Mobile Internet and Mental Health *

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Abstract

The past decade has seen a significant worsening of mental health in the U.S., which coincides with the rapid expansion of mobile internet. Combining 3G coverage data from 2007 to 2020 with the Behavioral Risk Factor Surveillance System data, we find that mental health deteriorates following the arrival of 3G internet: a 10-percentage-point increase in 3G coverage raises the number of poor mental health days by 0.02 days per month, corresponding to a 0.6% increase. The effects are larger among younger individuals and women. Regarding mechanisms, we provide evidence that these effects are consistent with increased social media use, reduced offline socializing, and lower physical activity.

Keywords: Internet access, mobile internet, mental health, social media

JEL Classification: I12, I18

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1 Introduction

Mental health problems have become a growing concern. According to the 2024 National Survey on Drug Use and Health (NSDUH), 23.4% of U.S. adults experienced any mental illness (AMI) in the past year, up from 17.7% in 2008—a 32% increase over 16 years. During the same period, the rate of serious mental illness (SMI) among adults rose from 3.7% to 5.6% (SAMHSA, 2025).[1] Mental health problems carry large costs for society. Estimates suggest that the societal burden of mental illness in the U.S. is on the order of $200 billion to $300 billion annually.[2] At the individual level, mental health problems can impair decision-making, reduce educational and labor market outcomes, and coexist with physical health conditions.[3]

Over the past decade, mobile internet technology has advanced rapidly, making internet access easier and more widespread. This technological shift has introduced a double-edged dynamic for mental health (Castellacci and Tveito, 2018). When used appropriately, mobile internet can enhance connectivity, improve access to resources, and offer opportunities for learning and self-expression. However, when misused or overused, it can harm mental health by promoting social isolation, increasing anxiety and depression, and reducing face-to-face interactions (Twenge et al., 2018).

In this paper, we study whether and how the expansion of mobile internet has affected mental health in the U.S. We focus on the rollout of third-generation (3G) networks, which substantially increased mobile data speeds and capacity, making web browsing and social media use on phones widely feasible. Studying this relationship presents several challenges. First, it requires detailed data on 3G internet access over time. To address this, we use 3G coverage maps from 2007 to 2020 provided by Collins Bartholomew's

[1]The 2024 NSDUH estimates rates of any mental illness (AMI) and serious mental illness (SMI) among adults aged 18 or older. AMI is defined as any mental, behavioral, or emotional disorder that meets DSM-IV criteria (excluding developmental disorders and substance use disorders). SMI refers to AMI cases that significantly interfere with one or more major life activities. Source: `https://www.samhsa.gov/data/data-we-collect/nsduh-national-survey-drug-use-and-health/national-releases/2024`. Accessed on February 10, 2026.

[2]The lower bound comes from Kessler et al. (2008), who estimate that serious mental illness reduces earnings by $193.2 billion annually (based on early-2000s data). More recent estimates range from $282 billion using a macroeconomic framework (Abramson et al., 2024) to $326 billion for major depressive disorder alone based on cost-accounting approaches (Greenberg et al., 2021).

[3]For example, Kessler et al. (2008) show that mental disorders reduce individual earnings in the U.S.; Currie and Stabile (2006) show that childhood mental health problems impair educational attainment and later labor market outcomes; and Scott et al. (2009) show that mental and physical health conditions frequently co-occur.

Mobile Coverage Explorer, which offers mobile network data at a 1×1-kilometer grid-cell resolution. The variation in 3G coverage across time and locations in the U.S. allows us to employ a two-way fixed effects model to estimate the effect of mobile internet on mental health. Second, 3G internet expansion may not be exogenous, raising concerns about endogeneity. We address this concern in two ways. We first implement an event study design that focuses on areas experiencing sharp increases in 3G coverage and find no evidence of differential pre-trends in mental health outcomes between areas with and without large expansions. We then implement a well-established instrumental variable (IV) strategy, using predetermined lightning climatology to instrument 3G coverage rate. This approach exploits the fact that higher lightning risk increases expected infrastructure damage and maintenance costs, thereby slowing the pace of 3G deployment. The IV estimates are qualitatively similar to our baseline results. Third, it is challenging to uncover the mechanisms behind any observed effect because no single dataset captures all relevant aspects of behavior. Mobile internet may influence mental health through multiple channels, such as changes in social media use, physical activity, and information access. To investigate these mechanisms, we combine multiple datasets that provide complementary information on internet usage patterns, time allocation between online and offline activities, and health-related search behavior. This approach allows us to explore how mobile internet changes behavior and, in turn, impacts mental health.

Our results show that 3G internet has a negative impact on mental health in the U.S.: a 10-percentage-point increase in 3G coverage in a region leads to an additional 0.02 days of poor mental health in the past 30 days, corresponding to a 0.6% increase relative to the 2007 baseline mean. Therefore, moving from no 3G coverage to full coverage would increase the number of days of poor mental health by approximately 0.22 days per month on average. We further explore the mechanisms through which 3G internet may affect mental health. First, we find that 3G expansion increases mobile internet subscriptions, reflecting greater internet accessibility and usage. Second, 3G coverage reduces physical activity and participation in face-to-face interactions. Third, we find that 3G expansion leads to greater social media use. These forms of online engagement have been associated in prior research with higher risks of anxiety and depression (e.g., Twenge and Campbell, 2018; Twenge et al., 2018; Braghieri et al., 2022). Finally, we find no effect of 3G expansion on the use of the internet to seek health-related information, suggesting that informational channels are unlikely to be a primary mechanism driving our results.

We contribute to the literature on the socioeconomic impacts of mobile internet expansion by providing causal evidence on its effects on adult mental health in the U.S. Prior work has largely emphasized political economy outcomes (Manacorda and Tesei, 2020; Guriev et al., 2021; Melnikov, 2022) and broader socioeconomic effects such as labor market dynamics (Chiplunkar and Goldberg, 2022; Bahia et al., 2023), economic well-being (Bahia et al., 2024), and migration (Adema et al., 2022). A growing literature examines the health implications of mobile internet, including evidence that mobile internet expansion in Africa reduces infant mortality, plausibly through improved health knowledge and behaviors (Flückiger and Ludwig, 2023; Mensah et al., 2026), and evidence from the U.S. that smartphone diffusion increases accidental injuries among young children, consistent with caregiver distraction (Palsson, 2017). However, evidence on the mental health effects of mobile internet for adults remains scarce, especially in high-income settings. We fill this gap by studying a mature market in which the marginal use of connectivity is more plausibly driven by social- and attention-based activities rather than by first-order improvements in access to information and services. Leveraging within-U.S. variation in the timing and intensity of mobile internet expansion, we estimate its impact on adult mental health. Our estimates broaden the evidence on the health effects of mobile internet beyond infant health in low-income contexts and speak directly to current U.S. policy debates on mobile internet access and well-being.

We also contribute to the literature on the determinants of mental health by (i) identifying mobile internet access as a technologically driven determinant of mental health and (ii) providing evidence on behavioral mechanisms by combining multiple complementary data sources. Existing work has examined determinants such as macroeconomic conditions (Golberstein et al., 2019), poverty (Ridley et al., 2020), unconditional cash transfers (Haushofer and Shapiro, 2016), and prenatal exposure to adverse shocks (Persson and Rossin-Slater, 2018). More closely related, recent work considers the effects of broadband internet. Evidence from Germany, Italy, Spain, and the U.S. suggests that expanded broad internet access can worsen mental health outcomes, particularly among younger individuals and women, using both self-reported measures and administrative data (e.g., Golin, 2022; Donati et al., 2025; Arenas-Arroyo et al., 2025; Churchill and

Johnson, 2026). Related work on social media reaches similar conclusions: exploiting quasi-experimental variation, Braghieri et al. (2022) show that Facebook access deteriorates college students' mental health, with evidence pointing to social comparisons as a mechanism, and Guo (2023) find that the introduction of visual social media is associated with worsening mental health outcomes among adolescent girls. While these studies provide important causal evidence, they often rely on a single survey or administrative source and offer limited direct evidence on the behavioral channels through which expanded connectivity affects mental health. We complement this work by focusing on mobile internet, using a nationally representative U.S. sample of adults, documenting heterogeneity by age and gender, and linking mental health outcomes to rich measures of mechanisms, including internet subscription, time use, social media adoption, and mental health–related search behavior, to more directly assess which behavioral channels are consistent with the estimated mental health effects.

The rest of the paper is organized as follows. Section 2 describes the conceptual framework. Section 3 introduces the data and variables. Section 4 explains the identification strategy. Section 5 shows the results. Section 6 explores the mechanisms. Section 7 concludes.

2 Conceptual Framework

Conceptually, access to the internet can have both positive and negative impacts on mental health (Castellacci and Tveito, 2018), which can be amplified by the accessibility and immediacy of mobile internet.

