Working Paper Series

#2025-007

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Published 18 February 2025

DOI: https://www.doi.org/10.53330/GYMA8538

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UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology
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Internet Access and Youth's Mental Health and Well-being: Evidence from Ethiopia

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Abstract

This paper provides one of the first robust evidence on 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 health disorders 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. The mechanism analysis suggests that passive internet use, particularly among youth from less advantaged socioeconomic backgrounds, might drive these negative outcomes. To address potential endogeneity, we employ instrumental variable techniques combined with fixed effects. The instrument is relevant based on network effect arguments and reasonably exogenous conditional on control variables and fixed effects. Our results offer policy implications regarding internet access and youth human capital development in the digital age and highlight the significance of social causes in shaping mental health.

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

JEL Classifications: I14, O33, J13.

*We would like to thank Robin Cowan, Bruno Martorano, Musa Hasen for many helpful comments and feedback and the Young Lives team for data access. This paper was also presented at the World Bank's The Pulse of Progress Harnessing High-frequency survey data for development research conference in 2024 in Washington, D.C.
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1 Introduction

The internet's potential for driving development has garnered significant enthusiasm, spurring universal connectivity initiatives from governments and development donors (Galperin & Viecens, 2017). Existing literature widely highlights the internet's positive impacts on development, including growth and income per capita promotion, and creation of new employment opportunities (Bertschek et al., 2015). These positive impacts are larger in developing countries, especially in the service sector and remote regions, where mobile networks and broadband internet enable telecommuting and help overcome geographical constraints. Regarding welfare and human development impact, there are benefits in education democratization and improvements in certain learning outcomes (Acemoglu et al., 2014; Aker et al., 2012), employment transition and labor mobility (Hartje & Hübler, 2017; Suri & Jack, 2016; Viollaz & Winkler, 2022).[1] When extended to broader societal outcomes, mobile broadband internet access exposes corruption in government, enhances citizen participation and environmental governance, and 'liberates' countries by fostering mass mobilization (Buntaine et al., 2024; Guriev et al., 2021; Manacorda & Tesei, 2020).

A rather optimistic picture of the impacts of broadband diffusion appears to emerge from the existing literature, particularly for less developed regions and countries. The internet, however, also introduces significant adverse effects, especially concerning well-being and human capital development. Harms including misinformation, scams, digital addiction, and mental health disorders have arisen at a pace faster than individual or societal awareness can keep up with (Firth et al., 2019; Loh & Kanai, 2016). Most of the existing literature on the internet's adverse effects, however, primarily focuses on developed countries. For example, studies from the US and Italy show that internet use crowds out quality time with family and friends and undermines social capital and civic engagement in the UK (Allcott et al., 2020; Geraci et al., 2022; Rotondi et al., 2017). At the individual level, smartphones and social media are known to be highly addictive and can cause self-control problems, negatively affecting mental health, especially among young people in the US and Europe (Allcott et al., 2022; Braghieri et al., 2022; Donati et al., 2022; Golin, 2022; McDool et al., 2020). Politically, social media algorithms create social and political bubbles and increase polarization in the US and UK (Gavazza et al., 2019; Levy, 2021). Furthermore, the internet has been linked to increased conflicts in both cyberspace and physical domain (Bharati et al., 2024; de Arimatéia da Cruz, 2014; Kostyuk & Gartzke, 2024) and is viewed as a 'repression technology'

[1] Although some of these papers concentrate on feature phones rather than smartphones in the earlier period before the widespread diffusion of mobile internet, smartphones and 3/4G networks are now widely available in Africa, including Ethiopia. Consequently, future analyses of mobile phones will predominantly focus on smartphones.

rather than a liberation one (Rød & Weidmann, 2015).

Due to historically low internet penetration in some regions and limitations in existing datasets, empirical evidence on the developmental impacts of internet access in developing countries is scant (Galperin & Viecens, 2017), and within this limited literature, many are often anecdotal. A 2024 New York Times report offers some of the earliest insights into the dangers posed by first-time wireless internet access to an isolated Amazonian tribe following the introduction of satellite coverage (Nicas, 2024a, 2024b).[2] While offering clear benefits, such as video chats with distant relatives, ability to call for help in emergencies, and elevated aspirations among young people for world travel and professional careers, negative outcomes are also evident. In less than a year after gaining satellite internet, teenagers have become attached to their phones and less motivated to work, with group chats filled with addictive social media, violent video games, scams, and age-inappropriate content.

Such significant negative effects on human capital development, particularly among young people, underscore the urgent need for timely studies on the developmental impacts of the internet in underdeveloped regions. However, the primary focus in the current development literature remains on addressing barriers to internet access and promoting greater usage. The lack of comprehensive studies on negative effects, alongside the apparently one-sided positive evidence in current literature, presents 'at best, an incomplete picture' (Goggin & McLelland, 2017), or worse, 'optimistic simplism' discourse of internet connectivity (Friederici et al., 2017). This emphasis overlooks the differential socioeconomic and geographical contexts, and potentially profound adverse effects on human development outcomes.

Youth and adolescents, in particular, face heightened negative effects on well-being and other aspects of human development due to their status as both a vulnerable demographic (Patel et al., 2016; Twenge & Campbell, 2019) and a tech-savvy group that adopts digital technologies and social media more than others (ITU, 2020, 2023). Psychological and mental disorders at young ages can accumulate and carry over beyond adolescence 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; UN, 2023; UNDP, 2022).

Internet use can have varied impacts on adolescents' mental health, with socioeconomic disparities worsening negative outcomes. While some evidence suggests stronger effects among students from lower socioeconomic status (SES) backgrounds in developed countries like the US and Norway (Abrahamsson, 2024; Braghieri et al., 2022), research on these in-

[2] Starlink service, starting from mid-2023, despite lacking electricity, phone screens light up at night, using battery power from solar panels.

equalities remains limited. Few studies have explored the mechanisms behind these unequal effects, such as Braghieri et al. (2022) on unfavorable social comparisons. Research also shows that passive internet use, such as scrolling through auto-recommended social media, exposes users to unhealthy comparisons and harmful content (Verduyn et al., 2015). This disproportionately affects disadvantaged youth – those with lower educational levels, wealth, or SES – compared to youth from advantaged backgrounds, who have more opportunities for healthier offline activities to help break the cycle of excessive online time and mindless scrolling that worsens mental health (George et al., 2020).

