety disorder (GAD), and mixed depression and anxiety are the most common manifestations of poor mental health (Huppert & So, 2013; Martínez et al., 2020).[7] In Ethiopia, Hunduma et al. (2024)'s descriptive study in 2020 shows that among in-school adolescents, there are high levels of internalizing problems,[8] which primarily consist of depression and anxiety.

The internet's impact on well-being varies across demographic groups, influenced by personal characteristics, capabilities, and cultural contexts (Castellacci & Tveito, 2018). Youth and adolescents, who face uncertainties during transitioning period to adulthood[9] (Achdut et al., 2021; Tanner & Arnett, 2016), have limited self-regulation and are more susceptible to peer pressure, making them vulnerable as they navigate and experiment with social media (O'Reilly et al., 2018). Donati et al. (2022) for instance, find a significant positive effect of broadband diffusion on mental disorders' diagnoses and hospitalizations among the younger age groups in Italy from 2001 to 2013,[10] while no such effect was detected for the older cohorts.

Negative mental health consequences resulting from internet use can lead to a depletion of personal, social, economic, or cultural resources. For instance, individuals could lose

[7] Depression and anxiety exhibit overlapping symptoms, such as sudden mood swings and social withdrawal, which can intensify feelings of isolation and loneliness. Depression has the potential to escalate to suicidal thoughts or actions (WHO, 2021).

[8] Internalizing problems involve inward-facing symptoms that impact an individual's internal emotional state; while externalizing problems, such as conduct issues, hypersensitivity, inattentiveness, impulsivity, and disruptive disorders, manifest as outward behaviors that impact an individual's social environment.

[9] Including identity formation, education, job-seeking, and relationship-building.

[10] Refers to those born between 1985-1995 (aged 6-16) in 2001.

personal or social resources, such as confidence or informal ties (van Dijk, 2019). In the long term, these effects can constrain human development by diminishing individuals' capabilities and productivity, thereby contributing to social immobility within and across generations (Golberstein et al., 2019; Goodman et al., 2011; UN, 2023; UNDP, 2022).

2.1.1 Determinants of mental health

Factors influencing the mental health include individual (i.e., gender, genetics, personality traits), household (wealth, living conditions, poverty, socioeconomic status), and community (cultural, infrastructure) (Allen et al., 2014; Ferschmann et al., 2022; Weissman et al., 2023). The core framework is based on the seminal work of Bronfenbrenner (1994) on determinants of mental health, situating the adolescent at the center of a multi-level socio-ecological model, including societal, structural, and cultural factors (macro), institutions and policy processes at the regional level (meso), and the interpersonal and family environment (micro). Our model specification is built upon this framework and incorporates a multitude of variables at the individual, household, and community or kebele levels in Ethiopia.

2.1.2 Youth's internet use sphere and impacts on well-being

Youth are the tech-savvy group who adopt digital technologies and social media more than any other groups, irrespective of region or country level of development (ITU, 2020, 2023). In Ethiopia, most users access the internet for social media, entertainment, and news (Adam et al., 2024).[11] For social media users in Ethiopia, escapism (using digital media to fill spare time), exchanging ideas with friends, and knowing about other people, besides acquiring information, are the top use motivations (Adam et al., 2024; Haile, 2024; Internews, 2023).[12]

Such use patterns can affect youth's mental health through multiple mechanisms. First, the uses of internet and smartphones reduce social interactions (Dwyer et al., 2018; Przybylski & Weinstein, 2013; Rotondi et al., 2017). Yet, for young adults in the digital age who feel disadvantaged, online social networks enhance social connections, which are less accessible through other means of communication (Wohn et al., 2013). Achdut et al. (2021), however, show that while online networking builds informal social capital that protects well-being, it is also linked to higher psychological distress, indicating contrasting effects.

There are also impact pathways through the dimensions of online use typology. Descriptive evidence indicates that most Ethiopian youth use social media to fill spare time, for 'escapism', or feel like a waste of time (Haile, 2024; Hussain & Hussain, 2023; Internews,

[11] 95, 79, and 67 percent respectively; followed by banking – 31 percent, others, and online learning.

[12] Facebook is the main platform for information sourcing, followed by Telegram, TikTok, YouTube.

2023), which can be linked to 'mindlessly scrolling' or passive internet use that has been shown in psychological and neuroscience literature to affect brain structure and dynamics, cause increased distraction and psychological distress (Arness & Ollis, 2023; Firth et al., 2024; Rast et al., 2021). Competition among social media platforms and the adjustment of recommender algorithms to boost user engagement have increased social media's addictiveness,[13] causing users craving to check social media more for gratification when having nothing to do (Hjetland et al., 2021; Rast et al., 2021).

Such passive internet use increases users' exposure to unhealthy content[14] and/or cyberbullying[15] (Beneito & Vicente-Chirivella, 2022; van Geel et al., 2014). It has been shown that the top risks on social media reported by Ethiopian students are harassment or bullying, wastage of time, exposure to porn, and hate speeches (Hussain & Hussain, 2023). Qualitative evidence and web-based diary design demonstrate that exposure to explicit content, cyberbullying, and sexual solicitations triggers post-traumatic stress disorder (PTSD) in adolescents, highlighting the 'dark side' of social media use (McHugh et al., 2018; O'Reilly et al., 2018). Social media also includes posts that normalize and even promote self-harm and suicidality among youth (Abi-Jaoude et al., 2020; O'Reilly et al., 2018). Furthermore, since posts on social media tend to be polished and highly curated, using social media enhances users' abilities to engage in unfavorable social comparisons in terms of wealth, popularity, or look (Appel et al., 2016; Fardouly et al., 2015), leading to negative feelings or insecurity about the self (Bucci et al., 2019; Primack et al., 2017).

Next, we explore explanations for the unequal impacts of internet use on youth well-being across different socioeconomic backgrounds.

2.2 The influence of relative poverty and inequality

The effects of internet use on individuals' mental health can have significant heterogeneities, influenced by wealth or socioeconomic status (SES) levels (Abrahamsson, 2024; George et al., 2020). This heterogeneity can be manifested in several ways.

First, while poverty issues such as overcrowding, food scarcity, and neighborhood stressors affects mental health directly (Burns, 2015), perceived relative poverty in terms of con-

[13] For example, Facebook in 2018 announced that the company's algorithm would be modified to prioritize posts from other users, especially family and friends, rather than news organizations and established brands (Acemoglu & Johnson, 2023), or recent innovations in short-form videos with push notifications, recommendations, and auto-scrolling (Baker, 2023; Yang et al., 2021).

[14] Age-inappropriate content, such as online pornography, peer-to-peer abusive behavior involving sexually suggestive or hostile comments, privacy breaches, and the undue influence of third parties such as advertisers.

[15] The use of digital media to post threatening messages, embarrassing photos, and rumors with the intent to harm others.

sumption or income can impact mental health through interpersonal comparisons, causing feelings of failure and 'social defeat' (Ridley et al., 2020). With the advent of social media, users from lower SES backgrounds experience stronger social comparison, since social media exposes them to more polished content in terms of wealth or body images (Appel et al., 2016; de Vries & Kühne, 2015; Fardouly et al., 2015), which is less likely to occur in offline settings. Achdut et al. (2021) shows that while subjective poverty and material deprivation predict psychological distress, online social network use amplifies this negative impact.[16]

Another more general explanation is that internet use patterns vary systematically by SES background, in which lower SES groups tend to engage in less diverse online activities, which are more often social networking, video watching, surfing the internet for news but not for other beneficial and healthy activities, compared to their socio-economically advantaged peers (Blank & Groselj, 2014; OECD, 2017). Time spent passively scrolling auto-recommended content on social media can produce multiple effects on mental health by increasing exposure to unhealthy content and promoting further social comparison, compared to the same time that is allocated to healthier activities (Sampasa-Kanyinga et al., 2014; Verduyn et al., 2015). Moreover, since youth from advantaged backgrounds have more alternatives for offline healthy tasks, which can alleviate digital distress, disadvantaged youth face the feedback loop of more online time, more mindless scrolling, and fewer healthy programs offline (Firth et al., 2024; George et al., 2020). This unequal effect can be further exacerbated through the ways users confront negative impacts. Scheerder et al. (2017) highlight differences in how internet users cope with negative outcomes,[17] in which highly educated people typically try to address negative outcomes by understanding causes, preventing recurrence, or protecting their children, while less educated individuals are less likely to take remedial actions.

2.3 COVID-19 and crisis period

Our data was gathered during the COVID-19 period, which coincides with a time when almost half of YL youth in Ethiopia had internet access. The COVID-19 background might complicate our analysis in several ways. Initially, social media could effectively disseminate information and support, easing concerns and anxieties. However, as the pandemic progressed, the spread of misinformation, amplified by negative and traumatizing news on the civil conflict in the Tigray region,[18] heightened fear, insecurity, and anxiety (Banati et al.,

[16] Survey data for young adults (20–29 years) in 2017 in Israel.

[17] Including economic (e.g., shopping addiction, online gambling), social (interpersonal issues), personal (physiological harms), and cultural (child pornography, cybercrime), which can evoke sadness or anxiety.

[18] Started from November 2020 to November 2022.

2020; DW, 2024; Favara et al., 2022), potentially by means of information overloading or uncertainty (Ambelu et al., 2021; Strasser et al., 2022) and/or negative sentiment contagion among social networks through "doomscrolling"[19] (Jones et al., 2021). Online classes during the pandemic also had mixed effects, in which youth without internet reported reduced well-being due to disrupted education (Simegn et al., 2021), while students with access raised concerns about online class difficulties and digital distress (Akpınar, 2021; Ford & Freund, 2022; Magson et al., 2021). Nevertheless, since our data were collected within the COVID-19 period (2020-2021), the pandemic serves as an exogenous shock impacting all individuals uniformly. Consequently, our findings maintain internal validity. The external validity might be affected, however, if applied to periods before or after the pandemic; given that users have less/more content available online and/or develop new or changed use habits. Future research with additional data might explore if there are significant differential impacts.

A stylized conceptual framework on the impacts of the internet on youth's mental health is illustrated in Figure 1 below, incorporating the multi-level socio-ecological model by Bronfenbrenner (1994) to include factors at individual, household, and community levels as root causes. Internet access and use can cover different dimensions of use typology, which is likely to include mindless scrolling, especially for youth in the attention economy. Specific mechanisms channeling internet use and youth's mental health and subjective well-being might cover time and social interaction replacement hypothesis, social comparison, risk exposure to harmful content, and screen fatigue. These pathways might be worsened during a crisis period due to COVID-19 restrictions, more time online and the rise of negative news.

Our data, methodologies, and empirical results are presented in the next sections.

3 Data and descriptive analyses

In response to the global COVID-19 pandemic, the Oxford Department of International Development Young Lives (YL) collected information about the impacts of the pandemic and appended an additional module on youth's mental health for its round 6 of the YL longitudinal surveys. The survey sample is from the same pool of earlier YL rounds conducted since the year 2002 with very low attrition rates for four developing countries, including Ethiopia (Young Lives, 2023b). YL households sample represents a wide range of living

[19]A word added in 2020 to the Oxford Dictionary, meaning: "obsessively checking online news for updates, especially on social media feeds, with the expectation that the news will be bad, such that the feeling of dread from this negative expectation fuels a compulsion to continue looking for updates in a self-perpetuating cycle.".

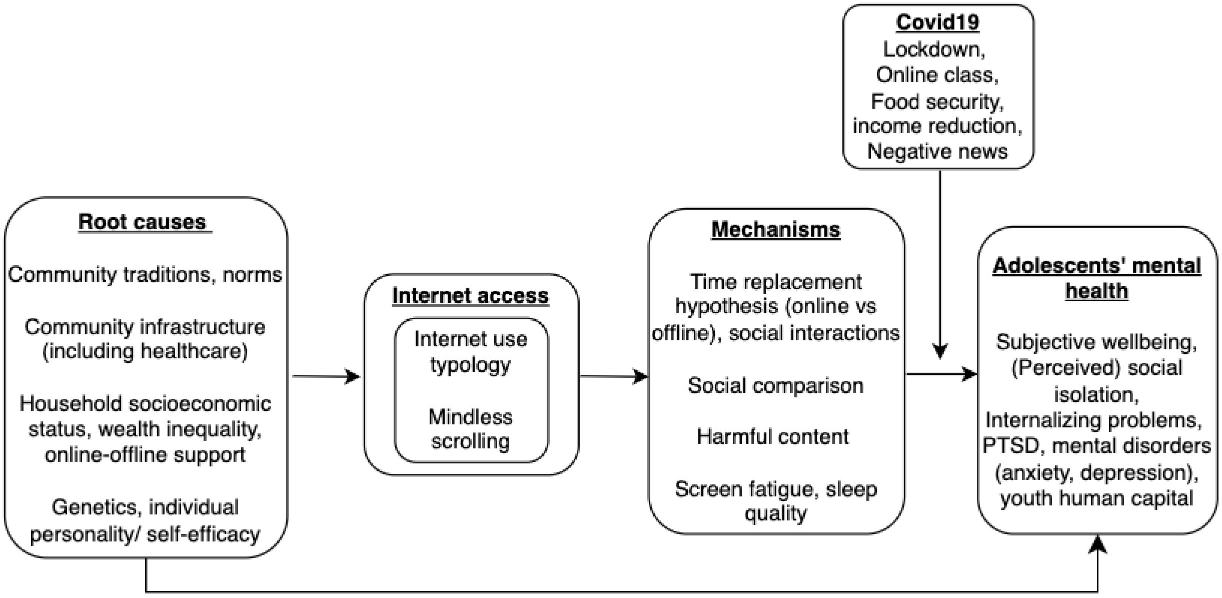

Figure 1: Stylized framework of internet and mental health problems.
Source: Authors' elaboration.

standards similar to the variability found in the Ethiopian population,[20] despite the fact that YL team deliberately oversampling poorer households (Young Lives, 2018).