On the positive side, the internet can improve mental well-being through several channels. First, it expands access to valuable digital services and applications, which generate substantial consumer benefits (Brynjolfsson et al., 2019). Second, it facilitates the maintenance and expansion of social networks, providing platforms for communication, emotional support, and the development of social capital, which is a key determinant of happiness and life satisfaction (Ellison et al., 2007; Oh et al., 2014). Online interactions can complement face-to-face communication among family and friends and may even create opportunities for new virtual connections. Third, mobile internet improves access to health information and mental health services, enabling individuals to seek support, information, and treatment more easily, while digital tools may help reduce barriers to care, including stigma (Naslund et al., 2016; Torous et al., 2020).

However, internet use can also have negative consequences. It may increase material and social aspirations, thereby reducing life satisfaction as users are exposed to others' curated achievements and positive experiences, potentially leading to envy and dissatisfaction (Verduyn et al., 2020). In addition, the internet can encourage addictive behaviors, such as gambling and excessive online gaming, which are associated with adverse social and health outcomes (Kuss and Griffiths, 2012). While some researchers argue that the internet helps maintain social relationships, evidence suggests that its benefits may be concentrated among extroverted individuals and those with strong existing social support, while potentially harming others by displacing time that could otherwise be spent on beneficial activities, such as in-person interactions, exercise, and sleep (Twenge and Campbell, 2018).

The conceptual ambiguity of the internet's effects is reflected in the empirical literature. Earlier studies find mixed associations between internet access and subjective well-being, with evidence of both benefits and diminishing returns (Kavetsos and Koutroumpis, 2011; Graham and Nikolova, 2013). More recent causal studies focusing directly on mental health outcomes tend to find adverse effects of expanded broadband access, particularly among younger users and women, using both self-reported measures and administrative diagnoses (Golin, 2022; Donati et al., 2025; Arenas-Arroyo et al., 2025; Churchill and Johnson, 2026). Related evidence on social media similarly points to potential mental health costs, with mechanisms such as social comparison playing an important role (Allcott et al., 2020; Braghieri et al., 2022). Taken together, this evidence supports the view that the relationship between internet access and mental health is theoretically ambiguous and likely depends on the type of technology, the intensity and purpose of use, and the affected population.

Importantly, mobile internet may amplify the effects of internet access on mental health. The expansion of 3G networks made mobile internet widely available, allowing individuals to access social media, entertainment, and information platforms throughout the day, without being tied to fixed locations. In the U.S., the sharp increase in 3G coverage between the late 2000s and early 2010s overlapped with the rapid diffusion of smartphones and mobile versions of major social media platforms, so that 3G availability effectively determined whether users could engage with social media while on the move. This constant connectivity may reinforce beneficial behaviors, such as seeking health information, but it also risks magnifying harmful patterns, including compulsive online engagement, reduced physical activity, and weakened offline social ties. Therefore, the rollout of 3G represents a critical technological shift that could significantly alter the balance of positive and negative impacts of internet access on mental health.

3 Data

Our empirical analysis examines the impact of 3G internet expansion on mental health. To do so, we combine several data sources, as described below.

Collins Bartholomew's Mobile Coverage Explorer (MCE): Our main explanatory variable, the 3G coverage rate, is constructed using data from Collins Bartholomew's Mobile Coverage Explorer (MCE). This dataset maps mobile network coverage reported by operators worldwide to the Global System for Mobile Communications Association (GSMA). It provides granular annual data on 2G, 3G, and 4G network coverage at the 1×1-kilometer grid cell level from 2007 to 2020. By definition, a grid cell covered by 4G is also considered covered by 3G.[4] Figure 1 illustrates the expansion of 3G networks in the U.S., mapping coverage in 2007, 2014, and 2020. In 2007, only a few locations had 3G service, whereas by 2020, most of the country was covered.

To merge the 3G internet data with other datasets, we compute population-weighted 3G coverage at the Metropolitan and Micropolitan Statistical Areas (MMSA), county, ZIP Code, and Designated Market Area (DMA) levels.[5] Specifically, we calculate a weighted average across all grid cells within each area, weighting 3G availability by population density.[6] The resulting population-weighted 3G coverage (our main independent variable) measures the share of the population with access to a 3G network in each MMSA, county,

[4] MCE data are unavailable for 2011 due to a transition in data management. We interpolate 2011 coverage by averaging 2010 and 2012 values, and show that results are robust to excluding 2011 from the sample.

[5] A DMA is a Nielsen-defined region whose population receives the same television and radio station offerings, and thus represents a specific local media market. We construct 3G coverage at the DMA level because Google Trends data—used in our mechanism analysis—are available only at this level. Source: `https://www.nielsen.com/dma-regions/`. Accessed April 15, 2024.

[6] Population density data are from NASA's Gridded Population of the World (GPW), which reports population density on a 1×1-kilometer grid. Source: `https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11`. Accessed April 15, 2024.

ZIP Code, and DMA.[7]

Behavioral Risk Factor Surveillance System Selected Metropolitan/Micropolitan Area Risk Trends (BRFSS SMART): Our measure of mental health comes from the BRFSS, a nationally representative health survey conducted by the Centers for Disease Control and Prevention (CDC). The survey was first fielded in 1984 across 15 states and was expanded to cover all 50 states and the District of Columbia by 1993. Each year, more than 400,000 adults (aged 18 or older) are interviewed by phone about their health-related behaviors, chronic health conditions, and preventive practices. To maintain representativeness, the CDC began including cell phone numbers in the sampling frame in 2010 and adopted an iterative proportional fitting method to compute sampling weights, replacing the earlier post-stratification method. To ensure comparability over time, we adjust the sampling weights following previous research (Simon et al., 2017; Carpenter and Sansone, 2021) and use the adjusted weights in our analysis.

The BRFSS enables localized analyses through the Selected Metropolitan/Micropolitan Area Risk Trends (SMART) files, which the CDC has published since 2002. The SMART data include respondents from MMSAs with at least 500 completed interviews in a given year. Not all MMSAs are included every year, as some fail to meet the sample size threshold for reliable substate estimates. For our main analysis, we use the SMART data covering 276 unique MMSAs across years. Figure 2 shows the geographic distribution of MMSAs in our sample, which are spread across the U.S., including the ten most populous metropolitan areas.[8]

Our main outcome of interest is the number of days with poor mental health during the past 30 days, derived from the following question: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" We also extract demographic variables, including age group, race, gender, and education level, from the SMART files. Our sample is restricted to respondents aged 18 to 64.

American Community Survey (ACS): We rely on the ACS 5-year estimates to

[7] Suppose geographic area c contains $|J_c|$ grid cells. The population-weighted 3G coverage rate is $3G_{c,t} = \frac{\sum_{j \in J_c} \text{Population}_{j,t} \times \mathbb{1}\{\text{Covered by 3G}\}_{j,t}}{\sum_{j \in J_c} \text{Population}_{j,t}}$.

[8] We choose the BRFSS SMART files over the main BRFSS dataset because, since 2013, the public version of the BRFSS has redacted respondents' county of residence. The SMART files allow identification at the MMSA level.

obtain local demographic and socioeconomic characteristics, as described in Section 4.[9] The ACS provides detailed local demographic information that allows us to control for local characteristics that could confound the relationship between 3G internet expansion and mental health outcomes. In addition, to explore potential mechanisms, we use ACS data on the share of households accessing the internet via mobile, cable, and satellite technologies.

We draw on additional data sources to explore the potential mechanisms through which 3G internet expansion may affect mental health:

MRI Consumer Survey: We use the MRI Consumer Survey, one of the largest consumer databases in the U.S., to measure internet and social media usage patterns. The survey collects responses from over 50,000 adults annually and has tracked media use since 2011. From this dataset, we extract information on the share of individuals who used any social networking websites or apps, as well as usage rates for specific platforms such as Facebook, YouTube, and Twitter. These data are available at the county level.

American Time Use Survey (ATUS): We use the ATUS to analyze changes in time allocation across activities. The ATUS is a nationally representative time diary survey conducted since 2003, with participants drawn from households that completed their eighth month in the Current Population Survey (CPS). One individual aged 15 or older is randomly selected from each household to report detailed information about their activities during the previous day. For our analysis, we focus on time spent on (1) sleeping, (2) socializing and attending events, (3) participating in sports, exercise, and recreation, and (4) making phone calls with family and friends.

Gallup U.S. Daily Poll: We also use data from the Gallup U.S. Daily Poll to measure changes in health behaviors and social and family well-being. These questions are consistently available only from 2014 to 2017. During this period, Gallup conducted repeated cross-sectional daily interviews of approximately 1,000 respondents, geocoded at the ZIP-code level. We focus on the following questions: "Approximately how many hours did you spend, socially, with friends or family yesterday?", "Your relationship with your spouse, partner, or closest friend is stronger than ever," "You always make time for regular trips or vacations with friends and family," and "You always feel good about your physical appearance." The last three items are reported on Likert scales and are recoded

[9] We use ACS 5-year estimates for 2005–2009 through 2018–2022, treating the middle year as corresponding to the year in other datasets, following Singleton (2019).

into binary indicators by assigning neutral responses to whichever of the two categories ("agree" vs. "disagree") is smaller, following Baseler et al. (2025).