Set against this backdrop, this paper bridges two strands of literature: one that paints an overly optimistic picture of the impact of internet diffusion on less developed countries, and another that highlights the negative effects on well-being and human development, which have thus far primarily been evidenced in developed countries. Profiting from the Young Lives longitudinal survey, we provide early empirical evidence demonstrating the adverse effects of internet diffusion on mental health and well-being among adolescents in Ethiopia. To alleviate endogeneity concerns by using observational data, we employ an instrumental variable (IV) approach combined with individual and time fixed effects (FE) in our estimations. Our instrument is the community's average internet access rates, following extant literature (Hübler & Hartje, 2016; Ma & Sheng, 2023; Rotondi et al., 2017). The IV is relevant based on network effect arguments and is reasonably exogenous conditional to control variables and the inclusion of FEs. Our results remain robust after multiple robustness tests, including additional community-level time-variant controls.

This paper contributes to the literature in three ways. First, our study is, as far as we know, among the first to analyze the negative outcomes of internet access on adolescents' well-being and human capital for the Global South. The results add to the literature by highlighting the nuanced effects of internet diffusion in low-income countries. Second, we contribute to the still largely under-explored literature on the unequal impacts of internet use on mental health and well-being, particularly for adolescents from different household wealth levels – a notable finding in the least developed countries context (OHRLLS, 2024). Third, our mechanism analysis reveals that disadvantaged youth tend to engage more in passive internet use, a pattern likely driven by addictive technology algorithms and exacerbated by systemic inequalities in support for addressing these negative effects (Acemoglu & Johnson, 2023; Scheerder et al., 2017). Our findings have important implications for youth health and human capital development policies in developing countries, particularly in the era of mobile digitalization. They also shed light on how the digital age is amplifying the Matthew effect, widening existing inequalities (Kümpel, 2020; Trucano, 2013).

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

2 Extant literature and background

Here, we synthesize the extant literature on internet use and youth mental health and key mechanisms behind the unequal effects on youth from different socioeconomic backgrounds.

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 anxiety and depression are the most common manifestations of poor mental health (Huppert & So, 2013; Martínez et al., 2020).[3] In Ethiopia, Hunduma et al. (2024)'s descriptive study in 2020 shows that among in-school adolescents, there are high levels of internalizing problems,[4] 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[5] have limited self-regulation and are more susceptible to peer pressure, making them vulnerable as they navigate and experiment with social media (Achdut et al., 2021; Tanner & Arnett, 2016). 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, while no such effect was detected for older people.

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 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

[3] 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).

[4] 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.

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

to social immobility within and across generations (Golberstein et al., 2019; Goodman et al., 2011; UN, 2023; UNDP, 2022).

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

Youth 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).[6] 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).[7]

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; Rotondi et al., 2017). Yet, for young adults who feel disadvantaged in the digital age, 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.

With risen digitalization, competition among social media platforms and the adjustment of recommender algorithms to boost user engagement have increased social media's addictiveness,[8] causing users craving to check social media for gratification when idle (Hjetland et al., 2021; Rast et al., 2021). Descriptive evidence shows that most Ethiopian youth use social media to pass time, for 'escapism', or feel like a waste of time (Haile, 2024; Hussain & Hussain, 2023; Internews, 2023). This behavior can be linked to 'mindlessly scrolling' or passive internet use, which 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).

Such passive internet use also increases users' exposure to unhealthy content[9] and/or cyberbullying[10] (Beneito & Vicente-Chirivella, 2022; van Geel et al., 2014). The top risks on

[6] 95, 79, and 67 percent respectively; followed by banking – 31 percent, others, and online learning.

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

[8] 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).

[9] 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.

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

social media reported by Ethiopian students include 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).

2.2 The influence of relative poverty and inequality

The effects of internet use on individuals' mental health can depend on levels of socioeconomic status (SES) (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, perceived relative poverty can impact mental health through interpersonal comparisons, causing feelings of failure and 'social defeat' (Burns, 2015; 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.

People in 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 (Blank & Groselj, 2014; C. Harris et al., 2017). Time spent passively scrolling auto-recommended content on social media increases exposure to unhealthy content and promotes 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.[11] While highly educated people typically try to address negative outcomes by understanding causes, preventing recurrence, or protecting their children, less educated individuals are less likely to take remedial actions.

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 data 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). The YL household sample represents a wide range of living standards similar to the variability found in the Ethiopian population,[12] 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.[13] 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.[14] This evaluative measure of SWB (Stone & Krueger, 2018) presents a global evaluation of one's

[11] 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.

[12] 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).

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

[14] 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).

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 based on individuals' age, gender, wealth,[15] education levels, and locations (Adam et al., 2024; ITU, 2023; Wassie et al., 2023).[16] During the pandemic, the internet access rate among youth aged 18-20 in Ethiopia in YL data was 45%.[17]

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 that the average infection rate during 2020-2021 in Ethiopia was 0.9%);[18] whether the household ever ran out of food since the outbreak of the COVID-19 pandemic (22% faced food insecurity issues); and whether household's income was reduced compared to before COVID-19 (48%).

Household wealth index, proposed 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

[15] 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.

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

[17] 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.

[18] 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).

the 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 disorder 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 well-being	2260	4.544	1.432	1	9
GAD-7	2262	1.700	2.801	0	18
PHQ-8	2257	1.649	2.733	0	17
Internet	2262	0.443	0.496	0	1
Household size	2262	5.774	1.983	1	15
Female	2262	0.475	0.499	0	1
Age	2262	18.933	0.759	17	20
Wealth index round 5	2218	0.424	0.173	0.006	0.881
(Believed) infected	2262	0.01	0.0838	0	1
Income decreases	2262	0.438	0.496	0	1
Run out of food	2262	0.194	0.395	0	1

4 Empirical strategy

Our base econometric model is as follows:

$$Y_{it} = \beta_0 + \beta_1 Internet_{it} + X_{it} + \mu_i + \phi_t + \epsilon_{it} \quad (1)$$

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 and ϕ_t are the individual and time fixed effects respectively; ϵ_{it} is the idiosyncratic error term.

The inclusion of individual fixed effects (FE) mitigates omitted variable bias (OVB) induced by time-invariant factors like genetic predisposition and community's infrastructure, which can affect both internet use and mental health (Allen et al., 2014; Currie & Morgan, 2020; Ferschmann et al., 2022; McDool et al., 2020). Additionally, one may raise concerns about other changes e.g., certain macroeconomic fluctuations might influence households' job prospects, and, subsequently, affect mental health of household members including adolescents'. The inclusion of time FE allows us to rule out such concerns.

There remain, however, other endogeneity concerns, including measurement bias since our main independent variable is internet access at household level, which is used as a 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, i.e., adolescent's mental health affects their internet use rather than the other way around, is less an issue given that internet variable is household internet access, not individual-level use; it is still possible that adolescents in households 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' well-being, like the case that a household gets richer and improves their living conditions, 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 already include time FE in the models.