Round 6 was conducted by phone, split into five separate calls conducted between 2020 and 2021. The data for the younger cohort (aged 18-20) are used for this study (Young Lives, 2018, 2023a). This age range is still considered part of the adolescent group, following the argument by Sawyer et al. (2018) regarding the delayed timing of role transitions from childhood to adulthood in our contemporary society.[21] Due to varied data components being collected differently between calls, our data panel structure is only available for Call 2 (data collected in August-October 2020) and Call 5 (October-December 2021).

3.1 Well-being and mental health variables

Our dependent variables are youth's well-being and mental health. Subjective well-being (SWB) is measured by a scale range from 1-9, with 9 being the highest well-being.[22] This evaluative measure of SWB (Stone & Krueger, 2018) presents a global evaluation of one's

[20]The data covers 20 study sites from five regions (Amhara; Oromia; SNNP - Southern Nations, Nationalities and Peoples' Region; Tigray; and Addis Ababa), where the majority (95%) of Ethiopian children live (Tafere, 2014).

[21]Including completion of education, marriage, and parenthood.

[22]Survey question is *"Suppose the ninth step, at the very top, represents the best possible life for you, and first step, at the bottom represents the worst possible life for you. Having in mind that scale, where on the ladder do you feel you personally stand at the present time?"*

life (Krueger & Schkade, 2008). Mental health disorders are measured by the symptoms of anxiety - Generalized Anxiety Disorder-7 (GAD-7) (seven questions) and of depression - Patient Health Questionnaire depression scale-8 (PHQ-8) (eight questions) over the past 14 days, with total scores ranging from 0 to 21 for GAD-7 and 0 to 24 for PHQ-8 (Favara et al., 2022) (for detailed questionnaires, see Table B1 in the appendix). Both GAD-7 and PHQ-8 are validated psychological measures of risks of anxiety and depression disorders and have been used as indicators of mental well-being in a wide range of social science studies (Braghieri et al., 2022; Huppert & So, 2013).

While being distinct indicators, SWB and mental disorders are correlated measures, and are all aspects of mental health, where health is not just defined by the absence of illness, but also by the presence of elevated levels of SWB (Keyes, 2013).

There are additional questions in Call 2 regarding daily time spent on studying, and things want to do after the pandemic, which we incorporate for analysis on broader human capital variables using IV estimation for cross-sectional data.

3.2 Internet access and content ecosystem

Young Lives COVID-19 survey asked if any member of the YL child's household has a smartphone or computer/ laptop with internet (Young Lives, 2023a). In contrast to fixed broadband, of which penetration rate has been less than one percent of the population, 3G broadband coverage has been near universal, though individual access remains unequal in terms of urban-rural, age, gender, wealth,[23] and education levels (Adam et al., 2024; ITU, 2023; Wassie et al., 2023).[24] During the COVID-19 period, the internet access rate among youth aged 18-20 in Ethiopia in YL data is 45%.[25]

3.3 Other variables

YL Round 6 also includes several variables relating to COVID-19 and its consequences on household's livelihood, including whether a participant has ever been believed or confirmed to be infected with COVID-19 since the start of the pandemic (it was reported in our data

[23]Average smartphone price is USD 60, which effectively excludes a quarter of the population who earn less than USD 2.15 a day; on the other hand price of 1GB prepaid data is among the cheapest in African countries, following increased competition in the Ethiopian mobile telecommunications market in 2018.

[24]E.g., 16 percent of individuals with primary school degree have internet, while 63 percent of individuals involved in tertiary education have.

[25]While the question does not differentiate between mobile or fixed internet, it is important to note that in poorer communities, a rise in internet access is usually more likely to be mobile broadband or SP usage rather than fixed broadband.

that the average infection rate during 2020-2021 in Ethiopia was 0.9%);[26] if their household ever ran out of food since the outbreak of the COVID-19 pandemic (22% faced food insecurity issues); and if household's income was reduced compared to before COVID-19 (48%). The percentage of having online classes in our dataset is very low (about 2.4%), so we could not perform a statistical test on this outcome.

Household wealth index, calculated by Briones (2017), is ranged from 0 to 1 and composed of three aspects - housing quality, access to service, and durable items. The distribution of household wealth index can be seen in Figure A1 in the appendix. Students were also asked about their perceived household wealth during the COVID-19 period. While education level affects internet access, its impact on mental health is inconclusive (Kim et al., 2020).

Summary statistics of key variables for our analysis are in Table 1 below. Bar graphs showing positive correlations between internet access and well-being and mental health disorders indicators in both survey calls can be seen in Figures A2, A3, and A4 in the appendix.

Table 1: Summary statistics

	N	Mean	Std.dev.	Min	Max
Subjective wellbeing	2816	4.657	1.501	1	9
GAD-7	2816	1.710	2.748	0	18
PHQ-8	2816	1.593	2.643	0	17
Internet	2820	0.441	0.496	0	1
Household size	2815	5.675	2.055	1	15
Female	3380	0.465	0.498	0	1
Age	2823	18.828	0.752	17	20
Wealth index round 5	3320	0.419	0.173	0.006	0.881
(Believed) infected	2811	0.009	0.094	0	1
Income decreases	2815	0.477	0.499	0	1
Run out of food	2820	0.218	0.413	0	1

4 Empirical Strategy

In this section, we present our main model specifications and identification strategy.

Correlation coefficients or estimates from cross-sectional ordinary least squares (OLS) models can be significantly biased due to unobserved heterogeneities. Such unobserved factors may include individual characteristics like genetic predisposition, extraversion, personalities, household living conditions, childhood circumstances, and community's infrastructure, all of which can affect both internet use and mental health (Allen et al., 2014; Currie & Morgan,

[26] The actual numbers of infected cases fluctuate between 2020 and 2021, though the number of fatalities is low and stable during the same period (D. Harris et al., 2021).

2020; Ferschmann et al., 2022; McDool et al., 2020). With panel data between calls over August 2020 and December 2021, the inclusion of individual and community fixed effects (FE) mitigates omitted variable bias (OVB) induced by time-invariant factors. Additionally, one may raise concern about other changes e.g., certain macroeconomic fluctuations might influence households' job prospects in a similar way, and, subsequently, affect mental health of household members including adolescents'. The inclusion of call or time FE allows us to rule out such concerns.

Following is our base econometric model:

$$Y_{it} = \beta_0 + \beta_1 Internet_{it} + X_{it} + \mu_i + \alpha_j + \phi_t + \epsilon_{it} \tag{1}$$

where Y_{it} is subjective well-being or mental health indicator (GAD-7 for anxiety and PHQ-8 for depression symptoms scores) of individual i at time t; $Internet_{it}$ is individual i's household internet access (1 = Yes and 0 otherwise); X_{it} denotes a set of time-varying individual and household level controls including COVID-19 impacts; μ_i, α_j, and ϕ_t are the individual, community, and time fixed effects respectively; ϵ_{it} is the idiosyncratic error term.

Equation (1) will be correctly identified under some restrictive conditions, i.e., that household internet access is not influenced by existing pre-trends, so that the treatment is "as good as random", at least after conditioning for individual and household fixed effects and time-varying controls as we have done. There remain, however, a number of endogeneity concerns that need to address. First, there is measurement bias since our main independent variable is internet access at household level, which is used as proxy for adolescents' internet use. This might produce downward bias in the estimations since the aspect of internet use that affects mental health is not binary but continuous and multidimensional, covering both quantity (how much time spent) and quality (what kinds of activities). Second, while reverse causality is less an issue given that internet variable is access, not use; it might be still the case that adolescents with higher subjective well-being are more likely to have internet access. Third, other time-varying controls might still influence both internet access and adolescents' wellbeing, like the case that a household gets richer or a neighborhood has better infrastructure; though within a relatively short time-frame of a year during COVID-19, these might have been less of a concern, given that we have already included time or call FE in the models.

To address these issues, we employ two main strategies. First, following extant literature (Hartje & Hübler, 2017; Hübler & Hartje, 2016; Ma & Sheng, 2023; Rotondi et al., 2017), we employ regional or local average internet access to instrument household-level internet access. The instrument variable (IV) is relevant based on the network effect arguments. From the supply side, telecommunications companies install infrastructure (e.g., cell towers) and provide their services (e.g., technical, sales) and conduct marketing for a geographical area. From the demand side, as people use internet and smartphones for information and communication for business or personal matters, one person's internet access often influences others' in the same community. Thus, following the extant literature, we use average internet access rates, excluding the household itself, at the community level or Kebele (neighborhoods or wards), the lowest administrative unit in Ethiopia, as our instrument.

Regarding exogeneity, community internet rates are likely to be exogenous, conditional on community level and individual and household characteristics. The instrument is (conditionally) correlated with mental health mainly through individual internet use, satisfying the exogeneity condition. It is also difficult to conceive why individual mental health could affect community-level internet access rates. Admittedly, the instrument can still correlate with individual mental health through community economic conditions (e.g., increased income and job opportunities). In our paper, we incorporate both community and time FEs together with IV (i.e. FE-IV models), alleviating the concerns. As a robustness test, we also calculate several time-variant community controls that might be correlated with both the instrument and individual mental health like community's average shares of households with income reductions or food shortages during COVID-19, and community average wealth level (data measured in YL Round 5 survey) interacted with a linear time trend. As presented in the robustness section 5.2, our results remain significant.

The IV approach can also address the issue of mismeasurement in the internet variable, given that community internet rates are of continuous spectrum (between 0 and 1), indicating network effect in which the more users or households having access, the more use time and/or online activities individuals engage in.

Our first-stage equation is:

$$Internet_{it} = \delta_0 + \delta_1 Community_{jt} + X_{it} + \eta_i + \gamma_j + \theta_t + \nu_{it} \tag{2}$$

where $Internet_{it}$ is individual i's household internet access; $Community_{jt}$ is the average internet access rate of cluster or Kebele (neighborhoods or wards), the lowest administrative unit in Ethiopia j; X_{it} are controls for individual and household characteristics, η_i, γ_j, and θ_t are the individual, community, and time fixed effects; ν_{it} is the idiosyncratic error term.

Second, we deploy a difference-in-difference (diff-diff) approach, by regressing the difference in well-being and mental health indicators against the difference in internet access between Call 5 and Call 2 using OLS estimation. By conducting diff-diff analysis, we rule out the OVB concern caused by the components of variations that are unchanged or fixed over time. This is also combined with IV approach since it might still be the case that households become wealthier then get internet access and also improve the well-being of household members, so that internet is not completely an exogenous intervention; as well as to account for any measurement error in the adolescents' internet use variable.

5 Results

In this section, we present the main results, followed by robustness tests, effect heterogeneity, and mechanism analyses.

5.1 Main results

Estimation results are presented in Table 2 below. As can be seen in Column (2) for FE-IV estimations, internet access results in reduced subjective well-being of adolescents. The effect sizes depict that youth having internet access have worse subjective well-being, a reduction of 1.6 points, compared to youth who do not have. First-stage regression results show that the instrument is positively correlated with the endogenous variable and has the expected sign, confirming its relevance. The first stage F-statistic is greater than the Stock-Yogo critical value, meaning that the instrument is not weak.

Results from FE-IV models in Columns (4) and (6)) show that the average anxiety and depression scores of adolescents who have internet access are 9.4 and 8.3 units higher than those who do not, after controlling for individual, household, and community characteristics, year effects, and addressing issues of endogeneity.

The significantly larger effect sizes in FE-IV compared to null results or smaller effect effect magnitudes by FE estimations as shown in Columns (1), (3), and (5) suggest that measurement errors and other time-variant OVBs e.g., household or community wealth or health infrastructure improvements or reductions have downwardly biased the OLS estimates.

Table 2: Internet and adolescents' mental health problems and subjective well-being

	Subjective well-being			**GAD-7**		**PHQ-8**	
	(1)	(2)		(3)	(4)	(5)	(6)
	FE	FE-IV		FE	FE-IV	FE	FE-IV
Internet	0.104	-1.556***		0.774***	9.389***	0.730***	8.342***
	(0.106)	(0.533)		(0.265)	(1.624)	(0.242)	(1.498)
1st-stage Community internet			0.976***				
			(0.134)				
(Believed) infected	0.267	0.418**	0.342*	2.506	3.162	-0.556	-1.540
	(0.280)	(0.205)	(0.203)	(2.073)	(3.214)	(0.961)	(1.610)
Income decreases	-0.0358	-0.0759	-0.0027	0.512***	0.937***	0.387**	0.753***
	(0.0906)	(0.115)	(0.0248)	(0.178)	(0.296)	(0.168)	(0.276)
Run out of food	0.314**	0.214	0.0511	0.119	0.744**	0.311	0.777**
	(0.153)	(0.187)	(0.0395)	(0.191)	(0.378)	(0.212)	(0.380)
Constant	4.453***			1.092***		1.104***	
	(0.0721)			(0.160)		(0.149)	
Observations	2272	1846	1846	2262	1836	2266	1840
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Call FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.658			0.596		0.627	
Adjusted R^2	0.305			0.179		0.243	
F-statistics		52.71	52.71		52.25		52.73

Notes: Each column reports estimated effects of internet access on mental health problem indicators: GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire-8. Well-being is subjective well-being, with a range between 1 (low well-being) and 9 (high well-being). Columns (1) and (4) are OLS results; columns (2) and (5) are FE; (3) and (6) are FE-IV. FE include individual, community, and call fixed effects. The instrument is the proportion of households in a community getting access to the internet, excluding one's own value. F-statistic is the Kleibergen-Paap rk Wald F statistic. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Next, we create a sub-sample to simulate a difference-in-difference scenario. To do this, we restrict the sample to people in Call 5 and who had no internet access during Call 2 of the survey. Additionally, we combine diff-diff with IV since household internet access might not be completely an exogenous intervention. The estimation results in odd-numbered columns for diff-diff and in even-numbered columns for combined IV and diff-diff are summarized in Table 3 below, providing similar results of reduced subjective well-being and increased mental disorders for Ethiopian adolescents, highlighting the robustness of our findings. Full results with control variables can be seen in Table B2 in the appendix.