Google Trends: To proxy for self-help behavior related to mental health, we obtain search frequency data from Google Trends. Google Trends provides information on the relative popularity of specific keywords across geographic areas and time. We focus on searches for mental health-related terms, including "mental health," "depression," "anxiety," and "counseling," over the period from 2007 to 2020. The Google Trends data are available at the DMA level.

Lastly, for our instrumental variable strategy that relies on the frequency of lightning strikes, we use the following dataset:

NASA's LIS/OTD Gridded Lightning Climatology Data Sets: We obtain data on lightning frequency from the LIS/OTD 0.5-Degree High Resolution Full Climatology, collected by NASA's Global Hydrology Resource Center (Cecil et al., 2017).[10] We calculate the average population-weighted frequency of lightning strikes at the MMSA level. Specifically, we weight each lightning strike by the population of its location and divide the sum of population-weighted strikes by the total area of the region. This yields the density of people potentially affected by lightning strikes per square kilometer in each MMSA.

4 Identification Strategy

In this section, we present our estimation strategies for studying the effect of 3G internet on mental health. Our main specification is a two-way fixed-effects (TWFE) regression that exploits continuous variation in MMSA-year 3G coverage. To address the concern that 3G rollout may be correlated with unobserved, time-varying MMSA shocks, we estimate an event study model that focuses on sharp 3G expansions and report robust staggered-adoption difference-in-differences (DiD) estimates that allow for heterogeneous treatment effects (de Chaisemartin and D'Haultfoeuille, 2022; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Finally, we implement an IV design used in prior work

[10]Two sensors collected lightning data: the Lightning Imaging Sensor (LIS) onboard the Tropical Rainfall Measuring Mission (TRMM) satellite and the Optical Transient Detector (OTD). The LIS, operating from 1997 to mid-2015, had a higher resolution but covered only between ±38 degrees latitude. Therefore, we use lightning data collected by the OTD, which operated between 1995 and 2000, as it provides full coverage of the U.S. The dataset reports the mean annual lightning frequency.

that instruments 3G expansion with lightning frequency (e.g., Manacorda and Tesei, 2020; Guriev et al., 2021).

4.1 Main Specification

Our main specification is a TWFE model:

$$Y_{i,m,t} = \alpha + \beta\, 3\mathrm{G}_{m,t} + X'_{i,m,t}\lambda + \varphi_m + \tau_t + \epsilon_{i,m,t} \tag{1}$$

where i, m, and t index individual, MMSA, and year, respectively. The outcome variable $Y_{i,m,t}$ measures respondent i's mental health in year t. The key explanatory variable, $3\mathrm{G}_{m,t}$, is the population-weighted 3G coverage rate in MMSA m in year t. The vector $X_{i,m,t}$ includes individual- and MMSA-level controls: respondent's age group, gender, race, and educational attainment; and MMSA population, unemployment rate, median age, median household income, and the shares of the population that are White, Black, Hispanic, male, and college-educated. MMSA fixed effects, φ_m, absorb time-invariant MMSA characteristics, while year fixed effects, τ_t, capture nationwide changes common to all MMSAs. We cluster standard errors at the MMSA level. The coefficient of interest, β, captures the effect of 3G expansion on mental health.

There is a concern that certain MMSA-level characteristics might be influenced by economic shocks related to 3G expansion. In practice, however, adding these controls sequentially leaves the estimated 3G effect largely unchanged (See results in Section 5), which mitigates concerns about bad controls. We therefore retain this full control set in the preferred specification to reduce omitted-variable bias.

4.2 Event Study

The identifying assumption underlying equation (1) is that the timing of 3G expansion is uncorrelated with unobserved, time-varying MMSA factors that also affect mental health. While this assumption cannot be tested directly, an event-study design allows us to assess pre-trends and to trace how mental health evolves around 3G expansions. Following Guriev et al. (2021), we focus on sharp increases in 3G coverage. Specifically, we define an event as the first year in which an MMSA experiences an increase in 3G coverage of more than 40 percentage points relative to the previous year. An advantage of sharp expansions is that they generate a discrete change in exposure, which helps distinguish immediate effects from subsequent adjustment when coverage does not continue to trend sharply. In the BRFSS SMART sample, 209 of the 276 MMSAs experience such an event during our study period.[11]

We estimate the following event-study specification:

$$Y_{i,m,t} = \alpha + \sum_{k=-4;k\neq-1}^{k=6} \beta_k D_{k(m,t)} + X'_{i,m,t}\lambda + \varphi_m + \tau_t + \epsilon_{i,m,t} \tag{2}$$

where $D_{k(m,t)}$ is a set of indicator variables that equal one if, for MMSA m in year t, the event is k years away. We omit $k = -1$ so that all coefficients are measured relative to the year before the event, and we choose four pre-periods and six post-periods based on the counts of observation years relative to the event reported in Appendix Table A.1. The coefficients β_k trace the dynamic path of mental health around the event; the pre-event coefficients ($k < -1$) provide a test for differential pre-trends, while the post-event coefficients ($k \geq 0$) capture the evolution of the effect after a sharp 3G expansion.

The event-study version of the TWFE model in equation (2) makes relatively strong assumptions regarding treatment-effect homogeneity. If these assumptions are violated, the estimator may place negative weights on treatment effects for certain groups and periods (e.g., de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). To verify that our results are robust to treatment-effect heterogeneity, we complement the TWFE event study with the alternative estimators proposed by de Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), and Sun and Abraham (2021), which remain valid under heterogeneous and dynamic treatment effects.

4.3 Instrumental Variable

To further address concerns about the endogeneity of 3G rollout, we implement a lightning-based IV strategy following prior work on mobile-network expansion (e.g., Manacorda and

[11] For the event-study analysis, we define an expansion event as the first year in which population-weighted 3G coverage in an MMSA increases by more than 40 percentage points. In theory, an annual increase of more than 50 percentage points cannot occur more than once within an MMSA, but 50-percentage-point increases are rare in our sample. We therefore focus on the 40-percentage-point threshold, which captures large, rapid expansions while retaining enough events. Results are robust when we define sharp expansions using 45-percentage-point thresholds.

Tesei, 2020; Guriev et al., 2021). The identifying idea is that persistently lightning-prone areas face higher expected equipment damage and maintenance costs because lightning-induced power disturbances can damage mobile-network infrastructure and accelerate equipment depreciation. This may slow the pace of 3G deployment (Andersen et al., 2012). We therefore use predetermined lightning exposure to predict differential 3G roll-out over time. Specifically, following Guriev et al. (2021), we use an indicator for MMSAs with above-median population-weighted lightning frequency per square kilometer, interacted with a linear time trend, as the instrument.

We estimate the following first-stage equation for MMSA m in year t:

$$3\mathrm{G}_{m,t} = \alpha + \gamma\, \mathbb{1}\{\text{High lightning}_m\} \times \text{Trend}_t + Z'_{m,t}\lambda + \varphi_m + \tau_t + \epsilon_{m,t}, \tag{3}$$

where $\mathbb{1}\{\text{High lightning}_m\}$ equals one if MMSA m's population-weighted lightning frequency per square kilometer is above the median across MMSAs, and Trend_t is a linear time trend. The vector $Z_{m,t}$ includes the MMSA-level controls from equation (1), as well as interactions between the linear time trend and geographic characteristics that may affect network deployment: the shares of uninhabited land and water area within the MMSA, log maximum elevation, and population density in 2000. In addition, following Guriev et al. (2021), we allow for differential trends by initial network presence by interacting the linear time trend with 3G coverage in 2007 and with an indicator for any 3G coverage in 2007.

5 Empirical Results

5.1 Main results

Table 2 reports estimates of how 3G expansion within an MMSA affects mental health, using our main specification (1). Column (1) includes only MMSA and year fixed effects; the coefficient on 3G coverage is 0.246 and statistically significant at the 5% level. Adding individual controls in column (2) leaves the estimate essentially unchanged, with a coefficient of 0.231. Column (3) further controls for MMSA-level characteristics and is our preferred specification; the coefficient is 0.220, remaining positive and significant at the 5% level. This implies that a 10 percentage point increase in 3G coverage leads to 0.02 additional days of poor mental health in the past 30 days, corresponding to a 0.6% increase relative to the 2007 baseline mean. Scaling linearly, moving from near-zero to near-universal 3G coverage increases poor-mental-health days by roughly 2.6 days per year on average in a given MMSA. Because 3G coverage measures availability rather than individual take-up, these estimates should be interpreted as intent-to-treat (ITT) effects for the average resident in an MMSA, combining effects operating through adoption and intensity of mobile internet use as well as spillovers to non-users.