To address these issues, following extant literature, we employ regional or local average internet access to instrument household-level internet access (Hübler & Hartje, 2016; Ma & Sheng, 2023; Rotondi et al., 2017). 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 or kebele (neighborhoods or wards) level, the lowest administrative unit in Ethiopia, as our instrument.

Regarding exogeneity, community internet rates are likely to be exogenous, conditional on individual, household, and community controls. 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). We alleviate these concerns by adding 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 covariates. As presented in section 5.2, our results remain robust to these additions. The IV approach can also address the issue of mismeasurement in dichotomous 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 (Björkegren, 2019).

Our first-stage equation is:

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

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

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 (Stock & Yogo, 2005).

Results from FE-IV models in Columns (4) and (6)) show that the average anxiety and depression scores of adolescents who had internet access are 9.3 and 8.3 units higher than those who did not, after controlling for individual, household, and community characteristics, time 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	0.109	-1.723***		0.719***	9.310***	0.668***	8.338***
	(0.104)	(0.557)		(0.267)	(1.603)	(0.254)	(1.486)
1st-stage Community internet			0.941***				
			(0.132)				
(Believed) infected	0.176	0.474**	0.341*	2.731	3.200	0.108	-1.528
	(0.263)	(0.234)	(0.204)	(1.972)	(3.188)	(0.651)	(1.604)
Income decreases	-0.057	-0.0818	-0.006	0.518***	0.937***	0.370**	0.744***
	(0.0905)	(0.116)	(0.0245)	(0.176)	(0.290)	(0.167)	(0.272)
Run out of food	0.302**	0.211	0.0470	0.110	0.740**	0.339	0.780**
	(0.149)	(0.189)	(0.039)	(0.186)	(0.373)	(0.209)	(0.377)
Constant	4.463***			1.113***			1.129***
	(0.0713)			(0.160)			(0.153)
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
R^2	0.643			0.589		0.613	
Adjusted R^2	0.284			0.175		0.223	
F-statistic		50.59	50.59		50.16		50.60

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. 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 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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,[19] including time more spent for studying.[20] 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.[21] 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 3 below, internet use is associated with 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 B2 in the appendix.

Table 3: Broader impacts on other human capital-related variables

	(1) (Perceived) study time	(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 only children in Call 2 due to data availability. The instrument for internet access 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[19] 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.

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

[21] 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 equals 1 if the answer value is 1-Going back to education and equals 0 if the answer value is greater than 2, thus excluding youth who are already in the labor force/ going back to work.

5.2 Robustness checks

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

Firstly, as community's averages of internet access might be correlated with 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 FE-IV results incorporating these variables remain robust, as shown in Table B3 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.

Second, we conduct a cross-sectional IV analysis using regional variations of cell towers coverage from OpenCellID data, a collaborative community project run by Unwired Labs (Pham & Caldarola, 2024; Viollaz & Winkler, 2022). We calculate the number of 3G towers whose signals collected per region on GIS software, using the information on cell towers' longitude and latitude, and date and time signal collected. Since OpenCellID recently changed their data publications and we cannot obtain historical cell towers data, we conduct a cross-sectional IV analysis by aggregating towers counts up to the year 2020. Results are shown in Table B4 in the appendix, with statistical significance and effect signs in line with theories, and Kleibergen-Paap rk Wald F-statistic above the minimum of 10.

Third, we conduct a difference-in-difference (DiD) estimation for a subsample of adolescents who did not have internet access in Call 2, dividing them into two groups, with and without internet access in Call 5, or treatment and control groups respectively, as a robustness test. Furthermore, we also combine DiD with kernel propensity score matching (PSM) to adjust for selection bias using observable characteristics at baseline (Li et al., 2021; Mu & van de Walle, 2011; Villa, 2016). This is done by matching the comparison individuals in the DiD estimate with the treatment group based on the predicted probability of getting internet access (the propensity score) by a kernel function (Heckman et al., 1997; Mu & van de Walle, 2011), using a probit link function. The impact estimates are then constructed by comparing the before and after in outcome measures for adolescents with those for the matched comparison observations.

The base DiD estimation is as follows:

$$Y_{it} = \beta_0 + \beta_1 treated_{it} + period_{it} + \beta_3(treated_{it} \times period_{it}) + \beta_4 X_{it} + \epsilon_{it} \tag{3}$$

where Y_{it} is subjective well-being or mental health indicator of individual i at time t; $treated_{it}$ is the treatment effect. It equals 0 if i belongs to the control group and equals 1 if i belongs to the treatment group. $period_{it}$ is time effect. It equals 0 if t is for call 2 and equals 1 if t is call 5; X_{it} denotes individual, household, and community level controls; ϵ_{it} is the error term.

The results are reported in Table B7 in the appendix, showing significant positive impacts on anxiety and depression scores for both DiD and PSM-DiD estimations, with slightly larger effect sizes for the latter. Table B5 shows that covariates balancing has been improved after kernel matching. The overall balance is satisfied. This can also be seen by the weak joint significance of the matched covariates (decreasing LR chi^2), and the reductions in bias scores in Table B7 (Callais, 2022; Callais & Young, 2023; Cumpton & Prince, 2018; Fan & Zhang, 2021; Li et al., 2021).

Fourth, we conduct another test for a subsample of observations who did not have internet in Call 2; and run IV estimates for cross-sectional data in Call 5. To alleviate self-selection bias or reverse causality of household internet adoption, i.e., households with higher subjective well-being are more likely to get internet access, we also add Call 2's mental health values as a control variable in the cross-sectional model for Call 5. Results in Table B8 in the appendix show significant effects of internet on well-being and mental disorders indicators in models with and without the lagged dependent variables.

5.3 Effect heterogeneity

Since the effects of internet use on individuals' mental health can have significant heterogeneity, 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. Table 4 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 level. The effect size is more than doubled and is statistically different from zero at the 1% significance 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.

Table 4: 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	-1.583	-1.589***	14.070***	6.608***	12.860***	5.579***
	(1.058)	(0.584)	(4.203)	(1.316)	(3.818)	(1.195)
(Believed) infected	0.360***	0.543	6.737***	0.845	-0.197	-1.658
	(0.119)	(0.374)	(1.189)	(3.836)	(1.185)	(1.424)
Income decreases	-0.005	-0.173	1.100**	0.876**	0.882*	0.721**
	(0.163)	(0.167)	(0.554)	(0.369)	(0.507)	(0.345)
Run out of food	0.497*	0.028	0.522	0.917*	0.377	1.000**
	(0.293)	(0.246)	(0.699)	(0.477)	(0.681)	(0.466)
Observations	902	868	898	862	902	868
Individual, Call FEs	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F-statistic	15.19	38.24	16.38	37.77	15.19	38.24

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Instead of dichotomizing the wealth index, we also employ models that interact internet use and the wealth index. Results are shown in Table B9 in the appendix, with effect signs in line with theory, though at a weaker significance level. There is a positive sign of the interaction term for well-being, indicating that while internet decreases subjective well-being, household wealth alleviates such effect. For anxiety and depression indexes, there are negative signs of the interaction terms, showing that wealth alleviates the positive influence of internet on youth's mental health disorders. The results suggest the moderating effect of wealth on the dynamics of internet and mental health outcomes.