Table 3: Diff-diff estimation of internet access and youth's mental health

	Diff. in SWB		**Diff. in GAD-7**		**Diff. in PHQ-8**	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Diff. in internet	-0.0180	-1.249**	2.299***	6.925***	1.737***	6.050***
	(0.203)	(0.592)	(0.488)	(1.137)	(0.414)	(0.991)
Observations	610	557	605	553	607	556
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.030		0.108		0.103	
Adjusted R^2	0.022		0.101		0.096	
F-statistic		106.10		104.84		105.72

Notes: The sample is limited to people who do not have internet in Call 2. Both dependent and internet variables are transformed by differences between Call 5 and Call 2. Each column reports estimated effects of internet access on adolescents' mental health. Covariates: (believed to be) infected by COVID-19, negative income shocks, run out of food, urban. F-statistic is the Cragg-Donald Wald F statistic. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Following Braghieri et al. (2022) to measure the downstream implications of poor mental health, we also run additional analyses for a number of human capital-related variables. YL survey in Call 2 had several items on time spent during a typical weekday,[27] including time more spent for studying.[28] There is also a question on "What are you most looking forward to do after COVID-19 is over?", and answers include going back to education.[29] We conduct IV estimations on the impact of internet use on these variables using linear probability models for binary dependent variables. As shown in Table 4 below, internet use is associated with

[27]Questionaire item: "Now I want you to think about how you spent your time during a typical weekday when the country was in full lockdown. Do you agree, partially agree or disagree with the following statement: 1=Agree; 2=Partially agree 3=Disagree." We recode these variables into binary format, with 1 equal Agree, and 0 for the rest.

[28]"I spent more time studying/ learning."

[29]Options include 1-Going back to education, 2-Going back to work/workplace, 3-Visit family, 4-Visit friends, 5-Go to the city center, 6-Go to the park, 7-Go out for dinner, 8-Play a team sport, 9-To go to church/ mosque/ temple/ ceremonies/ weddings, 10-None, 11-Other (specify). We create a new variable that has value 1 if the answer value is 1-Going back to education and 0 if the answer is greater than 2, to exclude

less time spent on studying and less aspiration to go back to education after COVID-19. The full table with other control variables is presented in Table B3 in the appendix.

Table 4: Broader impacts on other human capital-related variables

	(1) (Perceived) time spent studying	(2) Want to go back to education
Internet	-0.205***	-0.225**
	(0.0750)	(0.0927)
(Believed) infected	0.287*	0.272***
	(0.166)	(0.0506)
Income decreases	-0.0554**	-0.109***
	(0.0258)	(0.0256)
Run out of food	-0.0298	-0.188***
	(0.0289)	(0.0397)
Observations	1370	1162
Control	Yes	Yes
F-statistic	184.21	121.15

Notes: Samples include children in Call 2 due to data availability. The instrument for IV estimates is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on the likelihood having spent more time on studying or wanting to go back to school after COVID-19. Covariates: perceived wealth levels, household size, gender, (believed to be) infected by COVID-19, negative income shocks, run out of food, urban. F-statistic is the Kleibergen-Paap rk Wald F statistic. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Robustness checks

In this section, we present a number of tests showing the robustness of our results under some alternative or restrictive specifications.

Firstly, as community's averages of internet access might be correlated to other time-variant community controls that might be related to individual mental health, we calculate a number of variables at community level, including average rates of households with income reductions and food shortage during COVID-19; and average wealth index (measured in Round 5 survey in 2016, then interacted with linear time trend). Our results incorporating these variables remain robust, as shown in Table B4 in the appendix, with slightly stronger effect sizes for both anxiety and depression scores; but not for subjective well-being, though effect sign remains negative.

Secondly, we add Call 2's mental health values as a control variable in the cross-sectional

youth who is already in the labor force/ going back to work.

model for Call 5 to alleviate the endogeneity concern of self-selection, and the effect sizes become slightly stronger as presented in Table B5 in the appendix.

Third, in an effort to control for other regional-level factors that might affect both community internet diffusion and individual mental health, including differential effects of COVID-19 restrictions or different public resources and capacity to respond to COVID-19 impacts (D. Harris et al., 2021), we add regional fixed effects into the models, and our results remain robust, with slightly larger effect sizes than results in the main models, as can be seen in Table B6.

5.3 Effect heterogeneities

Since the effects of internet use on individuals' mental health can have significant heterogeneities, moderated by wealth or socioeconomic statuses as evidenced by Abrahamsson (2024) and George et al. (2020), we conduct effect heterogeneity analysis to compare the effects between two types of households. Using wealth index developed by Briones (2017), we divide the sample into two groups with low and high wealth levels.[30] Table 5 below shows that, as expected, adolescents from households with a lower wealth level have a significantly higher risk of mental health problems compared to adolescents from households with a higher one. The effect size is more than doubled and statistically different from zero at the 1% level for both anxiety (Columns (3) and (4)) and depression (Columns (5) and (6)) scores.

Interestingly, the effect on subjective well-being for the lower-wealth group is insignificant (Column (1)), while for the higher-wealth group, it is statistically significant (Column (2)), thus it seems that there is no significant impact of internet on subjective well-being dimension for the less advantaged group in Ethiopia during COVID-19.

[30] Using Stata command xtile, by clusters and call.

Table 5: Heterogeneity of effects of internet on mental health by SES

	SWB		GAD-7		PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth index	Lower	Higher	Lower	Higher	Lower	Higher
Internet	-1.578	-1.338**	14.07***	6.777***	12.86***	5.680***
	(1.059)	(0.529)	(4.209)	(1.345)	(3.824)	(1.222)
(Believed) infected	0.356***	0.399	6.735***	0.744	-0.198	-1.718
	(0.120)	(0.305)	(1.191)	(3.912)	(1.187)	(1.469)
Income decreases	-0.00316	-0.165	1.101**	0.868**	0.883*	0.736**
	(0.163)	(0.164)	(0.555)	(0.383)	(0.508)	(0.357)
Run out of food	0.493*	0.0450	0.519	0.951*	0.375	1.029**
	(0.293)	(0.241)	(0.701)	(0.490)	(0.682)	(0.477)
Observations	902	868	898	862	902	868
Individual, Call, Cluster FEs	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F-statistic	15.15	45.40	15.13	44.86	15.15	45.40

Notes: Effects of internet access by wealth groups. FE-IV estimates with individual, community, and call fixed effects. The instrument is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on mental health problem indicators: GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire-8. Well-being is subjective well-being, with a range between 1 (low well-being) and 9 (high well-being). The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Similar heterogeneity results using combined IV and diff-diff estimation can be seen in Table 6 below (full results with control variables are shown in Table B7 in the appendix).

Table 6: Heterogeneity effects of internet access and mental health - diff-diff estimations

	Diff. in SWB		Diff. in GAD-7		Diff. in PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth index	Low	High	Low	High	Low	High
Diff. in internet	-0.581	-1.372**	14.77***	3.539***	13.84***	3.528***
	(1.513)	(0.582)	(4.450)	(0.943)	(4.456)	(0.921)
Observations	275	234	273	232	275	234
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald Wald F statistic	18.27	107.94	18.04	106.44	18.27	107.94

Notes: The sample limited to people who do not have internet in Call 2. Both dependent and internet variables are transformed by differences between Call 5 and Call 2. IV estimates, the instrument is the proportion of households in a community getting access to the internet. Covariates: (believed to be) infected by COVID-19, negative income shocks, run out of food, urban. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We also employ models that include interaction terms between internet and wealth index for FE estimations, and find a negative sign of the interaction term, though at a weaker statistical level (Table B8 in the appendix), suggesting the moderating effect of wealth on internet and mental health problems.

Lastly, to test whether the heterogeneous effects caused by internet access are not contaminated by other differential impacts of the COVID-19 pandemic, we add additional dichotomous variables, including during the pandemic if young people's household had job loss, experienced input prices and food prices increased, as control variables in the FE-IV analyses. Effect heterogeneities between the two groups remain, as shown in Table B9 in the appendix.

In terms of gender heterogeneity, although some studies find stronger impacts for females, in our data, there is no detected effect heterogeneity for different gender groups (females and males), which might be due to self-reporting issues and/or different contextual characteristics and mechanisms. Results can be seen in Table B10 in the appendix.

We also tried heterogeneity analysis for urban-rural regions. However, the IV approach does not work for urban areas.[31] Additionally, there could be varied effects among different ethnic groups, though when we divide ethnic groups into majority (include Amhara and Oromo, together accounting for 49.6% in YL sample) and minority (the rest), there is no significant heterogeneity detected, and the IV does not work for the majority ethnic group.

While education level affects internet access, its impact on mental health is inconclusive (Kim et al., 2020). Indeed, when we add users' highest grade achieved[32] as a control variable in the FE-IV regressions, the internet's impact on mental health remains unchanged, as can be seen in the Table B11 in the appendix. Parents' education levels, however, affect the way children confront with the negative impacts of internet as shown by Scheerder et al. (2017), with differences being for groups with/without tertiary level. In our data, around 45% of YL mothers have zero year of schooling, and around 4.1% have post-secondary education (variable distribution can be seen in Figure A5 in the appendix, data from YL round 5 in 2016), thus we could not conduct statistical heterogeneity analysis for parental educational background.

YL also surveyed data for the older children cohort (aged 25-28 years old during 2020-2021). This age range is, however, not in the adolescent groups as argued by Sawyer et al.

[31] The community's average internet is insignificant in the first-stage results, and the F-statistic is very low.

[32] We create a new variable which equals highest grade completed if there is no missing value, or equals grade currently enrolled minus one if otherwise. During 2020-2021, highest grade attained increased by 0.42 years.

(2018), and the IV does not work for this group.[33]

In the next section, we present additional regression results as suggestive mechanisms explaining the main outcomes and the effect heterogeneity by wealth index as detected above.

5.4 Mechanisms analysis

In Call 2 survey, there are a number of additional variables that are relevant in explaining the results detected earlier. We run regressions for these variables as the dependent variables against internet, using IV estimations for linear probability models.

First, as discussed in the literature review section, internet use can change the time use patterns of adolescents both online and offline, with most young people in Ethiopia using social media to fill spare time or 'escapism' (Haile, 2024; Hussain & Hussain, 2023; Internews, 2023). Such passive internet use or mindless scrolling alternate brain structure and dynamics, causing increased distraction and psychological distress by e.g., craving to check social media more for gratification when having nothing to do (Arness & Ollis, 2023; Firth et al., 2024; Hjetland et al., 2021; Rast et al., 2021). Using the survey items on time spent during a typical weekday,[34] which include time spent on playing/ doing nothing,[35] we detect significant heterogeneity in the effect sizes of the internet variable. The results are presented in Table 7 below for both average and heterogeneous outcomes, where for brevity we only report the main independent variable, showing that household internet access results in adolescents spent more time on playing or doing nothing (Column (1)) while less likely meeting friends[36] (Column (4)). There is no significant effect on time for doing household chores[37] (Column (7)). Full results including control variables can be seen in Table B12 in the appendix.

Our outcomes corroborate evidence from mechanism analysis by McDool et al. (2020), who detected that internet use lessens the time spent on other beneficial activities[38] for British

[33]F-statistic is very low, and the IV is insignificant in the first-stage result.

[34]Questionaire item: "Now I want you to think about how you spent your time during a typical weekday when the country was in full lockdown. Do you agree, partially agree or disagree with the following statement: 1=Agree; 2=Partially agree 3=Disagree." We recode these variables into binary format, with 1 equal Agree, and 0 for the rest.

[35]"I spent more time playing/doing nothing."

[36]Survey question asking whether respondents had left their houses during the past seven days for recreation, meeting friends and family. Questionnaire item is "Did you leave the house during the past 7 days? Recreation, meeting friends and family.".

[37]"I spent more time on household chores than before", also in the time spent during a typical weekday item.

[38]Including: playing sports; face-to-face interaction with friends and family; going to youth clubs or other organized events; undertaking voluntary or community work; and attending out of school classes such as art, music etc.

adolescents.[39] These results reflect the effect on more 'mindlessly scrolling' or passive use of the internet, thus, less healthy activities (Arness & Ollis, 2023; Firth et al., 2024; MacLeod, 2023) in the age of the attention economy (Baker, 2023; Costello et al., 2023; Seaver, 2019; Yang et al., 2021).

Table 7: Internet access and suggestive mechanisms

	Time doing nothing			**Meeting friends**			**Time HH chores**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wealth	All	Low	High	All	Low	High	All	Low	High
Internet	0.148*	0.329**	0.147	-0.482***	-0.566**	-0.602**	-0.0178	-0.0392	0.0783
	(0.0777)	(0.142)	(0.151)	(0.0951)	(0.265)	(0.251)	(0.0823)	(0.210)	(0.189)
Observations	1418	454	435	1354	431	421	1419	454	435
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F stat.	179.55	38.79	41.58	186.38	40.34	34.74	179.55	38.79	41.58

Notes: Samples include children in Call 2 due to data availability. IV estimates, the instrument is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on the likelihood having spent more time on doing nothing. Covariates: perceived wealth levels, household size, gender, (believed to be) infected by COVID-19, negative income shocks, run out of food, urban. F-statistic is the Kleibergen-Paap rk Wald F-statistic. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In terms of effect heterogeneities, the effect magnitudes of internet access on time spent doing nothing are stronger for the lower wealth group (Column (2)) while the effect for the higher wealth group is insignificant and less than half in effect size (Column (3)), providing suggestive explanations for the effect heterogeneities detected in the section 5.3. YL adolescents from lower wealth or SES group who use internet are significantly (more) likely to perceive that they spend more time on playing/ doing nothing, compared to adolescents from higher SES group who do not (significantly) seem to feel so. This result indicates the systematic inequality in the patterns of internet use among lower versus higher socioeconomic status groups, e.g., more unsupervised screen time or more time spent passively consuming media (Blank & Groselj, 2014; George et al., 2020; OECD, 2017). Further online time and mindless scrolling during the pandemic could have promoted more social comparison (Verduyn et al., 2015; Yue et al., 2022), heightened the risk of exposure to age-inappropriate unhealthy content (Hussain & Hussain, 2023), and to negative news of the pandemic and civil war (Ambelu et al., 2021; Chekol et al., 2023; Huckins et al., 2020; Tareke et al., 2023) for the poorer group; while at the same time crowding out healthier activities online and offline that the richer group are endowed with and thus, affecting brain structure and dynamics, causing increased psychological distress (Arness & Ollis, 2023; Baym et al., 2020; Firth et al., 2024;

[39] Following superfast broadband rollout program subsidized by the government during 2012-2017.