The identifying assumption in this specification is that the timing of 3G internet expansion is uncorrelated with other unobserved factors that influence mental health. This assumption cannot be directly tested. We therefore use an event-study approach to assess pre-trends and to examine how mental health evolves around sharp 3G expansions.

5.2 Event Study

We next turn to the event-study design described in Section 4.2, which focuses on sharp 3G expansions and allows us to assess pre-trends and the dynamics of the effect around the event. Regression results are reported in Appendix Table A.2 and Figure 3. As shown in Figure 3, we do not observe pre-trends leading up to the event; instead, mental health deteriorates following the event, with the effect becoming more pronounced as time since the event increases. The absence of differential pre-trends supports the identifying assumption underlying our main specification, while the post-event dynamics indicate that the adverse effect of 3G expansion accumulates rather than dissipating over time.

Figure 3 also overlays the heterogeneity-robust estimators of de Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), and Sun and Abraham (2021) alongside the TWFE estimator. We observe a clear increase in poor mental health days after the event regardless of the estimator, supporting the robustness of our results to treatment-effect heterogeneity.

5.3 Instrumental Variable

Table 3 presents the IV results. Column (1) reports the first stage. The interaction between lightning intensity and the time trend is negative and statistically significant, indicating that MMSAs with greater lightning exposure experienced slower growth in 3G coverage over the sample period. Column (2) shows that instrumented 3G coverage has a positive and statistically significant effect on poor mental health days, confirming the main finding that average mental health deteriorates as 3G coverage expands. The IV and ordinary least squares (OLS) estimates are qualitatively similar, while the IV magnitude is larger, consistent with prior work using lightning-based instruments for mobile internet expansion (Guriev et al., 2021). It is possible that the mental-health effects of 3G expansion are larger in complier MMSAs—those in which 3G coverage responds to the lightning-based instrument—than in non-complier MMSAs where rollout is largely unaffected by lightning exposure (e.g., due to surge protection or equipment hardening). One potential explanation is that the ability to invest in power-surge protection and other network hardening is positively correlated with local economic development. More developed MMSAs may therefore be less exposed to lightning-related constraints and may also have characteristics that attenuate the adverse mental-health effects of 3G expansion.

5.4 Robustness Checks

In this section, we conduct a series of robustness checks to corroborate the main findings. The results remain robust and are detailed in the Appendix Tables.

Alternative measures of mental health conditions. We consider three alternative measures of mental health: an indicator of poor mental health days in the past month exceeding 14 days, an indicator of no poor mental health days in the past month, and whether the respondents were told to have depressive disorders. We adopt the CDC's standard of 14 days as the threshold for assessing frequent mental distress.[12] As reported in column (1) of Appendix Table A.3, people are more likely to experience frequent mental distress as 3G internet expands: a 10 percentage point increase in 3G coverage leads to a 0.06 percentage point increase in the likelihood of frequent mental distress, and the coefficient is significant at the 10% level. Likewise, people are less likely to report no mental issues in the past 30 days, as indicated in column (2). The dependent variable in column (3) is an indicator for depressive disorders, available from 2010 to 2020. Once again, we observe a negative impact of 3G internet expansion on mental health using this measure: a 10 percentage point increase in 3G coverage corresponds to a 0.4 percentage point rise in the probability of depressive disorders.

[12]"Adults were identified as having frequent mental distress if they reported having poor mental health for 14 or more days out of 30 days." Source: `https://www.cdc.gov/ncbddd/disabilityandhealth/easy-read-frequent-mental-distress.html`. Accessed on April 15, 2024.

Alternative measures of 3G coverage. In our main analysis, we use population-weighted 3G coverage and adjust it for significant decreases in coverage rates in 2010 resulting from the change in the mapping partner of the data source. In column (4), we use unweighted 3G coverage as the explanatory variable to examine whether weighting changes the results. The coefficient is still positive and significant, consistent with our main results reported in Table 2 that 3G internet worsens mental health.

Using balanced MMSA list. Figure 2 displays the location of the 276 MMSAs included in our main analysis. Since the BRFSS SMART only covers MMSAs with at least 500 completed interviews in a given year, the list of MMSAs can vary each year, which could bias our results if the MMSAs sampled each year were not comparable. Therefore, we restrict our sample to MMSAs that appear consistently in the BRFSS SMART from 2007 to 2020 to re-estimate our main model. This yields a balanced set of 85 MMSAs, accounting for approximately 74% of individual observations in the main estimation sample. Column (5) shows that our results are robust to using this balanced MMSA list.

Excluding influential years. We assess whether specific years drive our results. For instance, people's mental health tends to worsen during periods such as the Great Recession and the COVID-19 pandemic, which could potentially bias our estimates. To address this concern, we re-estimate our main specification while excluding observations from one year at a time. Appendix Table A.4 shows that our coefficient estimates remain stable when excluding a specific survey year from the main sample in each iteration.

Placebo test using 2G coverage. The availability of 3G may influence people's mental health in ways other than providing access to mobile broadband. To address these concerns, we investigate the impact of the expansion of 2G networks, which primarily enable voice and text-based communication and only limited, low-bandwidth data services. A notable difference between 2G and 3G networks is 3G's capacity for high-speed data transmission that supports social media, rich content consumption, and instant photo and video sharing, potentially evoking stronger emotional responses and therefore exerting a larger impact on mental health than text-based communication. If our main estimates were driven by general improvements in connectivity or other aspects of mobile network expansion rather than mobile internet access, we would anticipate similar effects from the expansion of 2G and 3G networks on mental health. Therefore, in column (1) of Appendix Table A.5, we use 2G coverage as the explanatory variable and find that the coefficient is not significant at conventional levels. In column (2), we show that the 3G effect estimates do not change materially after controlling for 2G availability. In sum, the adverse effect of 3G coverage on mental health appears to be primarily driven by mobile broadband access rather than by broader changes in mobile connectivity or telecommunications infrastructure.

Considering general health trends. We also examine whether 3G rollout coincides with changes in other health outcomes that could reflect broader health trends over the same period. The results are reported in Appendix Table A.6. In unadjusted inference, only the number of days with poor physical health in the past 30 days and the probability of having heart disease are statistically significant at the 10% level. A 10 percentage point increase in 3G coverage is associated with roughly 0.015 additional days of poor physical health per month and a 0.03 percentage point increase in the probability of having heart disease; these magnitudes are economically small. Because Appendix Table A.6 reports multiple outcomes, we control the false discovery rate (FDR) and compute sharpened two-stage q-values following Benjamini et al. (2006), as described in Anderson (2008). After this adjustment, none of the outcomes remain statistically significant at conventional levels: the smallest q-value is 0.386 (for poor physical health days and heart disease).

5.5 Heterogeneous Analysis

We explore potential heterogeneity in the effect of 3G internet on mental health across age and gender. The results are reported in Table 4.

First, we examine heterogeneity across age groups in column (1), with respondents aged 18–24 as the reference group. We find that the adverse impact of 3G internet on mental health is largest among the youngest respondents and broadly diminishes with age. For the youngest group (ages 18–24), a 10 percentage point increase in 3G coverage is associated with about 0.074 additional poor-mental-health days per month, which corresponds to roughly a 2.1% increase relative to the 2007 baseline mean. In contrast, for individuals aged 35 and older, the estimated impact is close to zero and economically negligible.

Second, we examine heterogeneity by gender in column (2). We find that 3G coverage significantly worsens mental health among female respondents: a 10 percentage point increase in 3G coverage increases poor-mental-health days for women by about 0.033 days per month, or approximately 0.9% relative to the 2007 baseline mean. The corresponding estimate for men is substantially smaller in magnitude. This finding aligns with prior studies such as Donati et al. (2025) and Golin (2022), which also document more adverse mental-health effects of broadband internet for women.

The stronger effects among younger individuals and women could arise because these groups use mobile internet more intensively or because they respond more strongly to a given level of use. We cannot directly distinguish the two channels, since no single dataset records individual mobile internet use and mental health for the same respondents. Existing evidence, however, is consistent with both. First, younger individuals and women spend more time on smartphones and social media and are more likely to use them, with women especially concentrated on the image- and video-based platforms most associated with poor mental health.[13] Second, adolescence and young adulthood are developmentally sensitive periods during which social media use is most strongly linked to poor mental health (Office of the U.S. Surgeon General, 2023), while women, especially younger women, are more exposed to severe forms of online harassment and to cyberbullying.[14]

6 Mechanisms

In this section, we explore the potential mechanisms through which 3G internet may affect mental health. We argue that the expansion of 3G internet facilitates easier access to the internet and may therefore change how individuals allocate their time between online and offline activities. It may also affect the types of activities they engage in online. For example, 3G internet increases the ease with which individuals can participate in social networks. Notably, a large majority of active social media users access these platforms

[13] Younger cohorts are consistently more dependent on smartphones than older cohorts (`https://www.pewresearch.org/internet/fact-sheet/mobile/`, accessed October 16, 2023). Women spend more time on social media than men (roughly 142 versus 124 minutes per day), have higher participation rates (78% versus 66%), and account for the majority of users on platforms such as Instagram, Snapchat, and TikTok (`https://datareportal.com/reports/digital-2024-deep-dive-the-time-we-spend-on-social-media`; `https://www.ofcom.org.uk/media-use-and-attitudes/online-habits/digital-differences-between-men-and-women-revealed`; `https://www.brandwatch.com/blog/men-vs-women-active-social-media/`, accessed June 11, 2026).