Additionally, as a robustness test to check 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 B10 in the appendix.

Lastly, following previous tests for the subsample of adolescents who did not have internet in Call 2, we run IV estimations for cross-sectional data in Call 5. Outcomes in Table B11 present significantly larger effects for the group with lower wealth index, corroborating heterogeneous effect evidence of internet on youth's mental health.

In terms of gender heterogeneity, although some studies find stronger impacts for women, in our data, there is no detected effect heterogeneity between females and males, which might be due to self-reporting issues and/or different contextual characteristics and mechanisms. Results can be seen in Table B12 in the appendix.

We also try heterogeneity analysis for urban-rural regions. However, the IV approach does not work for urban areas.[22] 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[23] 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 B13 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 in Figure A6 in the appendix, data from YL round 5 in 2016), thus we could not conduct statistical heterogeneity analysis for parental educational background.

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 Mechanism analysis

In this section, we run linear probability models estimations for several binary dependent variables, which are available in Call 2 data collection, that may serve as mechanisms for the effects detected earlier.

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, for example, craving to check

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

[23] 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.

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,[24] which include time spent on playing or doing nothing,[25] we detect significant heterogeneity in the effect sizes of the internet variable. The results are presented in Table 5 below for both the average and heterogeneous outcomes. 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 (Column (4)).[26] There is no significant effect on time for doing household chores (Column (7)).[27] Full results including control variables can be seen in Table B14 in the appendix.

Table 5: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Our findings corroborate evidence from a mechanism analysis by McDool et al. (2020), who found that internet use crowds out time spent on other beneficial activities for British adolescents.[28] 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,

[24]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.

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

[26]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.".

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

[28]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.

2023) in the age of the attention economy (Baker, 2023; Seaver, 2019; Yang et al., 2021).

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 playing or doing nothing, compared to adolescents from higher SES group who do not (significantly) seem to feel so. This result suggests that youth in the poorer group spend more unsupervized screen time or more time passively consuming media. Spending more time on 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), negative news of the pandemic, and civil war (Ambelu et al., 2021; Chekol et al., 2023; Tareke et al., 2023). These internet uses crowd 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; Firth et al., 2024; Rast et al., 2021), and as a result, intensifying the gaps in the consequences of internet's negative outcomes on mental health.

Past studies have shown that poorer mental health and well-being outcomes could be due to reduced social interactions (Dwyer et al., 2018; Przybylski & Weinstein, 2013; Rotondi et al., 2017). We test this hypothesis but no significant heterogeneity is detected, as shown in Columns (5) and (6) of Table 5. No unequal impacts are either found for time spent on doing household chores, as in columns (8) and (9), regarding the replacement hypothesis for household domestic physical activities.

6 Conclusion

Our study shows a robust relationship between internet use and youth mental health and subjective well-being in Ethiopia during 2020-2021, and additionally, on youth human capital regarding less time studying and reduced desire to return to education. Notably, there are stronger effects for the poorer groups with more than doubled effect magnitudes, indicating significantly unequal impacts on the disadvantaged groups. As far as we know, this is among the first papers offering robust evidence on the internet-youth mental health nexus, with significant impact heterogeneity in a least developed country context.

Our mechanisms analysis offers suggestive evidence supporting the effect of increased time spent on playing or doing nothing, which might indicate mindlessly scrolling or passive internet use, with a considerable effect heterogeneity between the poorer and richer groups. All in all, the highly unequal impacts on youth from less advantaged background raises an alarm about both the dark side of the internet and the growing trend of inequality. This shift highlights the importance of not only internet access but also the quality of use and its outcomes, indicating that the internet may reinforce existing social inequalities, or in other words, exacerbate the Matthew effects in the digital age.

As the internet becomes more widespread worldwide, especially following COVID-19, young people's increasing exposure to online content and activities can lead to worsening mental health and a decline in human capital, potentially leading to a global epidemic of mental disorders among younger generations (Østergaard, 2017) if no interventions are made. The responsibility ultimately lies with families and policymakers to regulate and guide internet use and online culture to foster 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).[29] This is particularly important in our technologically advanced and growingly competitive society, where 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). It also aligns with global development goals, which aim to go beyond conventional GDP and growth metrics[30] to measure people's well-being (Cénat, 2020; Kanbur et al., 2018; Stiglitz et al., 2009).[31]

While policies banning smartphones in schools show some positive results (Abrahamsson, 2024; Beneito & Vicente-Chirivella, 2022), adolescents often spend more time online at home. Banning smartphone use or texting at home may not work and could be counterproductive (Abouk & Adams, 2013), especially for adolescents and young adults who have more 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 useful information, policy and social interventions should aim to promoting awareness and use habits for optimal benefits. Practical policies may include campaigns to raise awareness about the harms and dangers of the digital space,[32] 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

[29] 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).

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

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

[32] 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).

formal (school) and informal (household, community) learning environments (Cobb, 2023; Malamud & Pop-Eleches, 2011).

Particularly, policies should focus on youth from less advantaged backgrounds to break the vicious cycle between mental illnesses and poverty which traps many young people in 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 more affordable access to resources and services. However, concerns remain regarding the abundance of unregulated material (Bucci et al., 2019) and the design of digital programs in terms of inclusive outreach and affordability (Banati et al., 2020). More importantly, addressing the root causes of socioeconomic inequality for children and adolescents is crucial, as these factors are important drivers of mental health but are often underestimated in current mental health practices (Burns, 2015; Kirmayer & Pedersen, 2014). These include not only reducing poverty and material deprivation (Achdut et al., 2021) but also leveling the playing field for youth in terms of education and providing better ICT pedagogical resources to ensure more productive use of internet resources (van Deursen & van Dijk, 2014; Vargas-Montoya et al., 2023).

While our analysis detects significant impacts of internet access on self-reported mental health, the actual incidence might be biased if there is self-reporting bias due to gender or cultural norms surrounding 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 more common in developed countries contexts. New data should also be collected to assess the long-run, life-cycle achievements. Future data availability can also be used to detect explicitly mechanisms like the 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 before and after the pandemic.