Rast et al., 2021), and as a result, intensifying the gaps in the consequences of internet's negative outcomes on mental health.

For the social interaction hypothesis as detected by Dwyer et al. (2018), Rotondi et al. (2017), and Przybylski & Weinstein (2013), no significant heterogeneity is detected, as shown in Columns (5) and (6) of Table 7. No unequal impacts are either found for time spent on doing household chores, as in columns (8) and (9), regarding replacement hypothesis for household domestic physical activities.

6 Conclusion and discussion

The empirical analyses in our paper show robust evidence of internet use and its effects on youth's mental health and subjective well-being in Ethiopia during 2020-2021, and additionally, on broader youth's human capital regarding less time studying and less wanting to go back to education. Notably, there are stronger effects for the poorer groups with more than doubled effect magnitudes, indicating the significantly unequal impacts for the disadvantaged groups. As far as we know, this is among the first papers offering robust evidence on the internet – youth's mental health nexus with significant impact heterogeneities in a least developed country context.

Our mechanisms analysis offers suggestive evidence supporting the effect on more time spent on playing/ doing nothing, which might indicate mindlessly scrolling or internet passive use (Arness & Ollis, 2023; Firth et al., 2024), with a considerable effect heterogeneity between the poorer and richer groups. All in all, the highly unequal impacts for youth from less advantaged background raises an alarming bell for both the dark side and the worsening inequality trend of the internet moving beyond access to use quality and outcomes, indicating the reinforcement of existing social inequalities (Scheerder et al., 2017; UN, n.d.; van Deursen & van Dijk, 2014), or in other words, the exacerbation of the Matthew effects in the digital age.

As the internet becomes more diffused worldwide, especially following COVID-19, young people's increasing exposure to online content and activities can result in worsened negative mental health and human capital, potentially leading to a global epidemic of mental disorders of the younger generations (Østergaard, 2017) if no interventions are made. The responsibility ultimately falls on families and policymakers to regulate and guide internet use and online culture for the development of a healthy and productive generation (PewResearchCenter, 2018), since on the other front, the business models of online content are just trying to maximize profits (Abi-Jaoude et al., 2020; Granic et al., 2020; Lauer, 2021).[40] This is important given that in our technologically advanced and growingly competitive society, human capital in general and *"emotional health [in particular] increasingly is considered an important determinant of earnings in all parts of the world"* (Becker, 1994), and aligns with global development goals to go beyond conventional GDP and growth[41] to measuring people's well-being[42] (Kanbur et al., 2018; Stiglitz et al., 2009).

While policies banning smartphones at school showing some positive results (Abrahamsson, 2024; Ali, 2024; Beneito & Vicente-Chirivella, 2022); adolescents spend more online time at home, and banning smartphone use or texting at home may not work and would be counterproductive (Abouk & Adams, 2013), especially for adolescents and young adults who take control over their personal devices outside the school environment. As said by an elderly tribe woman in the Amazon tribe mentioned earlier "But please don't take our internet away," and since the internet also provides other useful information, policy and social interventions should aim to promoting awareness and use habits for optimal benefits. Practical policies may include campaigns to increase awareness of the harms and dangers of the digital space,[43] even before internet's reach (Hosman, 2024); to manage the possible deleterious effects, and to implement coping strategies (Scheerder et al., 2017). These should be promoted in both formal (school) and informal (household, community) learning environments (Cobb, 2023; Malamud & Pop-Eleches, 2011).

Particularly, policies should be focused on youth from less advantaged background to break the vicious cycle between mental illness and poverty that spirals many young people into both socioeconomic and mental health disadvantages (Bauer et al., 2021; Cornia et al., 2020; Haushofer & Fehr, 2014). Mobile digital health care, for example, has the potential to address mental health care inequality by providing cheaper resources to information and services, but there have been concerns regarding the abundance of unregulated material (Bucci et al., 2019) and the designs of digital programs in terms of inclusive outreach and affordability (Banati et al., 2020). More importantly, however, are to address the root causes of socioeconomic inequality for children and adolescents, which are important drivers and still underestimated factors in mental health practices (Burns, 2015; Kirmayer & Pedersen, 2014). These include not only reducing poverty and material deprivation (Achdut et al., 2021) but also leveling

[40] The policy space for developing countries might be narrower compared to developed countries, for example, lately in the US, New York state lawmakers enacted legislation prohibiting social media platforms from exposing users under 18 to 'addictive' algorithmic content without parental consent (Singh & Dang, 2024).

[41] That have many limitations, even when used as a measure of market output.

[42] Which include both material living standards like household income, consumption, and subjective well-being of social connections and perceived quality of life.

[43] E.g., in the US recently, there has been a legislative call for a warning label to be added to social media apps, like in tobacco studies, to remind the harms caused to young people (Singh & Dang, 2024).

the playing fields for youth in terms of education, better ICT pedagogical resources for more productive use of internet resources (van Deursen & van Dijk, 2014; Vargas-Montoya et al., 2023).

While our analysis detects significant results for self-reported mental health, the actual incidence might be either higher or lower than the actual size if there is self-reporting bias due to gender or cultural norms of mental health stigma (Castellacci & Tveito, 2018). Thus, further information on healthcare diagnoses or hospitalization cases (Abrahamsson, 2024; Donati et al., 2022) might provide measurable economic impacts in terms of healthcare costs (Amaral-Garcia et al., 2022), though this is so far more common in developed countries context. New data should also be collected to measure the long-run, life-cycle achievements. Future data availability can also be used to detect explicitly mechanisms like social comparison hypothesis (Braghieri et al., 2022), increased risks to harmful content and cyberbullying causing PTSD (Beneito & Vicente-Chirivella, 2022; Currie & Morgan, 2020; McHugh et al., 2018), online class fatigue (Ford & Freund, 2022; Huckins et al., 2020), and negative news distress (Ambelu et al., 2021; Huckins et al., 2020), with potentially differential effects for the periods before and/or after the pandemic.

References

Abi-Jaoude, E., Naylor, K. T., & Pignatiello, A. (2020). Smartphones, social media use and youth mental health. *Canadian Medical Association Journal*, 192, E136–E141. https://doi.org/10.1503/cmaj.190434

Abouk, R., & Adams, S. (2013). Texting bans and fatal accidents on roadways: Do they work? or do drivers just react to announcements of bans? *American Economic Journal: Applied Economics*, 5, 179–199. https://doi.org/10.1257/app.5.2.179

Abrahamsson, S. (2024). Smartphone bans, student outcomes and mental health. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4735240

Acemoglu, D., & Johnson, S. (2023). *Power and progress our thousand-year struggle over technology and prosperity*. Hachette UK.

Achdut, N., Refaeli, T., & Tayri, T. M. S. (2021). Subjective poverty, material deprivation indices and psychological distress among young adults: The mediating role of social capital and usage of online social networks. *Social Indicators Research*, 158, 863–887. https://doi.org/10.1007/s11205-021-02729-0

Adam, L., Alemneh, E., Omar, N., & Partridge, A. (2024). Internet development in ethiopia: High-level findings from the after access survey. Retrieved May 15, 2024, from https://researchictafrica.net/wp/wp-content/uploads/2024/02/InternetDevelopmentinEthiopia%5C_RIA.pdf

Akpınar, E. (2021). The effect of online learning on tertiary level students' mental health during the covid19 lockdown. *The European Journal of Social & Behavioural Sciences*, 30, 52–62. https://doi.org/10.15405/ejsbs.288

Aldashev, A., & Batkeyev, B. (2021). Broadband infrastructure and economic growth in rural areas. *Information Economics and Policy*, 57, 100936. https://doi.org/10.1016/j.infoecopol.2021.100936

Ali, R. (2024, September). Smartphone bans in schools: Where is it happening and why? Retrieved October 15, 2024, from https://www.aa.com.tr/en/world/smartphone-bans-in-schools-where-is-it-happening-and-why/3328612

Allen, J., Balfour, R., Bell, R., & Marmot, M. (2014). Social determinants of mental health. *International Review of Psychiatry*, 26, 392–407. https://doi.org/10.3109/09540261.2014.928270

Amaral-Garcia, S., Nardotto, M., Propper, C., & Valletti, T. (2022). Mums go online: Is the internet changing the demand for health care? *The Review of Economics and Statistics*, 104, 1157–1173. https://doi.org/10.1162/rest_a_01033

Ambelu, A., Birhanu, Z., Yitayih, Y., Kebede, Y., Mecha, M., Abafita, J., Belay, A., & Fufa, D. (2021). Psychological distress during the covid-19 pandemic in ethiopia: An online cross-sectional study to identify the need for equal attention of intervention. *Annals of General Psychiatry*, 20, 22. https://doi.org/10.1186/s12991-021-00344-4

Appel, H., Gerlach, A. L., & Crusius, J. (2016). The interplay between facebook use, social comparison, envy, and depression. *Current Opinion in Psychology*, 9, 44–49. https://doi.org/10.1016/j.copsyc.2015.10.006

Arness, D. C., & Ollis, T. (2023). A mixed-methods study of problematic social media use, attention dysregulation, and social media use motives. *Current Psychology*, 42, 24379–24398. https://doi.org/10.1007/s12144-022-03472-6

Arshad, Q. K. U. D., Kashif, A. U., & Quershi, I. M. (2019). A review on the evolution of cellular technologies. *2019 16th International Bhurban Conference on Applied Sciences and Technology (IBCAST)*, 989–993. https://doi.org/10.1109/IBCAST.2019.8667173

Baker, C. (2023, June). *An influencer's world: A behind-the-scenes look at social media influencers and creators*. University Of Iowa Press.

Banati, P., Jones, N., & Youssef, S. (2020). Intersecting vulnerabilities: The impacts of covid-19 on the psycho-emotional lives of young people in low- and middle-income countries. *The European Journal of Development Research*, 32, 1613–1638. https://doi.org/10.1057/s41287-020-00325-5

Bauer, A., Garman, E., McDaid, D., Avendano, M., Hessel, P., Díaz, Y., Araya, R., Lund, C., Malvasi, P., Matijasevich, A., Park, A.-L., Paula, C. S., Ziebold, C., Zimmerman, A., & Evans-Lacko, S. (2021). Integrating youth mental health into cash transfer programmes in response to the covid-19 crisis in low-income and middle-income countries. *The Lancet Psychiatry*, 8, 340–346. https://doi.org/10.1016/S2215-0366(20)30382-5

Baym, N. K., Wagman, K. B., & Persaud, C. J. (2020). Mindfully scrolling: Rethinking facebook after time deactivated. *Social Media + Society*, 6, 205630512091910. https://doi.org/10.1177/2056305120919105

Becker, G. S. (1994). *Human capital: A theoretical and empirical analysis with special reference to education, third edition* (3rd ed.). The University of Chicago Press.

Beneito, P., & Vicente-Chirivella, Ó. (2022). Banning mobile phones in schools: Evidence from regional-level policies in spain. *Applied Economic Analysis*, 30, 153–175. https://doi.org/10.1108/AEA-05-2021-0112

Berdegué, J. A. (2005). *Pro-poor innovation systems* (tech. rep.). The International Fund for Agricultural Development.

Bergquist, L. F. (2021, April). *Barriers to technology adoption: What we know from micro empirics* (tech. rep.). STEG Macro Development Course.

Blank, G., & Groselj, D. (2014). Dimensions of internet use: Amount, variety, and types. *Information Communication and Society*, 17, 417–435. https://doi.org/10.1080/1369118X.2014.889189

Braghieri, L., Levy, R., & Makarin, A. (2022). Social media and mental health. *American Economic Review*, 112, 3660–3693. https://doi.org/10.1257/aer.20211218

Briones, K. J. (2017, November). 'how many rooms are there in your house?' constructing the young lives wealth index.

Bronfenbrenner, U. (1994). Ecological models of human development. Oxford: Elsevier.

Bucci, S., Schwannauer, M., & Berry, N. (2019). The digital revolution and its impact on mental health care. *Psychology and Psychotherapy: Theory, Research and Practice*, 92, 277–297. https://doi.org/10.1111/papt.12222

Burns, J. K. (2015). Poverty, inequality and a political economy of mental health. *Epidemiology and Psychiatric Sciences*, 24, 107–113. https://doi.org/10.1017/S2045796015000086

Castellacci, F., & Tveito, V. (2018). Internet use and well-being: A survey and a theoretical framework. *Research Policy*, 47, 308–325. https://doi.org/10.1016/j.respol.2017.11.007

Cénat, J. M. (2020). Globalization, internet and psychiatric disorders: Call for research and action in global mental health. *Neurology, Psychiatry and Brain Research*, 36, 27–29. https://doi.org/10.1016/j.npbr.2020.02.007

Chekol, M. A., Moges, M. A., & Nigatu, B. A. (2023). Social media hate speech in the walk of ethiopian political reform: Analysis of hate speech prevalence, severity, and natures. *Information, Communication & Society*, 26, 218–237. https://doi.org/10.1080/1369118X.2021.1942955

Chiang, S. (2024, May). Tech musk launches spacex's starlink internet services in indonesia, says more investments could come. Retrieved October 25, 2024, from https://www.cnbc.com/2024/05/20/musk-launches-spacexs-starlink-internet-services-in-indonesia.html

Cobb, C. L. (2023). Mental health and disadvantaged youth: Empowering parents as interventionists through technology. *American Psychologist*, 78, 927–940. https://doi.org/10.1037/amp0001156

CORDIS. (2021, April). Affordable and reliable internet access available to remote areas. https://doi.org/10.3030/777137

Cornia, G. A., Jolly, R., & Stewart, F. (2020, May). Covid-19 and children, in the north and in the south.