[14] Sources: `https://www.pewresearch.org/internet/2021/01/13/the-state-of-online-harassment/` and `https://www.pewresearch.org/internet/2022/12/15/teens-and-cyberbullying-2022/`. Accessed June 11, 2026.

via mobile internet, even when fixed internet connections are available.[15]

To empirically examine the effect of 3G internet on various aspects of internet use, we compile data as described in Section 3. When the unit of observation is the individual, we use the specification in equation (1). When the unit of observation is at the regional level (MMSA, county, or DMA), we employ the following TWFE specification:

$$Y_{c,t} = \alpha + \beta 3\mathrm{G}_{c,t} + X'_{c,t}\lambda + \varphi_c + \tau_t + \epsilon_{c,t} \tag{4}$$

where c and t denote the region and year, respectively. The variables $3\mathrm{G}_{c,t}$, $X_{c,t}$, φ_c, τ_t, and $\epsilon_{c,t}$ are defined analogously to those in the main specification.

6.1 Internet Subscriptions

As a first step, we examine whether the expansion of 3G networks increased internet connectivity. We use MMSA-level ACS data from 2017 to 2020 for this analysis.[16] We use the shares of households with broadband subscriptions, mobile internet, and overall internet access as outcomes. The results are reported in Table 5. We find that a 10 percentage point increase in 3G coverage raises the share of households with mobile internet by 0.44 percentage points. Relative to the sample mean, this corresponds to a 0.99% increase. Equivalently, moving from zero to full 3G coverage would increase mobile internet take-up by about 4.4 percentage points. Because these ACS measures are only available for 2017–2020, when 3G rollout was already relatively mature, this estimate likely captures the effect of expansion at a later margin and may understate the effect of earlier 3G rollout. The point estimate for overall internet access is also positive and statistically significant, though smaller than the effect on mobile internet, indicating

[15] In 2017, out of 3.196 billion active social media users, 2.958 billion, or 93%, accessed social media via mobile devices (source: `https://wearesocial.com/uk/blog/2018/01/global-digital-report-2018/`, accessed on July 19, 2020). In 2014, this share was slightly lower, but still constituted a significant 81% (source: `https://wearesocial.com/sg/special-reports/global-social-media-users-pass-2-billion`, accessed on July 19, 2020). According to YouTube, more than 70% of YouTube watch time comes from mobile devices (source: `https://www.youtube.com/intl/en-GB/about/press/`, accessed on July 19, 2020). Twitter reports that as early as 2012, two-thirds of its users were mobile, and by 2015, the proportion of mobile users had reached 80% (source: `https://www.statista.com/chart/1520/number-of-monthly-active-twitter-users/`, accessed on July 19, 2020). In contrast, the growth of mobile internet use outside of social media was much slower, with the average share of mobile traffic being only 16% in 2013 and 50% in 2017 (source: `https://www.broadbandsearch.net/blog/mobile-desktop-internet-usage-statistics`, accessed on July 19, 2020).

[16] Information on internet connection is available only from 2017 to 2020 in the ACS 5-year estimates data.

that 3G expansion raises connectivity primarily at the mobile margin. These findings are consistent with Guriev et al. (2021), who also show that 3G internet improves internet connectivity in a global sample.

6.2 Time Allocation and Social Well-being

We next examine whether it alters how people allocate their time. Using the 2007–2020 American Time Use Survey (ATUS), we study four activities that may be relevant for mental health: the average number of minutes spent each day on sleep, social events, sports, and calls with family and friends.[17] The results are reported in Table 6. A 10 percentage point increase in 3G coverage reduces time spent on sports by about 0.27 minutes per day, which corresponds to a 1.6% decline relative to the baseline mean of 16.8 minutes. This is equivalent to about 2 fewer minutes per week on average. The effects on social events, sleep, and calls with family and friends are also negative, but they are imprecisely estimated.

We then complement the ATUS analysis with Gallup U.S. Daily Poll measures of social engagement and social well-being. These results provide stronger evidence that 3G expansion may weaken offline social ties. In particular, Table 7 shows that a 10 percentage point increase in 3G coverage reduces reported time spent socializing with family or friends yesterday by 0.263 hours, or about 15.8 minutes, which is roughly a 4% decline relative to the baseline mean of 6.56 hours. This is equivalent to about 1.84 fewer hours per week. The same increase in coverage lowers the probability of reporting strong family or friend bonds by 0.35 percentage points and the probability of reporting regular trips with family or friends by 0.61 percentage points. Taken together, these findings suggest that mobile broadband expansion may reduce offline social engagement, exercise time and weaken family- and friend-oriented social ties.

6.3 Social Media

One drawback of the ATUS is that it does not cover time spent on social media, which has been shown to be a crucial factor negatively influencing mental health (Allcott et

[17] We are able to identify the MMSA of residence for around 80% of the ATUS sample. Sleep includes time spent both sleeping and lying awake. Social events cover socializing, communicating with others, and attending or hosting social gatherings. Sports includes only active participation, excluding spectating. Variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme values.

al., 2020; Braghieri et al., 2022). To complement our analysis on time allocation, we turn to social media usage information obtained from the MRI Consumer Survey. This survey provides data on the share of residents using social media at the county level. Specifically, we examine Facebook, YouTube, and Twitter, which are among the most widely used social media platforms in the U.S.[18] As reported in Table 8, a 10 percentage point increase in 3G coverage raises overall social media use by 0.16 percentage points, or about 0.30% of the baseline mean. The corresponding increases are 0.25 percentage points for Facebook and 0.17 percentage points for YouTube, equivalent to about 1.3% and 0.7% of their respective baseline means. By contrast, Twitter usage declines by 0.07 percentage points. This pattern may reflect differences in platform content: Facebook and YouTube rely more heavily on photo and video sharing, which may benefit more from mobile broadband access, whereas Twitter is more text-based. Overall, these findings suggest that 3G expansion modestly increases the extensive margin of social media usage. It is important to note, however, that our data capture only whether individuals use these platforms, not how intensively they use them. If 3G primarily affects time spent on social media rather than simple participation, these estimates may understate the true increase in exposure.

6.4 Search Behavior

As outlined in our conceptual framework, 3G internet can also have a positive impact on mental health through the information channel. Specifically, 3G internet reduces information friction and facilitates easier access to health-related information and professional help online. For example, Van Parys and Brown (2024) examine the context of broadband internet expansion in the U.S. and argue that such expansion improves health outcomes by providing better access to treatment information offered by Medicare. To test this hypothesis, we analyze Google Trends for terms such as "mental health," "anxiety," "depression," and "counseling" at the DMA level from 2007 to 2020, to see if better internet access improves self-help search behaviors. However, the analysis shown in Table 9 reveals no discernible pattern of effect, suggesting that the expansion of 3G internet does not notably increase engagement in mental health search behaviors.

[18] Source: `https://www.pewresearch.org/internet/fact-sheet/social-media/` . Accessed October 16, 2023.

While we cannot formally decompose the mediated share of the reduced-form effect, because the mechanism outcomes come from separate datasets and are measured in different units, benchmarking magnitudes against the main estimate suggests that the negative effects of 3G expansion on mental health may stem from reduced engagement in offline activities, such as socializing with family or friends and exercising, alongside increased social media usage. Despite the potential benefits of 3G internet, these adverse effects appear to outweigh the positive ones.

7 Conclusion

This paper studies the effect of mobile internet expansion on mental health in the U.S. Combining annual, geocoded 3G coverage data from 2007 to 2020 with weighted BRFSS microdata on U.S. adults, we exploit spatial and temporal variation in the rollout of 3G networks across MMSAs. We find that expanded 3G coverage worsens mental health: a 10-percentage-point increase in 3G coverage raises poor mental health days by about 0.02 days per month, or 0.6 percent relative to the 2007 baseline mean. This result remains robust across various specifications, accounting for potential confounding factors.

Younger adults and women experience larger adverse effects, consistent with the idea that mobile internet may have stronger consequences for groups more exposed to mobile and social-media use. Evidence from complementary datasets suggests that 3G expansion increased mobile internet subscriptions and social-media use while reducing offline socializing and physical activity. By contrast, we find little evidence that 3G expansion increased mental-health-related search behavior, suggesting that online health-information channels are unlikely to be the primary mechanism behind the main effect.