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Appendices

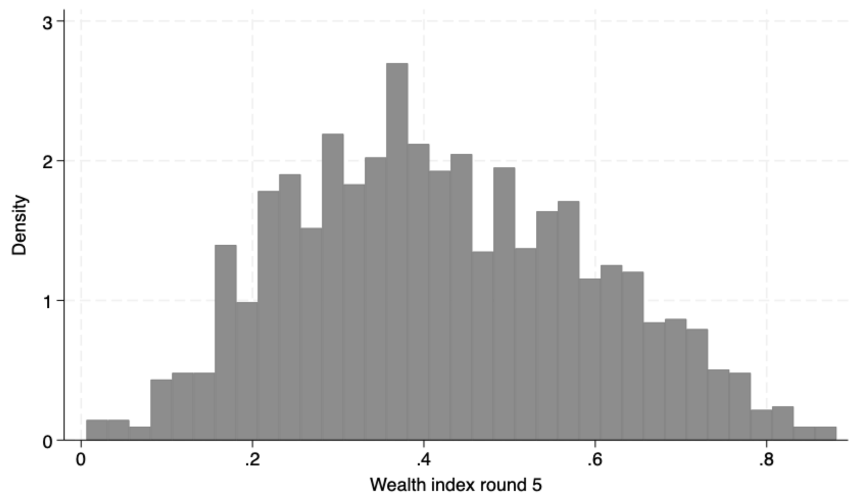

Figure A1: Wealth index distribution
Source: Authors', using YL data

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).

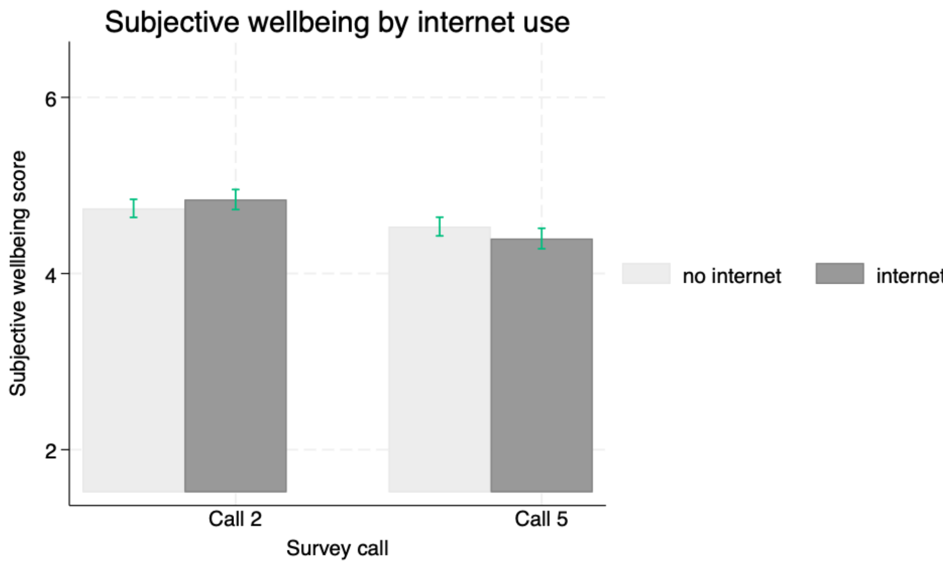

Figure A2: Internet access and subjective wellbeing
Source: Authors' illustration based on YL data

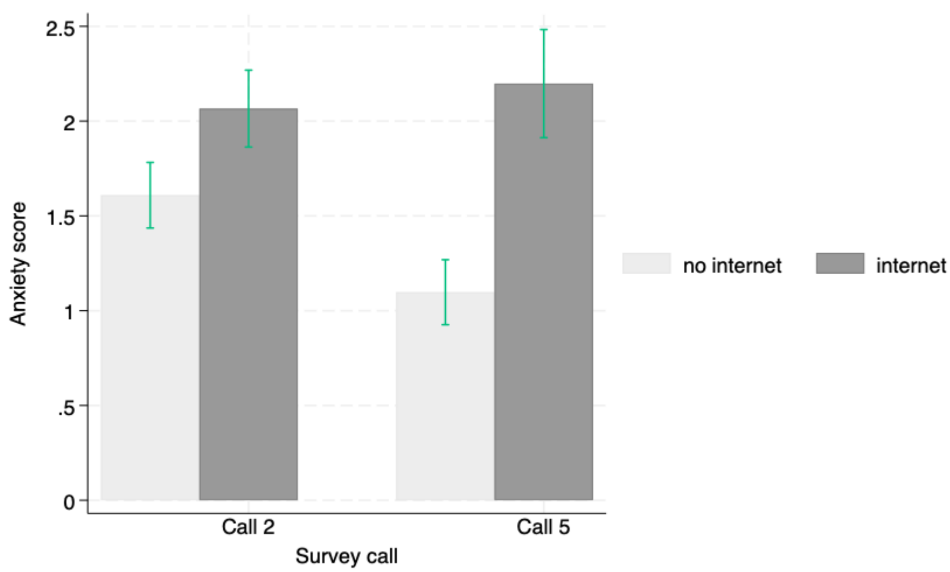

Figure A3: Internet access and anxiety scores (GAD-7)
Source: Authors' illustration based on YL data

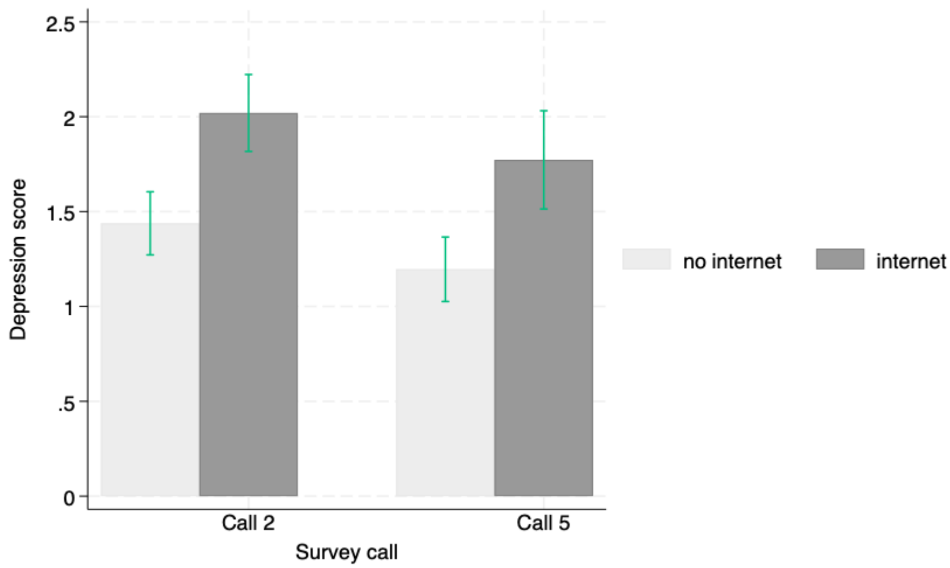

Figure A4: Internet access and depression scores (PHQ-8)
Source: Authors' illustration based on YL data