Costello, N., Sutton, R., Jones, M., Almassian, M., Raffoul, A., Ojumu, O., Salvia, M., Santoso, M., Kavanaugh, J. R., & Austin, S. B. (2023). Algorithms, addiction, and adolescent mental health: An interdisciplinary study to inform state-level policy action to protect youth from the dangers of social media. *American Journal of Law & Medicine*, 49, 135–172. https://doi.org/10.1017/amj.2023.25

Currie, C., & Morgan, A. (2020). A bio-ecological framing of evidence on the determinants of adolescent mental health - a scoping review of the international health behaviour in school-aged children (hbsc) study 1983–2020. *SSM - Population Health*, 12, 100697. https://doi.org/10.1016/j.ssmph.2020.100697

de Vries, D. A., & Kühne, R. (2015). Facebook and self-perception: Individual susceptibility to negative social comparison on facebook. *Personality and Individual Differences*, 86, 217–221. https://doi.org/10.1016/j.paid.2015.05.029

Diomidous, M., Chardalias, K., Magita, A., Koutonias, P., Panagiotopoulou, P., & Mantas, J. (2016). Social and psychological effects of the internet use. *Acta Informatica Medica*, 24, 66. https://doi.org/10.5455/aim.2016.24.66-69

Dlodlo, N., & Kalezhi, J. (2015). The internet of things in agriculture for sustainable rural development. *2015 International Conference on Emerging Trends in Networks and Computer Communications (ETNCC)*, 13–18. https://doi.org/10.1109/ETNCC.2015.7184801

Donati, D., Durante, R., Sobbrio, F., & Zejcirovic, D. (2022). Lost in the net? broadband internet and youth mental health.

Duchamp, S., & Congote, N. (2022, June). Internet connectivity brings opportunity to remote region where violence once lived. https://news.microsoft.com/source/features/work-life/internet-connectivity-brings-opportunity-to-remote-region-where-violence-once-lived/

DW. (2024, July). The weaponization of social media in ethiopia's tigray war. Retrieved June 15, 2024, from https://www.dw.com/en/facebooks-africa-problem-the-weaponization-of-social-media-in-ethiopias-tigray-war/a-69644721

Dwyer, R. J., Kushlev, K., & Dunn, E. W. (2018). Smartphone use undermines enjoyment of face-to-face social interactions. *Journal of Experimental Social Psychology*, 78, 233–239. https://doi.org/10.1016/j.jesp.2017.10.007

European Commission. (2018). Comparison of wired and wireless broadband technologies. https://ec.europa.eu/information_society/newsroom/image/document/2018-17/comparison_of_broadband_technologies_table_75B12AE2-FC37-D44B-C75B5885D383A0FE_51503.pdf

Evans, O. (2018). Connecting the poor: The internet, mobile phones and financial inclusion in africa. *Digital Policy, Regulation and Governance*, 20, 568–581. https://doi.org/10.1108/DPRG-04-2018-0018

Fardouly, J., Diedrichs, P. C., Vartanian, L. R., & Halliwell, E. (2015). Social comparisons on social media: The impact of facebook on young women's body image concerns and mood. *Body Image*, 13, 38–45. https://doi.org/10.1016/j.bodyim.2014.12.002

Favara, M., Freund, R., Porter, C., Sanchez, A., & Scott, D. (2022). Young lives, interrupted: Short-term effects of the covid-19 pandemic on adolescents in low- and middle-income countries. *The Journal of Development Studies*, 58, 1063–1080. https://doi.org/10.1080/00220388.2022.2029421

Ferschmann, L., Bos, M. G., Herting, M. M., Mills, K. L., & Tamnes, C. K. (2022). Contextualizing adolescent structural brain development: Environmental determinants and mental health outcomes. *Current Opinion in Psychology*, 44, 170–176. https://doi.org/10.1016/j.copsyc.2021.09.014

Firth, J., Torous, J., López-Gil, J. F., Linardon, J., Milton, A., Lambert, J., Smith, L., Jarić, I., Fabian, H., Vancampfort, D., Onyeaka, H., Schuch, F. B., & Firth, J. A. (2024). From "online brains" to "online lives": Understanding the individualized impacts of internet use across psychological, cognitive and social dimensions. *World Psychiatry*, 23, 176–190. https://doi.org/10.1002/wps.21188

Firth, J., Torous, J., Stubbs, B., Firth, J. A., Steiner, G. Z., Smith, L., Alvarez-Jimenez, M., Gleeson, J., Vancampfort, D., Armitage, C. J., & Sarris, J. (2019). The "online brain": How the internet may be changing our cognition. *World Psychiatry*, 18, 119–129. https://doi.org/10.1002/wps.20617

Ford, K., & Freund, R. (2022). Young lives under pressure: Protecting and promoting young people's mental health at a time of global crises. Retrieved February 15, 2024, from https://www.younglives.org.uk/publications/young-lives-under-pressure-protecting-and-promoting-young-peoples-mental-health-time

Friederici, N., Ojanperä, S., & Graham, M. (2017). The impact of connectivity in africa: Grand visions and the mirage of inclusive digital development. *THE ELECTRONIC JOURNAL OF INFORMATION SYSTEMS IN DEVELOPING COUNTRIES*, 79, 1–20. https://doi.org/10.1002/j.1681-4835.2017.tb00578.x

George, M. J., Jensen, M. R., Russell, M. A., Gassman-Pines, A., Copeland, W. E., Hoyle, R. H., & Odgers, C. L. (2020). Young adolescents' digital technology use, perceived impairments, and well-being in a representative sample. *The Journal of Pediatrics*, 219, 180–187. https://doi.org/10.1016/j.jpeds.2019.12.002

Goggin, G., & McLelland, M. (2017, February). *The routledge companion to global internet histories* (G. Goggin & M. McLelland, Eds.). Routledge. https://doi.org/10.4324/9781315748962

Golberstein, E., Gonzales, G., & Meara, E. (2019). How do economic downturns affect the mental health of children? evidence from the national health interview survey. *Health Economics*, 28, 955–970. https://doi.org/10.1002/hec.3885

Goodman, A., Joyce, R., & Smith, J. P. (2011). The long shadow cast by childhood physical and mental problems on adult life. *Proceedings of the National Academy of Sciences*, 108, 6032–6037. https://doi.org/10.1073/pnas.1016970108

Granic, I., Morita, H., & Scholten, H. (2020). Young people's digital interactions from a narrative identity perspective: Implications for mental health and wellbeing. *Psychological Inquiry*, 31, 258–270. https://doi.org/10.1080/1047840X.2020.1820225

Graydon, M., & Parks, L. (2020). 'connecting the unconnected': A critical assessment of us satellite internet services. *Media, Culture & Society*, 42, 260–276. https://doi.org/10.1177/0163443719861835

Haile, J. M. (2024). Social media for diffusion of conflict and violence in ethiopia: Beyond gratifications. *International Journal of Educational Development*, 108, 103063. https://doi.org/10.1016/j.ijedudev.2024.103063

Hanson, W. A. (2016). Satellite internet in the mobile age. *New Space*, 4, 138–152. https://doi.org/10.1089/space.2016.0019

Harris, C., Straker, L., & Pollock, C. (2017). A socioeconomic related 'digital divide' exists in how, not if, young people use computers. *PLOS ONE*, 12, e0175011. https://doi.org/10.1371/journal.pone.0175011

Harris, D., Baird, S., Ford, K., Hirvonen, K., Jones, N., Kassa, M., Meyer, C., Pankhurst, A., Wieser, C., & Woldehanna, T. (2021, November). The impact of covid-19 in ethiopia: Policy brief.

Hartje, R., & Hübler, M. (2017). Smartphones support smart labour. *Applied Economics Letters*, 24, 467–471. https://doi.org/10.1080/13504851.2016.1203054

Haushofer, J., & Fehr, E. (2014). On the psychology of poverty. *Science*, 344, 862–867. https://doi.org/10.1126/science.1232491

Hjetland, G. J., Schønning, V., Hella, R. T., Veseth, M., & Skogen, J. C. (2021). How do norwegian adolescents experience the role of social media in relation to mental health and well-being: A qualitative study. *BMC Psychology*, 9, 78. https://doi.org/10.1186/s40359-021-00582-x

Hosman, L. (2024, September). We must bring digital literacy to remote communities. https://www.ictworks.org/we-must-bring-digital-literacy-to-remote-communities/

Hübler, M., & Hartje, R. (2016). Are smartphones smart for economic development? *Economics Letters*, 141, 130–133. https://doi.org/10.1016/j.econlet.2016.02.001

Huckins, J. F., daSilva, A. W., Wang, W., Hedlund, E., Rogers, C., Nepal, S. K., Wu, J., Obuchi, M., Murphy, E. I., Meyer, M. L., Wagner, D. D., Holtzheimer, P. E., & Campbell, A. T. (2020). Mental health and behavior of college students during the early phases of the covid-19 pandemic: Longitudinal smartphone and ecological momentary assessment study. *Journal of Medical Internet Research*, 22, e20185. https://doi.org/10.2196/20185

Hunduma, G., Dessie, Y., Geda, B., Yadeta, T. A., & Deyessa, N. (2024). Prevalence and correlates of internalizing and externalizing mental health problems among in-school adolescents in eastern ethiopia: A cross-sectional study. *Scientific Reports*, 14, 3574. https://doi.org/10.1038/s41598-024-54145-2

Huppert, F. A., & So, T. T. C. (2013). Flourishing across europe: Application of a new conceptual framework for defining well-being. *Social Indicators Research*, 110, 837–861. https://doi.org/10.1007/s11205-011-9966-7

Hussain, S., & Hussain, S. (2023, July). Threats of social media among ethiopian youths. B P International (a part of SCIENCEDOMAIN International). https://doi.org/10.9734/bpi/rhst/v5/4412B

Internews. (2023, August). Ethiopian digital media information ecosystem assessment. Retrieved May 15, 2024, from https://internews.org/wp-content/uploads/2023/08/Ethiopian-Digital-Media-IEA%5C_edited-Final-SinglePage.pdf

ITU. (2020, November). Measuring digital development: Facts and figures 2020. Retrieved June 15, 2024, from https://www.itu.int/en/mediacentre/Pages/pr27-2020-facts-figures-urban-areas-higher-internet-access-than-rural.aspx

ITU. (2023). Digital development dashboard ethiopia. Retrieved December 15, 2023, from https://www.itu.int/en/ITU-D/Statistics/Documents/DDD/ddd%5C_ETH.pdf

Jack, B. K. (2011). *Constraints on the adoption of agricultural technologies in developing countries* (tech. rep.). J-PAL (MIT) and CEGA (UC Berkeley).

Jones, R., Mougouei, D., & Evans, S. L. (2021). Understanding the emotional response to covid-19 information in news and social media: A mental health perspective. *Human Behavior and Emerging Technologies*, 3, 832–842. https://doi.org/10.1002/hbe2.304

Kanbur, R., Patel, E., & Stiglitz, J. E. (2018, November). Sustainable development goals and the measurement of economic and social progress. OECD. https://doi.org/10.1787/9789264307278-4-en

Keyes, C. L. (2013). *Mental well-being international contributions to the study of positive mental health*. Springer Science + Business Media.

Kim, K. M., Kim, D., & Chung, U. S. (2020). Investigation of the trend in adolescent mental health and its related social factors: A multi-year cross-sectional study for 13 years.

International Journal of Environmental Research and Public Health, 17, 5405. https://doi.org/10.3390/ijerph17155405

Kirmayer, L. J., & Pedersen, D. (2014). Toward a new architecture for global mental health. *Transcultural Psychiatry*, 51, 759–776. https://doi.org/10.1177/1363461514557202

Krueger, A. B., & Schkade, D. A. (2008). The reliability of subjective well-being measures. *Journal of Public Economics*, 92, 1833–1845. https://doi.org/10.1016/j.jpubeco.2007.12.015

Kümpel, A. S. (2020). The matthew effect in social media news use: Assessing inequalities in news exposure and news engagement on social network sites (sns). *Journalism*, 21, 1083–1098. https://doi.org/10.1177/1464884920915374

Lauer, D. (2021). Facebook's ethical failures are not accidental; they are part of the business model. *AI and Ethics*, 1, 395–403. https://doi.org/10.1007/s43681-021-00068-x

Leong, C., Pan, S. L., Newell, S., & Cui, L. (2016). The emergence of self-organizing e-commerce ecosystems in remote villages of china: A tale of digital empowerment for rural development. *MIS Quarterly*, 40, 475–484. https://doi.org/10.25300/MISQ/2016/40.2.11

Loh, K. K., & Kanai, R. (2016). How has the internet reshaped human cognition? *The Neuroscientist*, 22, 506–520. https://doi.org/10.1177/1073858415595005

Ma, J., & Sheng, L. (2023). Internet use time and mental health among rural adolescents in china: A longitudinal study. *Journal of Affective Disorders*, 337, 18–26. https://doi.org/10.1016/j.jad.2023.05.054

MacLeod, D. (2023, February). Review of digital madness: How social media is driving our mental health crisis – and how to restore our sanity by nicholas kardaras. Retrieved July 15, 2024, from http://journaldialogue.org/reviews/review-of-digital-madness-how-social-media-is-driving-our-mental-health-crisis-and-how-to-restore-our-sanity-by-nicholas-kardaras/

Magson, N. R., Freeman, J. Y. A., Rapee, R. M., Richardson, C. E., Oar, E. L., & Fardouly, J. (2021). Risk and protective factors for prospective changes in adolescent mental health during the covid-19 pandemic. *Journal of Youth and Adolescence*, 50, 44–57. https://doi.org/10.1007/s10964-020-01332-9

Malamud, O., & Pop-Eleches, C. (2011). Home computer use and the development of human capital *. *The Quarterly Journal of Economics*, 126, 987–1027. https://doi.org/10.1093/qje/qjr008

Martínez, L., Valencia, I., & Trofimoff, V. (2020). Subjective wellbeing and mental health during the covid-19 pandemic: Data from three population groups in colombia. *Data in Brief*, 32, 106287. https://doi.org/10.1016/j.dib.2020.106287

Martínez-Domínguez, M., & Mora-Rivera, J. (2020). Internet adoption and usage patterns in rural mexico. *Technology in Society*, 60, 101226. https://doi.org/10.1016/j.techsoc.2019.101226

McDool, E., Powell, P., Roberts, J., & Taylor, K. (2020). The internet and children's psychological wellbeing. *Journal of Health Economics*, 69, 102274. https://doi.org/10.1016/j.jhealeco.2019.102274