Our findings have important policy implications. Despite the conveniences offered by 3G internet, policymakers must consider its adverse effects on mental health. There is a critical need to promote balanced internet usage and encourage offline activities, such as physical and social engagement, which can mitigate the negative impacts of increased screen time. Policies that direct users toward credible online health resources may help realize potential informational benefits that do not appear to arise automatically from expanded mobile internet access. Ultimately, these insights should inform the development of comprehensive public health policies that address the complexities of modern digital environments and their impacts on society.

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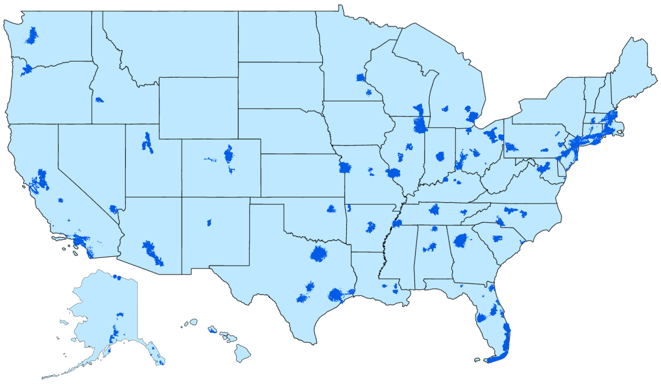
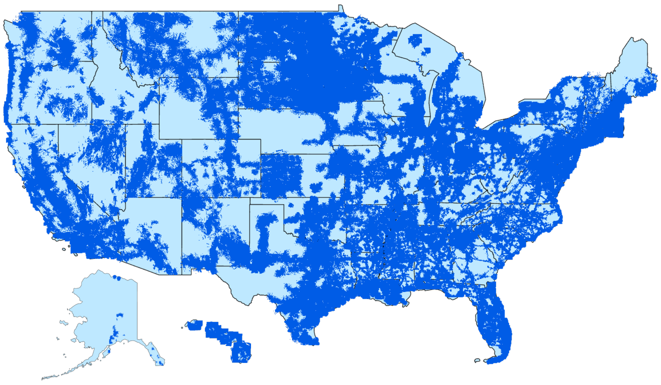
8 Figures and Tables



(a) 2007



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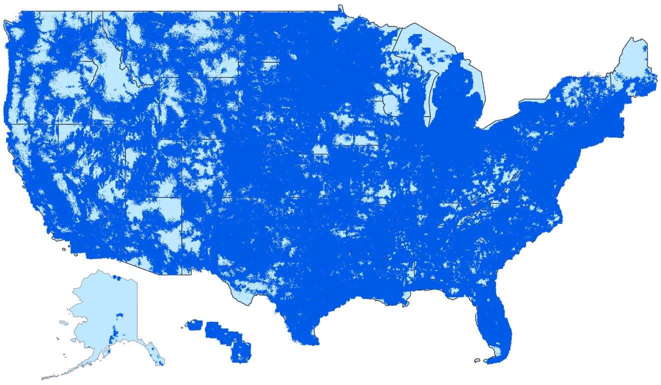
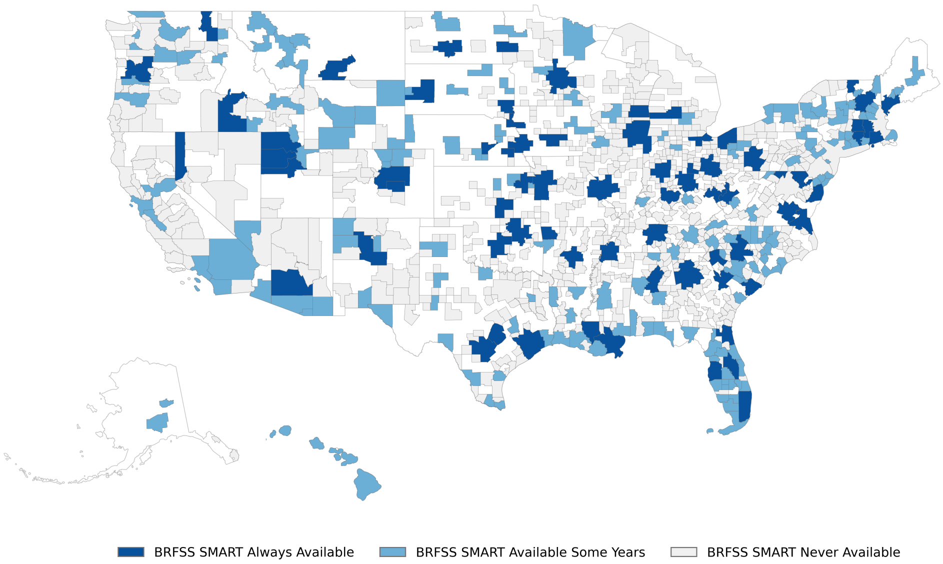


(c) 2020

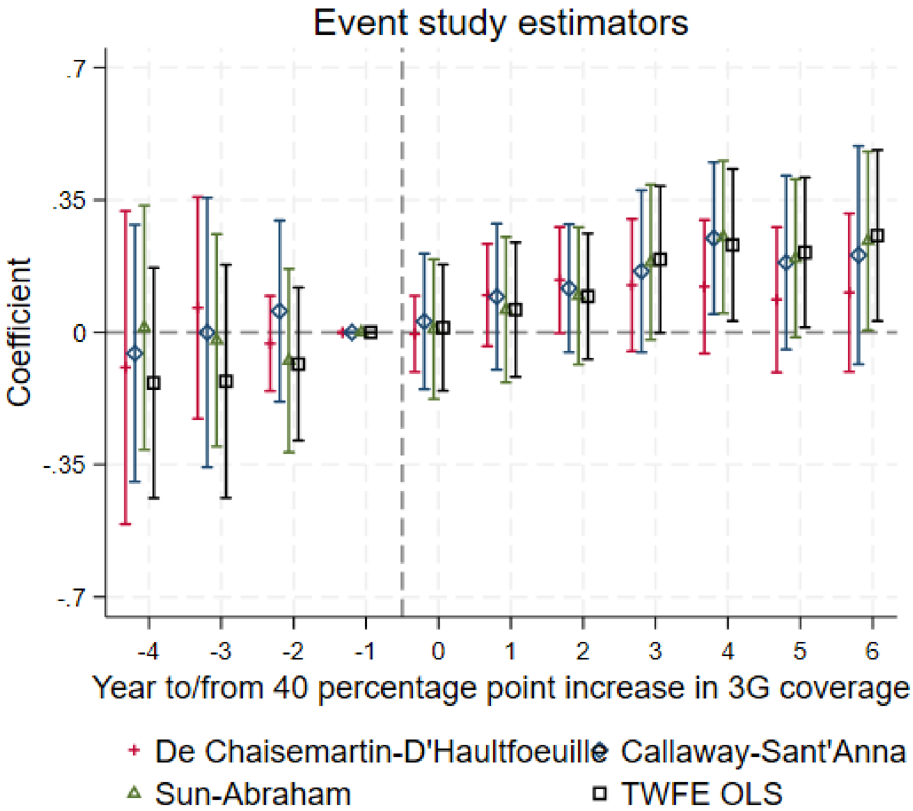
Notes: The three maps present 3G network coverage by grid cell in 2007, 2014, and 2020 in the U.S. Source: Collins Bartholomew's Mobile Coverage Explorer.

Figure 1: The Expansion of 3G Network Coverage between 2007 and 2020 in the U.S.



Notes: This figure displays the geographic distribution of metropolitan and micropolitan statistical areas (MMSAs) included in the 2007–2020 BRFSS SMART data. MMSA definitions are based on the Office of Management and Budget's 2013 delineation file.

Figure 2: Metropolitan/Micropolitan Areas (MMSAs) in the BRFSS SMART



Notes: This figure overlays the event-study plots constructed using several different estimators: a dynamic version of the TWFE model, equation (2), estimated using OLS; (de Chaisemartin and D'Haultfœuille, 2020); Sun and Abraham (2021); Callaway and Sant'Anna (2021). The outcome variable is the number of days with poor mental health in the past 30 days. The time variable is the survey wave, and the treatment group variable is defined by the event where 3G coverage increased by over 40 percentage points for the first time. The bars represent 95 percent confidence intervals. Standard errors are clustered at the MMSA level.