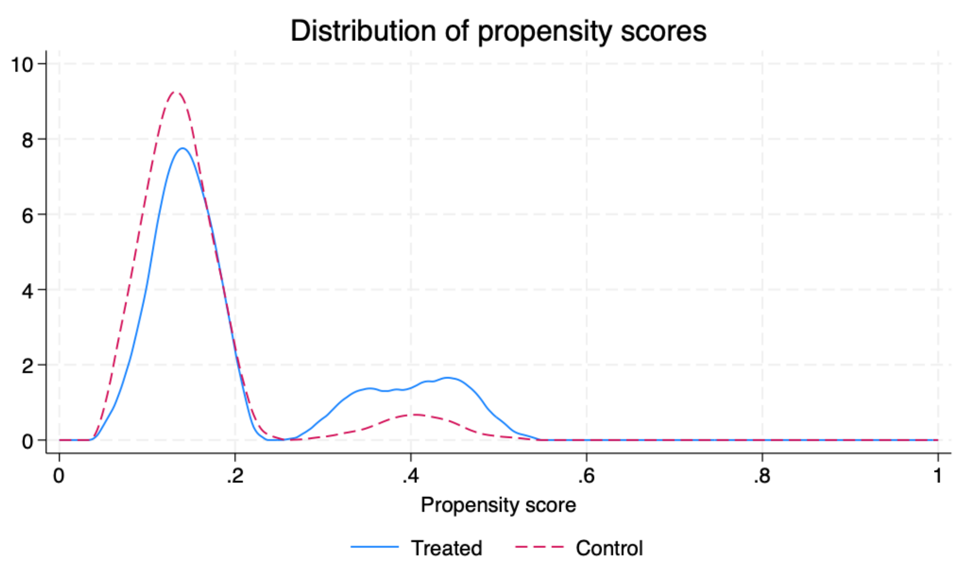

Figure A5: Distribution of propensity scores
Source: Authors', using YL data

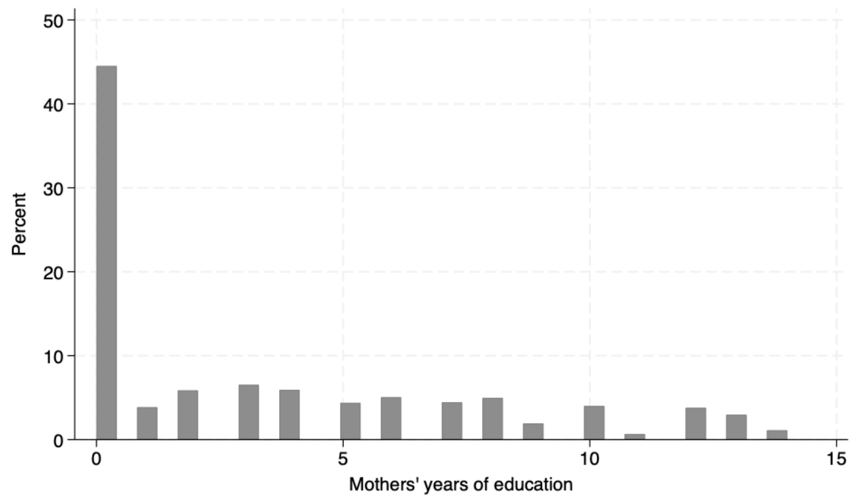

Figure A6: Mothers' education variable distribution
Source: Authors', using YL data

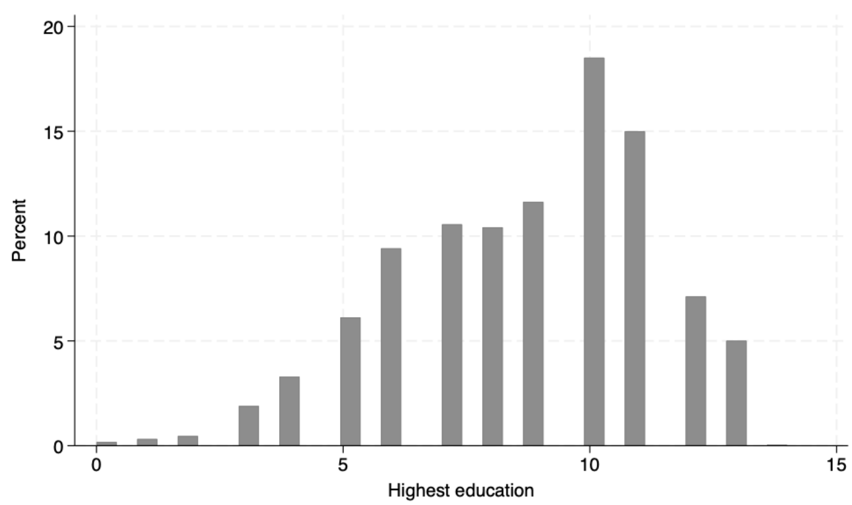

Figure A7: YL children's education variable distribution
Source: Authors', using YL data

Table B2: 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
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. 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: Robustness test with time-variant community controls

	(1) GAD-7	(2) PHQ-8
Internet	11.840***	9.613***
	(1.893)	(1.609)
Community income reductions	2.252***	2.189***
	(0.785)	(0.645)
Community food shortages	0.869	0.169
	(0.913)	(0.862)
Community average wealth level	0.651	-0.046
	(0.577)	(0.469)
Other control	Yes	Yes
Individual, Cluster, Call FEs	Yes	Yes
Observations	1836	1840
Kleibergen-Paap Wald F statistic	66.10	67.45

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. Covariates: (believed to be) infected by COVID-19, negative income shocks, run out of food. 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 B4: Cross-section IV regressions using regional cell towers coverage

	SWB (1)		GAD-7 (2)	PHQ-8 (3)
Internet	-1.794***		1.725**	2.740***
	(0.430)		(0.713)	(0.700)
1st-stage regional 3G towers		0.00118***		
		(0.000125)		
Comfortable	-1.839***	-0.115	0.193	0.546
	(0.225)	(0.0701)	(0.398)	(0.345)
Struggle	-2.449***	-0.169**	0.530	0.970***
	(0.234)	(0.0719)	(0.413)	(0.366)
Poor	-3.659***	-0.273***	2.012***	2.405***
	(0.266)	(0.0728)	(0.483)	(0.437)
Destitute	-4.205***	-0.494***	3.962***	2.521**
	(0.666)	(0.144)	(1.061)	(0.980)
Female	0.0935	-0.0287	0.323**	0.360**
	(0.0823)	(0.0208)	(0.138)	(0.141)
(Believed) infected	1.538***	0.263**	0.627	0.740
	(0.552)	(0.121)	(0.643)	(0.865)
Income decreases	-0.238***	-0.0831***	0.453***	0.414***
	(0.0910)	(0.0214)	(0.153)	(0.159)
Run out of food	-0.0113	0.0707**	0.180	0.139
	(0.107)	(0.0289)	(0.190)	(0.188)
Urban area	0.681***	0.406***	-0.363	-0.826**
	(0.231)	(0.0248)	(0.342)	(0.347)
Constant	7.620***	0.375***	0.180	-0.553
	(0.289)	(0.0708)	(0.527)	(0.465)
Observations	1653	1653	1655	1657
Kleibergen-Paap rk Wald F-statistic		88.101		