McHugh, B. C., Wisniewski, P., Rosson, M. B., & Carroll, J. M. (2018). When social media traumatizes teens. *Internet Research*, 28, 1169–1188. https://doi.org/10.1108/IntR-02-2017-0077

Mingliu & Wolff, R. (2004). Crossing the digital divide: Cost-effective broadband wireless access for rural and remote areas. *IEEE Communications Magazine*, 42, 99–105. https://doi.org/10.1109/MCOM.2003.1267107

Nicas, J. (2024a, June). The internet's final frontier: Remote amazon tribes. Retrieved June 15, 2024, from https://www.nytimes.com/2024/06/02/world/americas/starlink-internet-elon-musk-brazil-amazon.html

Nicas, J. (2024b, June). No, a remote amazon tribe did not get addicted to porn. Retrieved June 15, 2024, from https://www.nytimes.com/2024/06/11/world/americas/no-a-remote-amazon-tribe-did-not-get-addicted-to-porn.html

OECD. (2017, April). Students' use of ict outside of school. https://doi.org/10.1787/9789264273856-17-en

OHRLLS. (2024). List of ldcs. https://www.un.org/ohrlls/content/list-ldcs

O'Reilly, M., Dogra, N., Whiteman, N., Hughes, J., Eruyar, S., & Reilly, P. (2018). Is social media bad for mental health and wellbeing? exploring the perspectives of adolescents. *Clinical Child Psychology and Psychiatry*, 23, 601–613. https://doi.org/10.1177/1359104518775154

Østergaard, S. D. (2017). Taking facebook at face value: Why the use of social media may cause mental disorder. *Acta Psychiatrica Scandinavica*, 136, 439–440. https://doi.org/10.1111/acps.12819

Park, S. (2017). Digital inequalities in rural australia: A double jeopardy of remoteness and social exclusion. *Journal of Rural Studies*, 54, 399–407. https://doi.org/10.1016/j.jrurstud.2015.12.018

Patel, V., Chisholm, D., Parikh, R., Charlson, F. J., Degenhardt, L., Dua, T., Ferrari, A. J., Hyman, S., Laxminarayan, R., Levin, C., Lund, C., Mora, M. E. M., Petersen, I., Scott, J., Shidhaye, R., Vijayakumar, L., Thornicroft, G., & Whiteford, H. (2016). Addressing the burden of mental, neurological, and substance use disorders: Key messages from disease control priorities, 3rd edition. *The Lancet*, 387, 1672–1685. https://doi.org/10.1016/S0140-6736(15)00390-6

PewResearchCenter. (2018, April). The future of well-being in a tech-saturated world. Retrieved June 12, 2024, from https://www.pewresearch.org/internet/2018/04/17/the-future-of-well-being-in-a-tech-saturated-world/

Primack, B. A., Shensa, A., Sidani, J. E., Whaite, E. O., yi Lin, L., Rosen, D., Colditz, J. B., Radovic, A., & Miller, E. (2017). Social media use and perceived social isolation among young adults in the u.s. *American Journal of Preventive Medicine*, 53, 1–8. https://doi.org/10.1016/j.amepre.2017.01.010

Przybylski, A. K., & Weinstein, N. (2013). Can you connect with me now? how the presence of mobile communication technology influences face-to-face conversation quality. *Journal of Social and Personal Relationships*, 30, 237–246. https://doi.org/10.1177/0265407512453827

Rast, R., Coleman, J. T., & Simmers, C. S. (2021). The darkside of the like: The effects of social media addiction on digital and in-person communication. *The Journal of Social Media in Society*, 10, 175–201.

Ridley, M., Rao, G., Schilbach, F., & Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*, 370. https://doi.org/10.1126/science.aay0214

Rotondi, V., Stanca, L., & Tomasuolo, M. (2017). Connecting alone: Smartphone use, quality of social interactions and well-being. *Journal of Economic Psychology*, 63, 17–26. https://doi.org/10.1016/j.joep.2017.09.001

Rouse, M. (2017, January). Cellular. https://www.techopedia.com/definition/6412/cellular

Salemink, K., Strijker, D., & Bosworth, G. (2015). Rural development in the digital age: A systematic literature review on unequal ict availability, adoption, and use in rural areas. *Journal of Rural Studies*, 54, 360–371. https://doi.org/10.1016/j.jrurstud.2015.09.001

Sampasa-Kanyinga, H., Roumeliotis, P., & Xu, H. (2014). Associations between cyberbullying and school bullying victimization and suicidal ideation, plans and attempts among canadian schoolchildren. *PLoS ONE*, 9, e102145. https://doi.org/10.1371/journal.pone.0102145

Sawyer, S. M., Azzopardi, P. S., Wickremarathne, D., & Patton, G. C. (2018). The age of adolescence. *The Lancet Child & Adolescent Health*, 2, 223–228. https://doi.org/10.1016/S2352-4642(18)30022-1

Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of internet skills, uses and outcomes. a systematic review of the second- and third-level digital divide. *Telematics and Informatics*, 34, 1607–1624. https://doi.org/10.1016/j.tele.2017.07.007

Seaver, N. (2019). Captivating algorithms: Recommender systems as traps. *Journal of Material Culture*, 24, 421–436. https://doi.org/10.1177/1359183518820366

Selim, M. (2020). Distance learning and its effectiveness in improving literacy, education and skills development for remote population and for overcoming the challenges of covid 19. *2020 Sixth International Conference on e-Learning (econf)*, 66–71. https://doi.org/10.1109/econf51404.2020.9385522

Simegn, W., Dagnew, B., Yeshaw, Y., Yitayih, S., Woldegerima, B., & Dagne, H. (2021). Depression, anxiety, stress and their associated factors among ethiopian university students during an early stage of covid-19 pandemic: An online-based cross-sectional survey. *PLOS ONE*, 16, e0251670. https://doi.org/10.1371/journal.pone.0251670

Singh, K., & Dang, S. (2024, June). Us surgeon general calls for social media warning labels to protect adolescents. Retrieved June 15, 2024, from https://www.reuters.com/world/us/us-surgeon-general-calls-social-media-warning-labels-protect-adolescents-2024-06-17/

Smart, C., Donner, J., & Graham, M. (2016). 'connecting the world from the sky'. *Proceedings of the Eighth International Conference on Information and Communication Technologies and Development*, 1–11. https://doi.org/10.1145/2909609.2909659

Stiglitz, J. E., Sen, A., & Fitoussi, J.-P. (2009). Report by the commission on the measurement of economic performance and social progress.

Stone, A. A., & Krueger, A. B. (2018, November). Understanding subjective well-being. OECD. https://doi.org/10.1787/9789264307278-9-en

Stovall, J. (2024, October). Starlink satellite network.

Strasser, M. A., Sumner, P. J., & Meyer, D. (2022). Covid-19 news consumption and distress in young people: A systematic review. *Journal of Affective Disorders*, 300, 481–491. https://doi.org/10.1016/j.jad.2022.01.007

Tafere, Y. (2014). Education aspirations and barriers to achievement for young people in ethiopia.

Tanner, J. L., & Arnett, J. J. (2016). The emergence of emerging adulthood: The new life stage between adolescence and young adulthood. Routledge.

Tareke, S. A., Lelisho, M. E., Hassen, S. S., Seid, A. A., Jemal, S. S., Teshale, B. M., Wotale, T. W., & Pandey, B. K. (2023). The prevalence and predictors of depressive, anxiety, and stress symptoms among tepi town residents during the covid-19 pandemic lockdown in ethiopia. *Journal of Racial and Ethnic Health Disparities*, 10, 43–55. https://doi.org/10.1007/s40615-021-01195-1

Trucano, M. (2013, June). The matthew effect in educational technology. Retrieved October 25, 2024, from https://blogs.worldbank.org/en/education/matthew-effect-educational-technology

Twenge, J. M., & Campbell, W. K. (2019). Media use is linked to lower psychological well-being: Evidence from three datasets. *Psychiatric Quarterly*, 90, 311–331. https://doi.org/10.1007/s11126-019-09630-7

UN. (n.d.). Digital inclusion. Retrieved July 15, 2024, from https://www.un.org/techenvoy/sites/www.un.org.techenvoy/files/general/Definition%5C_Digital-Inclusion.pdf

UN. (2023). Contribution to the global digital compact. Retrieved July 15, 2024, from https://www.un.org/youthenvoy/wp-content/uploads/2023/05/Contribution-to-Global-Digital-Compact.pdf

UNDP. (2022). *Human development report 2021/2022: Uncertain times, unsettled lives shaping our future in a transforming world*. United Nations Development Programme, Human Development Report Office (HDRO). https://hdr.undp.org/system/files/documents/global-report-document/hdr2021-22pdf%5C_1.pdf

USAID. (2022, June). Barriers to investing in last-mile connectivity.

van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2014). The digital divide shifts to differences in usage. *New Media & Society*, 16, 507–526.

van Dijk, J. (2019). *The digital divide*. Polity Press.

van Geel, M., Vedder, P., & Tanilon, J. (2014). Relationship between peer victimization, cyberbullying, and suicide in children and adolescents. *JAMA Pediatrics*, 168, 435. https://doi.org/10.1001/jamapediatrics.2013.4143

Vargas-Montoya, L., Gimenez, G., & Fernández-Gutiérrez, M. (2023). Ict use for learning and students' outcomes: Does the country's development level matter? *Socio-Economic Planning Sciences*, 87, 101550. https://doi.org/10.1016/j.seps.2023.101550

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. *Journal of Experimental Psychology: General*, 144, 480–488. https://doi.org/10.1037/xge0000057

Wassie, G., Wondie, Y., Anagaw, B., & Zemene, F. (2023). Internet services maturity in ethiopia: Impacts on the digital economy and identification of areas for improvement with policy recommendations. https://doi.org/http://dx.doi.org/10.2139/ssrn.4647198

WEF. (2020, November). How has technology changed - and changed us - in the past 20 years? Retrieved August 18, 2024, from https://www.weforum.org/agenda/2020/11/heres-how-technology-has-changed-and-changed-us-over-the-past-20-years/

Weissman, D. G., Hatzenbuehler, M. L., Cikara, M., Barch, D. M., & McLaughlin, K. A. (2023). State-level macro-economic factors moderate the association of low income with brain structure and mental health in u.s. children. *Nature Communications*, 14, 2085. https://doi.org/10.1038/s41467-023-37778-1

WHO. (2021, November). Mental health of adolescents. Retrieved September 15, 2024, from https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health

Woggon, M. (2022, July). A brief history of touchscreen technology: From the iphone to multi-user videowalls. Retrieved October 26, 2024, from https://www.forbes.com/councils/forbestechcouncil/2022/07/20/a-brief-history-of-touchscreen-technology-from-the-iphone-to-multi-user-videowalls/

Wohn, D. Y., Ellison, N. B., Khan, M. L., Fewins-Bliss, R., & Gray, R. (2013). The role of social media in shaping first-generation high school students' college aspirations: A social capital lens. *Computers & Education*, 63, 424–436. https://doi.org/10.1016/j.compedu.2013.01.004

Yang, Z., Griffiths, M. D., Yan, Z., & Xu, W. (2021). Can watching online videos be addictive? a qualitative exploration of online video watching among chinese young adults. *International Journal of Environmental Research and Public Health*, 18, 7247. https://doi.org/10.3390/ijerph18147247

Young Lives. (2018, January). Young lives survey design and sampling (round 5) ethiopia. Retrieved March 15, 2024, from https://www.younglives.org.uk/publications/survey-design-and-sampling-round-5-ethiopia

Young Lives. (2023a). A guide to listening to young lives at work calls 1 to 5 constructed files. https://www.younglives.org.uk/publications/guide-listening-young-lives-work-calls-1-5-constructed-files

Young Lives. (2023b, March). Attrition report: Fourth call listening to young lives at work: Covid-19. Retrieved April 15, 2024, from https://www.younglives.org.uk/sites/default/files/2023-04/yl-covid-19-phonesurvey4-attritionreport.pdf

Yue, Z., Zhang, R., & Xiao, J. (2022). Passive social media use and psychological well-being during the covid-19 pandemic: The role of social comparison and emotion regulation. *Computers in Human Behavior*, 127, 107050. https://doi.org/10.1016/j.chb.2021.107050

Appendices

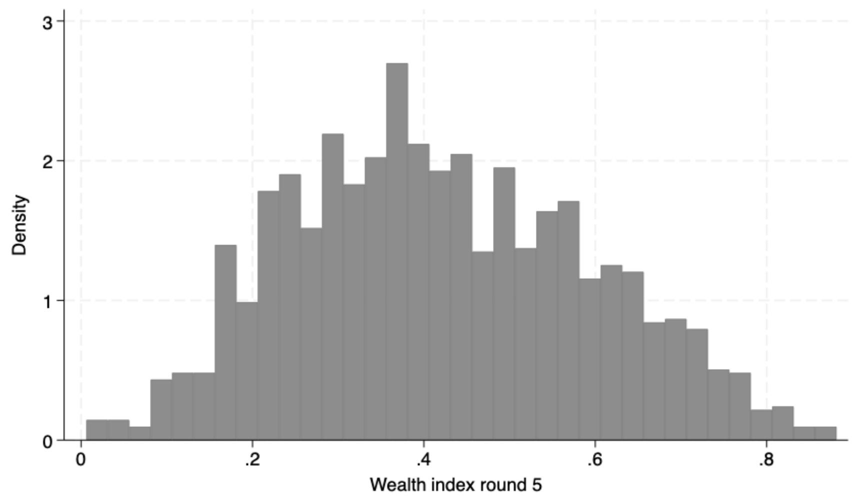

Figure A1: Wealth index distribution
Source: Authors', using YL data

Table B1: Mental health symptoms questionnaires

Indicators	**Question items**	**Scales**
Generalized Anxiety Disorder-7 (GAD-7)	In the past 2 weeks, have you been? 1. Feeling nervous, anxious or on edge; 2. Not being able to stop or control worrying; 3. Worrying too much about different things; 4. Trouble relaxing/ Can't relax; 5. Being so restless that it's hard to sit still; 6. Becoming easily annoyed or irritable; 7. Feeling afraid as if something awful might happen. (Likert scales from not at all, several days, to nearly every day).	Scores between 5 - 9, between 10 - 14, and above 15 represent mild, moderate, and severe anxiety symptoms, respectively
Patient Health Questionnaire depression scale-8 (PHQ-8)	In the past 2 weeks, have you been? 1. Little interest or pleasure in doing things; 2. Feeling down, depressed or hopeless; 3. Trouble falling or staying asleep, or sleeping too much; 4. Feeling tired or having little energy; 5. Poor appetite or overeating; 6. Feeling bad about yourself - or that you are a failure or have let yourself or your family down; 7. Trouble concentrating on things, such as reading the newspaper or watching television; 8. Moving or speaking so slowly that other people could have noticed. Or the opposite - being so fidgety or restless that you have been moving around a lot more than usual.	Score between 5 - 9 indicates mild, 10 - 14 moderate, 15 - 19 moderately severe, and scores above 19 severe, depressive symptoms. (Likert scales from not at all, several days, to nearly every day).