Figure 3: Event Study Analysis

Table 1: Summary Statistics

	Mean	Min	Max	N
Panel A: MMSA-level variables				
3G coverage	0.78	0.00	1.00	2,164
Median age	37.58	24.30	54.20	2,164
Unemployment rate	6.89	1.70	18.90	2,164
Population (in 1,000,000)	1.32	0.02	14.42	2,164
Median household income	58,969	30,581	138,370	2,164
% White	79.71	18.90	98.50	2,164
% Black	12.53	0.20	62.90	2,164
% Hispanic	12.55	0.80	95.60	2,164
% Male	48.65	45.50	57.70	2,164
% Bachelor's degree and above	30.78	7.50	58.30	2,164
% Internet subscription	81.11	40.60	93.80	1,094
% Broadband internet	80.63	39.60	93.10	1,094
% Mobile internet	60.51	23.40	87.60	1,094
% Mobile internet only	9.23	3.40	26.30	1,094
% Landline internet	67.47	24.60	83.90	1,094
% Satellite internet	6.04	2.00	16.70	1,094
Panel B: Individual variables from the BRFSS SMART				
# Poor mental health days (last 30 days)	3.98	0.00	30.00	2,240,922
Age 44 or younger	0.42	0.00	1.00	2,240,922
White	0.79	0.00	1.00	2,240,922
Black	0.11	0.00	1.00	2,240,922
Hispanic	0.09	0.00	1.00	2,240,922
Male	0.43	0.00	1.00	2,240,922
Bachelor's degree and above	0.43	0.00	1.00	2,240,922
Panel C: Individual variables from the ATUS				
Sleep (min)	526.54	210.00	930.00	93,809
Social event (min)	44.37	0.00	440.00	93,809
Sports (min)	16.37	0.00	283.00	93,809
Call w/ family & friends (min)	3.97	0.00	117.00	93,809
Panel D: Individual variables from the Gallup U.S. Daily Poll				
Hours spent socializing with family or friends yesterday	6.49	0.00	24.00	52,024
Strong family or friend bonds	0.77	0.00	1.00	682,480
Regular trips with family or friends	0.53	0.00	1.00	689,831
Feels good about physical appearance	0.59	0.00	1.00	530,520
Panel E: Social media usage variables from the MRI				
% Social media user	68.22	30.22	91.79	28,114
% Facebook user	44.26	4.36	79.47	34,360
% YouTube user	36.51	3.29	71.62	34,360
% Twitter user	7.59	0.00	31.82	31,233
Panel F: Google Trends index				
Mental health	37.45	0.00	100.00	35,112
Anxiety	45.43	0.00	100.00	35,280
Depression	47.25	0.00	100.00	35,280
Counseling	41.93	0.00	100.00	35,112

Notes: This table reports the summary statistics of the sample. Panel A shows MMSA-level variables, including 3G coverage rate, median age, unemployment rate, population, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree; variables related to internet subscriptions, available from 2017 to 2020, are restricted to MMSAs that are also included in the BRFSS SMART. Panel B shows individual-level variables from the BRFSS SMART, including the number of days with poor mental health in the past 30 days, indicators for age 44 or younger, race, gender, and holding a bachelor's degree or above. The mean of individual variables is weighted using adjusted weights. Panel C shows individual-level variables from the ATUS, including minutes of sleeping, attending social events, participating in sports, and making phone calls with family and friends. Panel D shows individual-level variables from the Gallup U.S. Daily Poll, available from 2014 to 2017, including hours spent socializing with family or friends yesterday and indicators for reporting strong family or friend bonds, regular trips with family or friends, and feeling good about one's physical appearance. Panel E shows county-level variables related to social media usage, including the share of the population that uses social media, Facebook, YouTube, and Twitter. Panel F shows the Google Trends index for keywords including "mental health," "anxiety," "depression," and "counseling."

Table 2: The Effects of 3G Internet on Mental Health

	(1) Poor mental health days	(2) Poor mental health days	(3) Poor mental health days
3G coverage	0.246**	0.231**	0.220**
	(0.098)	(0.097)	(0.093)
Baseline mean	3.545	3.545	3.545
Individual controls	No	Yes	Yes
MMSA controls	No	No	Yes
MMSA fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	2,240,922	2,240,922	2,240,922
Adjusted R^2	0.005	0.024	0.024

Notes: This table presents the results of estimating specification (1). The unit of observation is an individual. The dependent variable is the number of days with poor mental health in the past 30 days. The explanatory variable is 3G coverage at the MMSA level in a given year. Individual controls include age group, gender, race, and educational level; MMSA controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. The sample covers the years 2007 to 2020. Standard errors are reported in parentheses, clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 3: Lightning Strikes, 3G Coverage, and Mental Health

	(1) 3G coverage	(2) Poor mental health days
$\mathbb{1}\{\text{High lightning}_m\} \times t$	-0.011**	
	(0.005)	
3G coverage		0.679***
		(0.198)
Individual controls	Yes	Yes
MMSA controls	Yes	Yes
MMSA fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2,240,922	2,240,922
Adjusted R^2	0.740	0.024

Notes: This table presents the instrumental-variable results. The excluded instrument is an indicator for MMSAs with above-median population-weighted mean annual lightning frequency per square kilometer interacted with a linear time trend. The lightning measure is predetermined and constructed from NASA LIS/OTD lightning climatology. Column (1) reports the first stage, where the dependent variable is population-weighted 3G coverage at the MMSA-year level. Column (2) reports the second stage, where the dependent variable is the number of poor mental health days in the past 30 days. The unit of observation is an individual; MMSA-year treatment and instrument values are assigned to individuals based on their MMSA and survey year. Individual controls include age group, gender, race, and educational level; MMSA controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. Both stages also include interactions between the linear time trend and the shares of uninhabited land and water area, log maximum elevation, population density in 2000, 3G coverage in 2007, and an indicator for any 3G coverage in 2007. The sample covers the years 2007 to 2020. Standard errors are clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 4: Heterogeneity Analysis

	(1) Age	(2) Gender
3G coverage	0.735***	0.326***
	(0.202)	(0.095)
3G coverage		
× Age 25 to 34	-0.314**	
	(0.142)	
× Age 35 to 44	-0.667***	
	(0.194)	
× Age 45 to 54	-0.623***	
	(0.212)	
× Age 55 to 64	-0.830***	
	(0.187)	
× Male		-0.214***
		(0.077)
Individual controls	Yes	Yes
MMSA controls	Yes	Yes
MMSA fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2,240,922	2,240,922
Adjusted R^2	0.024	0.024

Notes: This table presents the results of heterogeneity analysis. The dimension of heterogeneity on which the analysis is conducted is listed at the top of the column. The unit of observation is an individual. The dependent variable is the number of days with poor mental health in the past 30 days. The explanatory variables are 3G coverage at the MMSA level in a given year and its interaction with the heterogeneity variables. In the first column, the age group 18 to 24 is the omitted group. In the second column, females are the omitted group. Individual controls include age group, gender, race, and educational level; MMSA controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. The sample covers the years 2007 to 2020. Standard errors are reported in parentheses, clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 5: Discussion on Mechanisms: Internet Subscriptions

	(1) Internet	(2) Broadband internet	(3) Mobile internet	(4) Mobile internet only	(5) Landline internet	(6) Satellite internet
3G coverage	0.017**	0.018*	0.044*	-0.002	0.022	-0.013
	(0.008)	(0.010)	(0.022)	(0.014)	(0.022)	(0.010)
Baseline mean	0.739	0.730	0.444	0.089	0.587	0.068
MMSA controls	Yes	Yes	Yes	Yes	Yes	Yes
MMSA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,094	1,094	1,094	1,094	1,094	1,094
Adjusted R^2	0.978	0.978	0.982	0.919	0.984	0.950

Notes: This table presents the results of estimating specification (4). The unit of observation is an MMSA. The dependent variable is listed at the top of each column. The explanatory variable is 3G coverage at the MMSA level in a given year. MMSA controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. The sample covers the years 2017 to 2020. Standard errors are reported in parentheses, clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 6: Discussion on Mechanisms: Time Allocation

	(1) Sleep	(2) Social event	(3) Sports	(4) Call w/ family & friends
3G coverage	-1.529	-1.026	-2.722**	-0.078
	(3.916)	(2.395)	(1.366)	(0.467)
Baseline mean	504.705	41.301	16.845	3.421
Individual controls	Yes	Yes	Yes	Yes
MMSA controls	Yes	Yes	Yes	Yes
MMSA fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	93,809	93,809	93,809	93,809
Adjusted R^2	0.039	0.008	0.021	0.014

Notes: This table presents the results of estimating specification (1) using outcomes from the ATUS. The unit of observation is an individual. The dependent variable is listed at the top of each column. The explanatory variable is 3G coverage at the MMSA level in a given year. Individual controls include age, gender, race, and educational level obtained from the ATUS; MMSA controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. The sample covers the years 2007 to 2020. Standard errors are reported in parentheses, clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 7: Discussion on Mechanisms: Social Well-Being

	(1) Hours Spent Socializing with Family or Friends Yesterday	(2) Strong Family or Friend Bonds	(3) Regular Trips with Family or Friends	(4) Feels Good about Physical Appearance
3G coverage	-2.632*	-0.035*	-0.061***	0.040
	(1.350)	(0.019)	(0.022)	(0.033)
Baseline mean	6.555	0.777	0.526	0.590
Individual controls	Yes	Yes	Yes	Yes
ZIP-code fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	20,671	350,188	352,310	263,852
Adjusted R^2	0.151	0.076	0.077	0.054