Notes: The sample is limited to people who do not have internet in Call 2. Cross-sectional IV analysis. IV is the total number of 3G towers collected up to 2020 per region. Each column reports estimated effects of internet access on adolescents' mental health. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B5: Differences in means before and after matching

	Unmatched		Matched		**Diff. (3) vs (4)**
	Treatment	Control	Treatment	Control	P-value
	(1)	(2)	(3)	(4)	(5)
Wealth index	0.386	0.334	0.371	0.363	0.530
Female	0.534	0.478	0.531	0.504	0.514
Urban area	0.311	0.079	0.276	0.276	1.000
Income decreases	0.660	0.532	0.643	0.609	0.390
Run out of food	0.146	0.069	0.102	0.083	0.430
Observations	103	504	98	496	-

Table B6: Probit estimates of propensity scores

	Household internet access
Wealth index	0.463
	(0.460)
Female	0.101
	(0.125)
Urban area	0.841***
	(0.181)
Income decreases	0.241*
	(0.130)
Run out of food	0.260
	(0.209)
Constant	-1.474***
	(0.200)
Observations	607
Pseudo R-squared	0.0762

Notes: Samples include children in Call 2 only. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B7: Difference-in-difference (DiD) and kernel propensity matching (PSM) estimation of internet access and youth's mental health

	SWB		**GAD-7**		**PHQ-8**	
	(1)	(2)	(3)	(4)	(5)	(6)
	DiD	**PSM-DiD**	**DiD**	**PSM-DiD**	**DiD**	**PSM-DiD**
Diff-in-diff	0.0777	-0.137	2.015***	2.268***	1.174**	1.741***
	(0.203)	(0.222)	(0.488)	(0.488)	(0.492)	(0.492)
Time/call	-0.146	-0.0778	-0.566***	-0.670***	-0.313*	-0.525***
	(0.106)	(0.125)	(0.173)	(0.211)	(0.169)	(0.199)
Treated	-0.297**	-0.165	-0.202	-0.418	-0.0973	-0.310
	(0.141)	(0.151)	(0.295)	(0.283)	(0.323)	(0.307)
Wealth index round 5	1.417***		-1.729***		-2.169***	
	(0.320)		(0.552)		(0.595)	
Female	0.0543		-0.0317		-0.160	
	(0.0845)		(0.147)		(0.146)	
Urban area	-0.683***		0.852***		0.914***	
	(0.140)		(0.282)		(0.305)	
Income decreases	-0.0641		0.335*		0.145	
	(0.0953)		(0.175)		(0.171)	
Run out of food	0.0630		-0.332		-0.557***	
	(0.118)		(0.212)		(0.207)	
Constant	4.277***	4.532***	2.003***	1.737***	2.312***	1.681***
	(0.149)	(0.0873)	(0.233)	(0.167)	(0.245)	(0.156)
Observations	1211	1188	1206	1179	1208	1183
LR chi^2 - Unmatched		98.19		98.19		98.19
LR chi^2 - Matched		8.95		9.80		8.52
$p > chi^2$ - Unmatched		0.000		0.000		0.000
$p > chi^2$ - Matched		0.111		0.081		0.130
MeanBias - Unmatched		26.1		26.1		26.1
MeanBias - Matched		12.2		13.2		11.5
MedBias - Unmatched		10.3		10.3		10.3
MedBias - Matched		9.1		10.3		8.8

Notes: The sample is limited to people who do not have internet in Call 2. Each column reports estimated effects of internet access on adolescents' mental health. Odd-numbered columns are results for single DID with covariates, even-numbered columns are DiD with kernel propensity-score matching PSM. Stata command diff is sourced from Villa (2016). Covariates balancing test command is pstest in Stata following Leuven (n.d.). Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B8: IV robustness test with lag dependent variables

	SWB		GAD-7		PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
Internet	-2.874***	-2.628***	5.436***	5.636***	3.862***	4.395***
	(0.461)	(0.450)	(0.812)	(0.821)	(0.753)	(0.759)
SWB in call 2		0.107***				
		(0.0384)				
GAD-7 in call 2				0.166***		
				(0.0421)		
PHQ-8 in call 2						0.300***
						(0.0418)
Comfortable	-1.902***	-1.793***	2.431***	2.367***	2.324***	2.022***
	(0.436)	(0.421)	(0.767)	(0.766)	(0.711)	(0.698)
Struggle	-1.968***	-1.878***	2.897***	2.845***	2.757***	2.415***
	(0.435)	(0.420)	(0.766)	(0.765)	(0.710)	(0.698)
Poor	-3.896***	-3.719***	3.824***	3.925***	2.830***	2.817***
	(0.467)	(0.453)	(0.822)	(0.824)	(0.763)	(0.750)
Destitute	-6.279***	-6.062***	7.769***	8.051***	10.20***	10.48***
	(1.483)	(1.428)	(2.610)	(2.611)	(2.421)	(2.383)
HH size	0.0802**	0.0812**	-0.103*	-0.0549	-0.182***	-0.0973*
	(0.0334)	(0.0321)	(0.0587)	(0.0603)	(0.0545)	(0.0552)
Female	0.0277	-0.00837	-0.0830	-0.0926	-0.134	-0.0633
	(0.121)	(0.117)	(0.214)	(0.214)	(0.198)	(0.195)
(Believed) infected	-0.749	-0.699	4.896*	3.478	3.725	1.929
	(1.456)	(1.400)	(2.563)	(2.595)	(2.377)	(2.360)
Income decreases	0.150	0.158	0.0593	0.238	-0.0777	0.306
	(0.155)	(0.149)	(0.273)	(0.277)	(0.254)	(0.255)
Run out of food	0.368**	0.397***	-0.643**	-0.573**	-0.717***	-0.596**
	(0.157)	(0.152)	(0.277)	(0.278)	(0.257)	(0.254)
Urban area	1.296***	1.274***	-1.884***	-2.015***	-1.490***	-1.865***
	(0.300)	(0.288)	(0.528)	(0.532)	(0.490)	(0.491)
Constant	6.402***	5.759***	-1.427*	-2.057**	-0.257	-1.239
	(0.490)	(0.523)	(0.863)	(0.888)	(0.800)	(0.812)
Observations	557	557	555	553	556	556
Cragg-Donald Wald F statistic	103.916	100.625	103.290	100.986	103.538	99.200