Source: formatted from Young Lives (2023a).

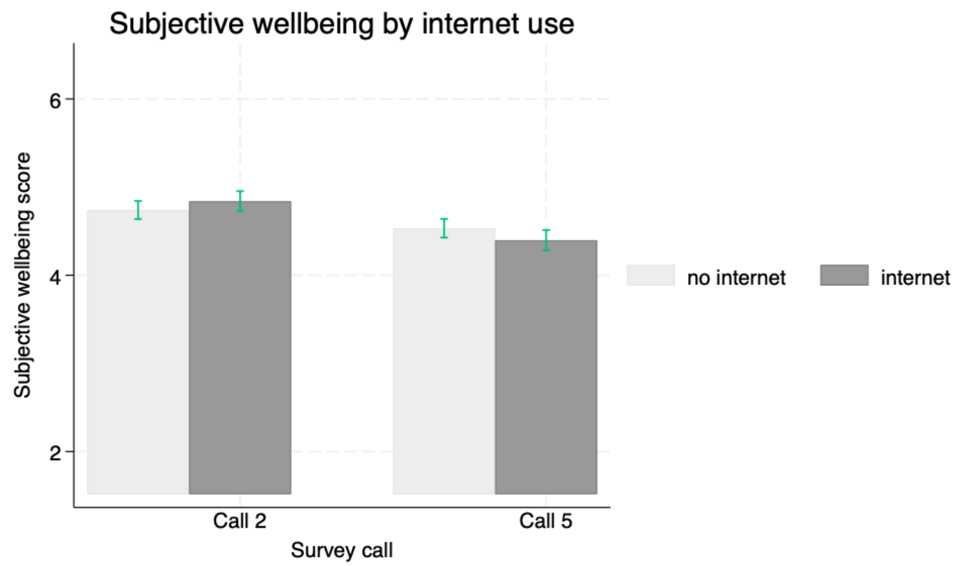

Figure A2: Internet access and subjective wellbeing
Source: Authors' illustration based on YL data

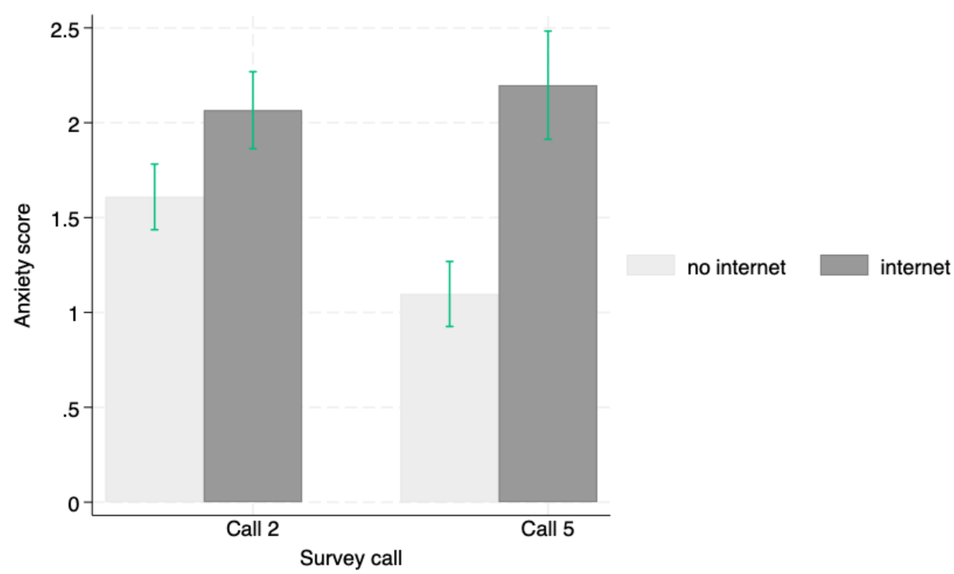

Figure A3: Internet access and anxiety scores (GAD-7)
Source: Authors' illustration based on YL data

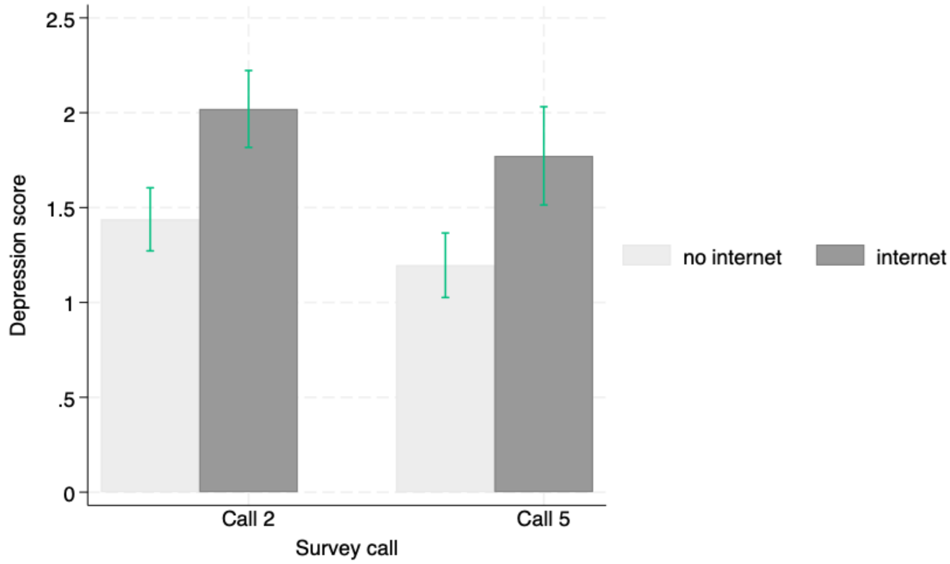

Figure A4: Internet access and depression scores (PHQ-8)
Source: Authors' illustration based on YL data

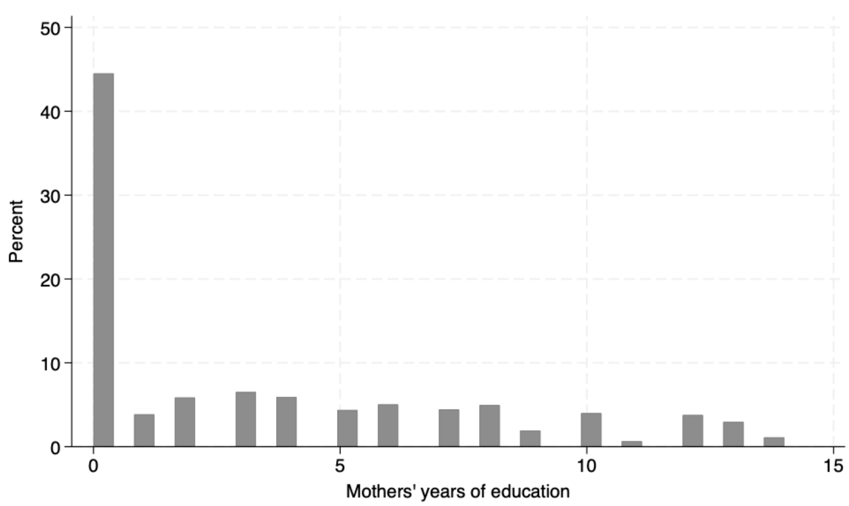

Figure A5: Mothers' education variable distribution
Source: Authors', using YL data

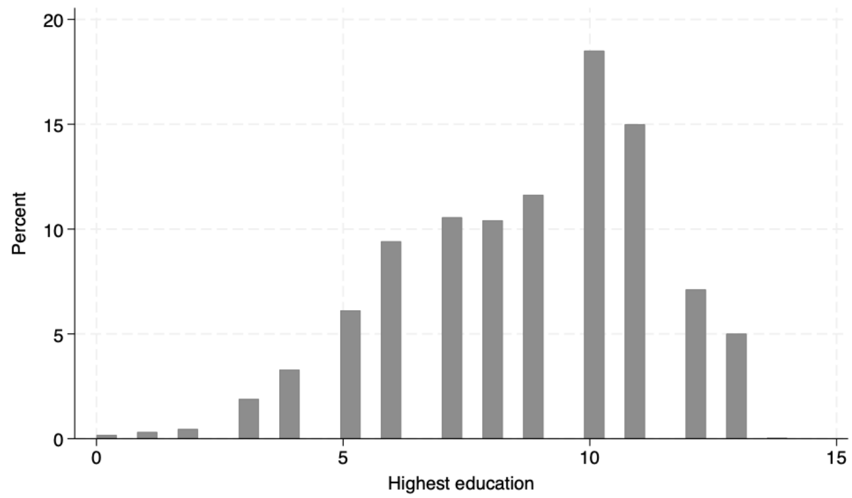

Figure A6: YL children's education variable distribution
Source: Authors', using YL data

Table B2: Diff-diff estimation of internet access and youth's mental health

	Diff. in SWB		**Diff. in GAD7**		**Diff. in PHQ8**	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Diff. in internet	-0.0180	-1.249**	2.299***	6.925***	1.737***	6.050***
	(0.203)	(0.592)	(0.488)	(1.137)	(0.414)	(0.991)
(Believed) infected	-0.933***	-0.564	-0.569	-2.139	0.120	-1.340
	(0.253)	(1.895)	(0.697)	(3.633)	(0.689)	(3.172)
Income decreases	-0.179	-0.137	1.995***	1.827***	1.880***	1.615***
	(0.165)	(0.186)	(0.366)	(0.358)	(0.336)	(0.312)
Run out of food	0.675***	0.594***	-0.558	0.126	-0.747**	-0.0483
	(0.173)	(0.197)	(0.357)	(0.379)	(0.340)	(0.330)
Urban area	0.433*	1.104***	-0.516	-2.684***	-0.898*	-2.836***
	(0.227)	(0.388)	(0.521)	(0.743)	(0.492)	(0.649)
Constant	-0.303***	-0.154	-1.208***	-1.929***	-0.839***	-1.488***
	(0.107)	(0.132)	(0.206)	(0.256)	(0.172)	(0.222)
Observations	610	557	605	553	607	556
R^2	0.030		0.108		0.103	
Adjusted R^2	0.022		0.101		0.096	
F-statistic		106.10		104.84		105.72

Notes: The sample limited to people who do not have internet in Call 2. Both dependent and internet variables are transformed by differences between Call 5 and Call 2. Each column reports estimated effects of internet access on adolescents' mental health. F-statistic is the Cragg-Donald Wald F statistic. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Broader impacts on other human capital-related variables

	(1) (Perceived) time spent studying	(2) Want to go back to education
Internet	-0.205***	-0.225**
	(0.0750)	(0.0927)
Comfortable	0.0123	0.0705
	(0.0710)	(0.0800)
Struggle	-0.117	-0.0638
	(0.0720)	(0.0848)
Poor	0.0749	0.141
	(0.0786)	(0.0858)
Destitute	0.171	-0.473**
	(0.225)	(0.191)
Female	0.00573	-0.0481**
	(0.0238)	(0.0243)
(Believed) infected	0.287*	0.272***
	(0.166)	(0.0506)
Income decreases	-0.0554**	-0.109***
	(0.0258)	(0.0256)
Run out of food	-0.0298	-0.188***
	(0.0289)	(0.0397)
Urban area	0.140***	0.227***
	(0.0437)	(0.0624)
Constant	0.332***	0.867***
	(0.0778)	(0.0871)
Observations	1370	1162
Control	Yes	Yes
F-statistic	184.21	121.15

Notes: Samples include children in Call 2 due to data availability. The instrument for IV estimates is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on the likelihood having spent more time on studying and want to go back to school after COVID-19. Covariates: perceived wealth levels, household size, gender, (believed to be) infected by COVID-19, negative income shocks, run out of food, urban. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B4: Robustness test with community time-variant controls

	SWB		GAD-7		PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
Internet	-1.361**	-0.890*	9.710***	11.21***	8.427***	9.656***
	(0.533)	(0.500)	(1.629)	(1.865)	(1.488)	(1.635)
Community wealth	0.542		0.516		0.0317	
	(0.360)		(1.062)		(0.973)	
Community income reductions		0.310		2.574***		2.166***
		(0.263)		(0.744)		(0.648)
Community food shortages		0.855***		0.639		0.185
		(0.302)		(0.892)		(0.874)
(Believed) infected	0.253	0.268*	2.974	2.608	-1.560	-1.969
	(0.202)	(0.155)	(3.301)	(3.518)	(1.645)	(1.860)
Income decreases	-0.0856	-0.137	0.936***	0.519	0.756***	0.406
	(0.114)	(0.121)	(0.305)	(0.373)	(0.281)	(0.337)
Run out of food	0.263	-0.280	0.827**	0.125	0.771**	0.440
	(0.191)	(0.263)	(0.393)	(0.688)	(0.385)	(0.730)
Observations	1826	1846	1816	1836	1820	1840
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic	52.34	54.15	51.84	53.33	52.38	54.20

Notes: Each column reports estimated effects of internet access on mental health problem indicators: GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire–8. FE-IV estimates, the instrument is the proportion of households in a community having access to the internet. FEs include individual, year, and cluster FEs. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B5: Robustness test with lag dependent variables