Notes: This table presents the results of estimating specification (1) using outcomes from the Gallup U.S. Daily Poll. The dependent variable is listed at the top of each column. The main explanatory variable is ZIP-code-level 3G coverage in a given year. The sample is restricted to years in which these Gallup questions are consistently available (2014–2017). Individual controls include gender, race, marital status, education, employment status, and income level obtained from the Gallup U.S. Daily Poll. Columns (2)–(4) are based on Likert-scale responses (1–5) that are converted into binary indicators. Standard errors are reported in parentheses and clustered at the state level. * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Table 8: Discussion on Mechanisms: Social Media Usage

	(1) Social media	(2) Facebook	(3) YouTube	(4) Twitter
3G coverage	0.016***	0.025***	0.017***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Baseline mean	0.533	0.199	0.239	0.042
County controls	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	28,089	34,325	34,325	31,203
Adjusted R^2	0.896	0.941	0.909	0.817

Notes: This table presents the results of estimating specification (4). The unit of observation is a county. The dependent variable is listed at the top of each column. The explanatory variable is 3G coverage at the county level in a given year. County controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. The years covered by the sample vary. Standard errors are reported in parentheses, clustered at the county level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 9: Discussion on Mechanisms: Search Behavior

	(1) Mental health	(2) Anxiety	(3) Depression	(4) Counseling
3G coverage	-2.755	-2.041	-0.608	-1.890
	(2.744)	(2.912)	(2.296)	(2.771)
Baseline mean	22.973	13.300	36.246	29.005
DMA fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	35,112	35,280	35,280	35,112
Adjusted R^2	0.663	0.780	0.669	0.696

Notes: This table presents the results of estimating specification (4). The unit of observation is a DMA. The dependent variable is listed at the top of each column. The explanatory variable is 3G coverage, measured annually at the DMA level. The sample covers the years 2007 to 2020 at monthly frequency, and the regressions include DMA, year, and month fixed effects. Standard errors are reported in parentheses, clustered at the DMA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Appendices

A Figures and Tables

Table A.1: Counts of Observations Based on Years to/from the Event

Years to/from the Event	Count	Percent
-4	15,332	0.85
-3	14,710	0.81
-2	54,057	2.98
-1	105,507	5.82
0	1,010,177	55.71
1	102,858	5.67
2	114,496	6.31
3	112,625	6.21
4	104,087	5.74
5	93,859	5.18
6	85,652	4.72
Total	1,813,360	100.00

Notes: This table presents the counts of observations based on years to/from the event, defined as when 3G coverage increases by more than 40 percentage points compared to the previous year. The unit of observation is an individual.

Table A.2: Event Study: Two Way Fixed Effects Model

	(1) Poor mental health days
3G sharp increase$_{t-4}$	-0.134
	(0.155)
3G sharp increase$_{t-3}$	-0.129
	(0.157)
3G sharp increase$_{t-2}$	-0.084
	(0.103)
3G sharp increase$_{t}$	0.012
	(0.085)
3G sharp increase$_{t+1}$	0.060
	(0.091)
3G sharp increase$_{t+2}$	0.095
	(0.085)
3G sharp increase$_{t+3}$	0.193*
	(0.099)
3G sharp increase$_{t+4}$	0.231**
	(0.103)
3G sharp increase$_{t+5}$	0.211**
	(0.101)
3G sharp increase$_{t+6}$	0.256**
	(0.115)
Individual controls	Yes
MMSA controls	Yes
MMSA fixed effects	Yes
Year fixed effects	Yes
Observations	1,813,360
Adjusted R^2	0.023

Notes: This table presents the results of estimating specification (2). The unit of observation is an individual. The dependent variable is the number of days with poor mental health in the past 30 days. The event occurs when 3G coverage increases by more than 40 percentage points compared to the previous year. The reference year is the year before the event. Individual controls include age group, gender, race, and educational level; MMSA controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. The sample covers the years 2007 to 2020. Standard errors are reported in parentheses, clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table A.3: Robustness Check

	(1)	(2)	(3)	(4)	(5)
	Poor mental health days ≥ 14	Poor mental health days $= 0$	Depressive disorder	Poor mental health days	Poor mental health days
3G coverage	0.006*	-0.021***	0.041***		0.280**
	(0.003)	(0.007)	(0.013)		(0.114)
3G coverage (unweighted)				0.250**	
				(0.122)	
Baseline mean	0.104	0.628	0.168	3.545	3.545
Individual controls	Yes	Yes	Yes	Yes	Yes
MMSA controls	Yes	Yes	Yes	Yes	Yes
MMSA fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Sample	Baseline	Baseline	Baseline	Baseline	Balanced MMSAs
Observations	2,240,922	2,240,922	1,588,869	2,240,922	1,665,926
Adjusted R^2	0.019	0.035	0.035	0.024	0.026

Notes: This table presents the results of the robustness check for the main specification. The unit of observation is an individual. The dependent variable is shown at the top of each column. The explanatory variable is 3G coverage at the MMSA level in a given year. Individual controls include age group, gender, race, and educational level; MMSA controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. The sample covers the years 2007 to 2020 (except for column (3), which covers the years 2010 to 2020). Standard errors are reported in parentheses, clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table A.4: Exclusion of One Year from the Sample

	(1) 2007	(2) 2008	(3) 2009	(4) 2010	(5) 2011	(6) 2012	(7) 2013	(8) 2014	(9) 2015	(10) 2016	(11) 2017	(12) 2018	(13) 2019	(14) 2020
3G coverage	0.272**	0.300***	0.207**	0.198**	0.226**	0.209**	0.240**	0.205**	0.206**	0.218**	0.222**	0.209**	0.198**	0.210**
	(0.117)	(0.106)	(0.094)	(0.098)	(0.092)	(0.095)	(0.093)	(0.094)	(0.092)	(0.093)	(0.094)	(0.091)	(0.090)	(0.092)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MMSA controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MMSA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,062,255	2,072,802	2,070,364	2,068,875	2,033,294	2,044,002	2,074,283	2,088,880	2,097,216	2,086,886	2,097,832	2,102,965	2,114,505	2,117,827
Adjusted R^2	0.025	0.025	0.025	0.024	0.025	0.025	0.025	0.024	0.025	0.024	0.024	0.024	0.024	0.024

Notes: This table reports estimates from re-estimating the main specification while excluding one year at a time from the sample. The unit of observation is an individual, and the dependent variable is the number of days with poor mental health in the past 30 days. The omitted year is shown at the top of each column. The explanatory variable is 3G coverage at the MMSA level in a given year. Individual controls include age group, gender, race, and educational level; MMSA controls include population, unemployment rate, median age, median household income, and the shares of the population that are White, Black, Hispanic, male, and have at least a bachelor's degree. The sample covers the years 2007–2020. Standard errors are reported in parentheses and clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table A.5: The Effects of 2G and 3G Internet on Mental Health

	(1) Poor mental health days	(2) Poor mental health days
3G coverage		0.217**
		(0.095)
2G coverage	0.108	0.096
	(0.122)	(0.122)
Individual controls	Yes	Yes
MMSA controls	Yes	Yes
MMSA fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2,240,922	2,240,922
Adjusted R^2	0.024	0.024

Notes: The table presents the effect of 2G and 3G coverage on mental health. The unit of observation is an individual. The dependent variable is the number of days with poor mental health in the past 30 days. The explanatory variable varies across columns. Individual controls include age group, gender, race, and educational level; MMSA controls include population, unemployment rate, median age, median household income, and the share of the population that is White, Black, Hispanic, male, and has at least a bachelor's degree. The sample covers the years 2007 to 2020. Standard errors are reported in parentheses, clustered at the MMSA level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table A.6: The Effects of 3G Internet on Other Health Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Health care	Poor physical health days	Heart disease	Stroke	Cancer	Bronchitis
3G coverage	-0.003	0.147*	0.003*	-0.000	0.006	0.001
	(0.006)	(0.085)	(0.002)	(0.001)	(0.005)	(0.006)
	[1.000]	[0.386]	[0.386]	[1.000]	[0.627]	[1.000]
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
MMSA controls	Yes	Yes	Yes	Yes	Yes	Yes
MMSA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,230,822	2,234,156	2,257,679	2,265,417	1,756,047	1,565,695
Adjusted R^2	0.105	0.038	0.035	0.015	0.055	0.029

Notes: This table presents estimates of the effects of 3G internet on other health outcomes. The unit of observation is an individual. The dependent variable is shown at the top of each column. The explanatory variable is 3G coverage at the MMSA level in a given year. Individual controls include age group, gender, race, and educational level; MMSA controls include population, unemployment rate, median age, median household income, and the shares of the population that are White, Black, Hispanic, male, and have at least a bachelor's degree. The sample covers the years 2007–2020, except for column (5), which covers the years 2011–2020. Standard errors are reported in parentheses, clustered at the MMSA level. Sharpened (two-stage) q-values controlling the false discovery rate within the family of outcomes in this table are reported in square brackets beneath the standard errors, following Benjamini et al. (2006) and Anderson (2008).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.