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. 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 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 FE	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 B10: 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	-1.176	-1.830***	10.75***	4.354***	10.03***	3.298***
	(0.999)	(0.612)	(3.185)	(0.986)	(2.964)	(0.945)
Job loss	-0.382*	0.0112	0.629	2.095***	0.952	2.003***
	(0.210)	(0.251)	(0.710)	(0.461)	(0.701)	(0.445)
Input price increased	-0.00130	0.364	1.307**	1.323***	1.010*	1.064***
	(0.222)	(0.234)	(0.610)	(0.393)	(0.562)	(0.367)
Food price increased	0.0472	-0.239	-0.337	-0.448	-0.447	-0.596
	(0.273)	(0.265)	(0.699)	(0.413)	(0.658)	(0.445)
(Believed) infected	0.233	0.146	6.636***	7.248***	-0.0835	1.257**
	(0.227)	(0.299)	(1.730)	(0.503)	(0.746)	(0.499)
Income decreases	0.0423	-0.315	0.619	0.181	0.610	0.162
	(0.196)	(0.192)	(0.508)	(0.313)	(0.475)	(0.320)
Run out of food	0.586*	0.123	0.271	0.431	0.0373	0.388
	(0.349)	(0.265)	(0.609)	(0.360)	(0.616)	(0.425)
Observations	772	748	768	742	772	748
Individual, Call FEs	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	18.122	35.450	18.066	35.118	18.122	35.450

Notes: Effects of internet access by wealth groups. FE-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 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 B11: Heterogeneity of effects of internet on mental health by SES in IV models using Call 5 data

	Well-being		GAD-7		PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth index	Lower	Higher	Lower	Higher	Lower	Higher
Internet	-4.358***	-2.233***	12.10***	2.778***	9.581***	1.952***
	(1.399)	(0.408)	(3.197)	(0.618)	(2.838)	(0.597)
Comfortable	-2.754***	-1.489***	4.575*	1.183*	4.193**	1.364**
	(1.048)	(0.442)	(2.394)	(0.669)	(2.126)	(0.647)
Struggle	-2.827***	-1.201***	4.492*	1.641**	4.336**	1.561**
	(1.032)	(0.451)	(2.355)	(0.683)	(2.092)	(0.659)
Poor	-4.672***	-3.322***	5.486**	2.364***	4.274**	1.873**
	(1.070)	(0.521)	(2.442)	(0.789)	(2.170)	(0.762)
Destitute	-7.186***	0	10.01**	0	12.29***	0
	(1.982)	(.)	(4.524)	(.)	(4.019)	(.)
HH size	0.0867	0.0711	-0.182	0.0495	-0.287**	-0.0363
	(0.0573)	(0.0461)	(0.131)	(0.0699)	(0.116)	(0.0675)
Female	0.0147	-0.0202	-0.337	-0.0515	-0.356	-0.0342
	(0.208)	(0.166)	(0.475)	(0.251)	(0.421)	(0.242)
(Believed) infected	0	-1.936	0	4.745**	0	3.452*
	(.)	(1.343)	(.)	(2.033)	(.)	(1.964)
Income decreases	0.143	0.110	0.523	0.156	0.451	-0.142
	(0.259)	(0.217)	(0.592)	(0.328)	(0.526)	(0.317)
Run out of food	0.579**	0.169	-0.445	-1.280***	-0.714	-1.056***
	(0.260)	(0.219)	(0.594)	(0.331)	(0.527)	(0.320)
Urban area	1.530**	1.724***	-5.188***	0.535	-4.198***	0.346
	(0.641)	(0.463)	(1.465)	(0.701)	(1.301)	(0.677)
Constant	7.072***	6.107***	-3.130	-0.923	-1.498	-0.156
	(1.091)	(0.529)	(2.492)	(0.802)	(2.213)	(0.774)
Observations	275	234	274	233	275	234
Cragg-Donald Wald F statistic	17.274	105.032	17.181	104.308	17.274	105.032

Notes: Effects of internet access by wealth groups for sample who did not have internet in 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 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. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B12: Heterogeneity of effects of internet on mental health by gender

	SWB		GAD-7		PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
Internet	-2.039**	-1.296*	8.998***	9.633***	7.697***	8.947***
	(0.794)	(0.779)	(2.114)	(2.405)	(1.972)	(2.198)
(Believed) infected	1.023*	0.103	-0.745	7.248***	-1.992	-0.713
	(0.568)	(0.110)	(4.770)	(1.062)	(2.952)	(0.516)
Income decreases	-0.0583	-0.0997	1.092**	0.869**	0.674*	0.810**
	(0.200)	(0.137)	(0.474)	(0.369)	(0.407)	(0.372)
Run out of food	0.319	0.179	0.0902	1.382**	0.290	1.325**
	(0.293)	(0.250)	(0.462)	(0.614)	(0.439)	(0.631)
Observations	850	996	846	990	846	994
Individual, Call FEs	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic	25.74	26.23	25.31	26.23	25.72	26.28

Notes: Effects of internet access by wealth groups. FE-IV estimates with individual 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 B13: Effects of internet on mental health with education as control

	Well-being		GAD-7		PHQ-8	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE-IV	FE	FE-IV	FE	FE-IV
Internet	0.0715	-1.969***	0.674**	9.456***	0.698***	8.765***
	(0.107)	(0.604)	(0.269)	(1.679)	(0.262)	(1.583)
Highest education	0.0644*	0.134***	0.110	-0.158	-0.0210	-0.282**
	(0.0372)	(0.0494)	(0.0672)	(0.122)	(0.0686)	(0.126)
(Believed) infected	0.177	0.510**	2.692	3.185	0.0890	-1.580
	(0.276)	(0.257)	(1.969)	(3.191)	(0.651)	(1.623)
Income decreases	-0.0741	-0.141	0.497***	1.021***	0.370**	0.874***
	(0.0922)	(0.123)	(0.181)	(0.311)	(0.173)	(0.296)
Run out of food	0.327**	0.187	0.0612	0.854**	0.370*	0.956**
	(0.153)	(0.199)	(0.196)	(0.403)	(0.216)	(0.412)
Constant	3.924***		0.198		1.296**	
	(0.316)		(0.576)		(0.576)	
Observations	2216	1804	2206	1794	2210	1798
Individual, Call FEs	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic		47.62		47.87		47.67

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 B14: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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