	(1) SWB	(2) GAD-7	(3) PHQ-8
Internet	-2.628***	5.636***	4.395***
	(0.450)	(0.821)	(0.759)
L3.Well-being	0.107***		
	(0.0384)		
L3.GAD-7		0.166***	
		(0.0421)	
L3.PHQ-8			0.300***
			(0.0418)
Comfortable	-1.793***	2.367***	2.022***
	(0.421)	(0.766)	(0.698)
Struggle	-1.878***	2.845***	2.415***
	(0.420)	(0.765)	(0.698)
Poor	-3.719***	3.925***	2.817***
	(0.453)	(0.824)	(0.750)
Destitute	-6.062***	8.051***	10.48***
	(1.428)	(2.611)	(2.383)
HH size	0.0812**	-0.0549	-0.0973*
	(0.0321)	(0.0603)	(0.0552)
Female	-0.00837	-0.0926	-0.0633
	(0.117)	(0.214)	(0.195)
(Believed) infected	-0.699	3.478	1.929
	(1.400)	(2.595)	(2.360)
Income decreases	0.158	0.238	0.306
	(0.149)	(0.277)	(0.255)
Run out of food	0.397***	-0.573**	-0.596**
	(0.152)	(0.278)	(0.254)
Urban area	1.274***	-2.015***	-1.865***
	(0.288)	(0.532)	(0.491)
Constant	5.759***	-2.057**	-1.239
	(0.523)	(0.888)	(0.812)
Observations	557	553	556
Cragg-Donald Wald F statistic	100.63	100.99	99.20

Notes: Each column reports estimated effects of internet access on mental health problem indicators: GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire–8. The sample is limited to people who do not have internet access in call 2. IV estimates, the instrument is the proportion of households in a community having access to the internet. Covariates: perceived wealth levels, household size, gender, (believed to be) infected by COVID-19, negative income shocks, run out of food, urban. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B6: Robustness test with regional control

	(1) GAD-7	(2) PHQ-8	(3) SWB
Internet	9.557***	8.537***	-1.549***
	(1.663)	(1.535)	(0.542)
Regional FE	Yes	Yes	Yes
Individual, Cluster, Call FEs	Yes	Yes	Yes
Observations	1836	1840	1846
Kleibergen-Paap Wald F statistic	51.12	51.62	51.60

Notes: Each column reports estimated effects of internet access on mental health problem indicators: GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire–8. FE-IV estimates, the instrument is the proportion of households in a community having access to the internet. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B7: Heterogeneity effects of internet access and mental health - diff-diff estimations

	Diff. in SWB		**Diff. in GAD-7**		**Diff. in PHQ-8**	
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth index	Low	High	Low	High	Low	High
Diff. in internet	-0.581	-1.372**	14.77***	3.539***	13.84***	3.528***
	(1.513)	(0.582)	(4.450)	(0.943)	(4.456)	(0.921)
(Believed) infected	0	-0.976	0	-2.158	0	-0.393
	(.)	(0.621)	(.)	(1.898)	(.)	(1.829)
Income decreases	-0.100	0.00271	1.485**	2.228***	1.718**	1.625***
	(0.242)	(0.276)	(0.753)	(0.502)	(0.710)	(0.479)
Run out of food	0.749***	0.522*	0.281	-0.588	-0.192	-0.345
	(0.257)	(0.290)	(0.700)	(0.465)	(0.664)	(0.466)
Urban area	0.685	1.437**	-6.645***	0.0970	-6.287***	-1.339
	(0.665)	(0.690)	(2.553)	(1.721)	(2.315)	(1.647)
Constant	-0.295	-0.0919	-1.971***	-1.706***	-1.666***	-1.421***
	(0.185)	(0.204)	(0.392)	(0.340)	(0.337)	(0.297)
Observations	275	234	273	232	275	234
F-statistic	18.27	107.94	18.04	106.44	18.27	107.94

Notes: The sample limited to people who do not have internet in Call 2. Both dependent and internet variables are transformed by differences between Call 5 and Call 2. IV estimates, the instrument is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on the likelihood having spent more time on doing nothing. F-statistic is the Cragg-Donald Wald F statistic. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B8: Heterogeneity of effects of internet on mental health with interaction terms

	SWB		GAD-7		PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
Internet	-0.0479	-0.0877	2.148***	2.116***	1.233	1.171
	(0.326)	(0.327)	(0.822)	(0.819)	(0.771)	(0.770)
Wealth index round 5	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Internet × Wealth index round 5	0.388	0.549	-3.383*	-3.258	-1.216	-0.968
	(0.718)	(0.714)	(2.002)	(1.996)	(1.932)	(1.938)
(Believed) infected	0.260	-0.000197	2.633	2.432	-0.534	-0.922
	(0.291)	(0.274)	(2.070)	(2.088)	(0.983)	(0.999)
Income decreases	-0.0289	0.0722	0.528***	0.607***	0.399**	0.551***
	(0.0913)	(0.0873)	(0.179)	(0.182)	(0.169)	(0.168)
Run out of food	0.334**	0.134	0.134	-0.0213	0.275	-0.0249
	(0.156)	(0.140)	(0.190)	(0.156)	(0.217)	(0.185)
Constant	4.427***	4.405***	1.222***	1.204***	1.140***	1.104***
	(0.0773)	(0.0772)	(0.196)	(0.195)	(0.193)	(0.193)
Observations	2226	2226	2218	2218	2220	2220
Individual, Cluster FEs	Yes	Yes	Yes	Yes	Yes	Yes
Call FE	Yes	No	Yes	No	Yes	No
R^2	0.655	0.651	0.595	0.594	0.624	0.621
Adjusted R^2	0.298	0.290	0.175	0.174	0.234	0.230

Notes: Effects of internet access by wealth groups. Each column reports estimated effects of internet access on mental health problem indicators: GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire-8. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B9: Heterogeneity of effects of internet on mental health by SES with additional COVID-19 controls

	SWB		GAD-7		PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth	Lower	Higher	Lower	Higher	Lower	Higher
Internet	-1.169	-1.542***	10.75***	4.439***	10.03***	3.330***
	(1.000)	(0.548)	(3.190)	(1.015)	(2.970)	(0.977)
Job loss	-0.380*	-0.0288	0.629	2.059***	0.953	2.011***
	(0.210)	(0.241)	(0.711)	(0.468)	(0.702)	(0.452)
Input price up	-0.0117	0.312	1.305**	1.293***	1.007*	1.063***
	(0.223)	(0.227)	(0.614)	(0.404)	(0.566)	(0.375)
Food price up	0.0641	-0.232	-0.333	-0.436	-0.444	-0.595
	(0.275)	(0.256)	(0.705)	(0.420)	(0.663)	(0.449)
(Believed) infected	0.224	0.129	6.634***	7.226***	-0.0854	1.263**
	(0.229)	(0.288)	(1.733)	(0.509)	(0.748)	(0.504)
Income decreases	0.0466	-0.292	0.619	0.178	0.611	0.174
	(0.197)	(0.188)	(0.509)	(0.327)	(0.477)	(0.332)
Run out of food	0.577*	0.144	0.269	0.442	0.0351	0.394
	(0.350)	(0.257)	(0.612)	(0.366)	(0.618)	(0.432)
Observations	772	748	768	742	772	748
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	18.06	44.02	18.00	43.71	18.06	44.02

Notes: Effects of internet access by wealth groups. FE-IV estimates with individual, community, and call fixed effects. The instrument is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on mental health indicators: Well-being is subjective well-being, with a range between 1 (low well-being) and 9 (high well-being); GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire-8. F-statistic is the Kleibergen-Paap Wald F-statistic. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B10: Heterogeneity of effects of internet on mental health by gender

	GAD-7		PHQ-8		SWB	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
Internet	9.252***	9.521***	7.832***	8.782***	-1.764**	-1.284*
	(2.187)	(2.389)	(2.029)	(2.169)	(0.730)	(0.779)
(Believed) infected	-0.901	7.241***	-2.074	-0.722	0.856*	0.0996
	(4.885)	(1.065)	(3.020)	(0.514)	(0.481)	(0.110)
Income decreases	1.091**	0.872**	0.688	0.813**	-0.0452	-0.0976
	(0.496)	(0.367)	(0.424)	(0.369)	(0.197)	(0.137)
Run out of food	0.0948	1.356**	0.297	1.286**	0.304	0.177
	(0.476)	(0.609)	(0.449)	(0.624)	(0.291)	(0.250)
Observations	846	990	846	994	850	996
Individual, Call, Cluster FEs	846	990	846	994	850	996
Kleibergen-Paap rk Wald F statistic	26.90	26.20	27.32	26.25	27.35	26.20

Notes: Effects of internet access by wealth groups. FE-IV estimates with individual, community, and call fixed effects. The instrument is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on mental health problem indicators: GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire-8. Well-being is subjective well-being, with a range between 1 (low well-being) and 9 (high well-being). The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B11: Effects of internet on mental health with education as control

	GAD-7		PHQ-8		Well-being	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE-IV	FE	FE-IV	FE	FE-IV
Internet	0.738***	9.503***	0.761***	8.705***	0.0642	-1.771***
	(0.268)	(1.686)	(0.249)	(1.576)	(0.109)	(0.567)
Highest education	0.112*	-0.158	-0.0245	-0.279**	0.0593	0.132***
	(0.0667)	(0.123)	(0.0677)	(0.126)	(0.0373)	(0.0484)
(Believed) infected	2.471	3.156	-0.580	-1.574	0.275	0.445**
	(2.070)	(3.209)	(0.962)	(1.616)	(0.289)	(0.221)
Income decreases	0.491***	1.018***	0.391**	0.875***	-0.0519	-0.130
	(0.184)	(0.315)	(0.174)	(0.298)	(0.0922)	(0.120)
Run out of food	0.0797	0.856**	0.345	0.948**	0.343**	0.195
	(0.199)	(0.406)	(0.216)	(0.412)	(0.156)	(0.196)
Constant	0.156		1.298**		3.958***	
	(0.572)		(0.574)		(0.317)	
Observations	2206	1794	2210	1798	2216	1804
Individual, Call, Cluster FEs	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		50.88		50.90		50.84

Notes: Effects of internet access by wealth groups. FE-IV estimates with individual, community, and call fixed effects. The instrument is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on mental health problem indicators: GAD-7: Generalized Anxiety Disorder-7; PHQ-8: Patient Health Questionnaire-8. Well-being is subjective well-being, with a range between 1 (low well-being) and 9 (high well-being). The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B12: Internet access and suggestive mechanisms, table showing control variables

	Time doing nothing			**Meeting friends**			**Time HH chores**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wealth	All	Low	High	All	Low	High	All	Low	High
Internet	0.148*	0.329**	0.147	-0.482***	-0.566**	-0.602**	-0.0178	-0.0392	0.0783
	(0.0777)	(0.142)	(0.151)	(0.0951)	(0.265)	(0.251)	(0.0823)	(0.210)	(0.189)
Comfort.	-0.168**	-0.559**	-0.183	-0.0936	0.0912	-0.118	0.151**	0.263	0.345***
	(0.0753)	(0.229)	(0.135)	(0.0741)	(0.219)	(0.127)	(0.0717)	(0.208)	(0.119)
Struggle	-0.0932	-0.598***	-0.117	-0.0905	0.0517	-0.0730	0.123*	0.162	0.301**
	(0.0777)	(0.232)	(0.141)	(0.0783)	(0.223)	(0.139)	(0.0747)	(0.211)	(0.127)
Poor	-0.153*	-0.520**	-0.137	-0.255***	-0.00731	-0.195	0.251***	0.392*	0.431***
	(0.0811)	(0.229)	(0.153)	(0.0817)	(0.219)	(0.150)	(0.0792)	(0.209)	(0.141)
Destitute	0.261	-0.0459	0.635***	-0.393	0.103	-0.245	0.569***	0.537	0.967***
	(0.197)	(0.305)	(0.172)	(0.264)	(0.367)	(0.555)	(0.180)	(0.340)	(0.177)
Female	0.0183	0.0848**	0.0342	-0.130***	-0.143**	-0.141***	0.339***	0.235***	0.237***
	(0.0228)	(0.0381)	(0.0411)	(0.0289)	(0.0557)	(0.0547)	(0.0247)	(0.0471)	(0.0465)
Infected	0.232	0	-0.301***	0.286*	0	-0.310***	-0.0639	0	-0.597***
	(0.154)	(.)	(0.0560)	(0.149)	(.)	(0.0646)	(0.136)	(.)	(0.0935)
Income	0.00766	0.124***	0.00908	-0.0373	-0.0320	-0.0656	-0.0959***	-0.0697	-0.168***
	(0.0243)	(0.0414)	(0.0409)	(0.0313)	(0.0551)	(0.0562)	(0.0268)	(0.0483)	(0.0479)
Food	0.111***	0.156**	0.113	0.208***	0.0358	0.148	0.0532	-0.0107	0.126
	(0.0330)	(0.0737)	(0.0738)	(0.0374)	(0.0901)	(0.0929)	(0.0327)	(0.0834)	(0.0838)
Urban	0.0131	-0.0746	-0.0104	0.254***	0.328*	0.413**	-0.0382	-0.0804	-0.141
	(0.0506)	(0.103)	(0.114)	(0.0603)	(0.191)	(0.181)	(0.0493)	(0.141)	(0.136)
Const.	0.282***	0.507**	0.276*	0.784***	0.521**	0.769***	0.283***	0.226	0.184
	(0.0806)	(0.226)	(0.152)	(0.0800)	(0.213)	(0.168)	(0.0794)	(0.207)	(0.148)
Obs.	1418	454	435	1354	431	421	1419	454	435
F stat.	179.55	38.79	41.58	186.38	40.34	34.74	179.55	38.79	41.58

Notes: Samples include children in Call 2 due to data availability. IV estimates, the instrument is the proportion of households in a community getting access to the internet. Each column reports estimated effects of internet access on the likelihood having spent more time on doing nothing. Covariates: perceived wealth levels, household size, gender, (believed to be) infected by COVID-19, negative income shocks, run out of food, urban. F-statistic is the Kleibergen-Paap rk Wald F-statistic. The critical value of the Stock-Yogo test with 10% tolerance is 16.38. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$