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Abstract

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JEL Classification: I12, I31, L82, L86

Keywords: mental health, internet, ADSL, 3G

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Broadband Internet and Youth Mental Health*

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1 Introduction

As of 2017 about 11% of the world population suffered from some kind of mental disorder (Ritchie and Roser, 2018). Such disorders cause mortality and morbidity, and affect many aspects of life such as decision-making, educational and labor market outcomes, and criminal behavior (Currie and Stabile, 2006; Biasi et al., 2019; Shapiro, 2020; Anderson et al., 2015; Haushofer and Fehr, 2014).[1]

The incidence of mental disorders has sharply increased over the past decades, especially among younger people (Patel et al., 2016). Many commentators have ascribed this trend to the diffusion of internet and social media which, over the same time, has dramatically changed the way individuals spend their time and interact with each other (Castellacci and Tveito, 2018). Public concerns about the potentially detrimental effect of digital technologies on mental health are reinforced by information from industry insiders such as Frances Haugen, former Facebook employee, who, testifying in front of the US Congress stated that "[Facebook] is generating self-harm and self-hate, especially for vulnerable groups, like teenage girls".[2]

The potential effect of internet on (youth) mental health has also attracted the interest of academics from various fields, from medicine to psychology and, more recently, economics. Yet, empirical evidence in this regard is still limited and rather mixed with some studies documenting a significant negative effect (Allcott et al., 2021; Braghieri et al., 2021) and others finding no clear evidence in this direction (George et al., 2020; Odgers and Jensen, 2020). One of the main limitations of most previous work on this issue is its reliance on self-reported measures of mental well-being which are potentially problematic for at least two reasons. First, an individual's perception of her own mental health can be biased and inaccurate (Braghieri et al., 2021). Second, it may be directly influenced by the use of digital technologies, above and beyond the impact of the latter on actual health conditions (Podsakoff et al., 2003).[3]

This paper overcomes this problem using novel administrative data from Italy on the universe of young patients admitted to any Italian hospital between 2001 and 2013 who were diagnosed with a mental health disorder. Combining this information with data on access to broadband internet at the municipal level over the same period, we can study how the advent of the internet affected mental health outcomes, and how this effect varied by cohort (i.e., older vs. younger) and by type of disorder (i.e., depression, anxiety, substance abuse, eating, personality, and sleep

[1] Bloom et al. (2012) estimate the global cost of mental disorders in 2010 at USD 2.5 trillion. Mental health conditions are among the leading causes of Disability Adjusted Life Years (DALYs) globally and have the highest impact on individuals in early-to-mid-adulthood (Patel et al., 2016).

[2] "Protecting Kids Online: Testimony from a Facebook Whistleblower", US Senate, Subcommittee on Consumer Protection, Product Safety, and Data Security Hearing, October 5, 2021.

[3] For journalistic accounts on how digital platforms may directly affect self-perceived mental health see https://www.vox.com/the-goods/2021/9/30/22696338/pathologizing-adhd-autism-anxiety-internet-tiktok-twitter.

disorders).

Our empirical strategy exploits differences across Italian municipalities in the timing of the introduction of broadband technology (ADSL) due to the relative position in the pre-existing voice telecommunications infrastructure. Specifically, since ADSL-based internet services could only be offered in municipalities connected to high-order telecommunication exchanges (Urban Group Stage, UGS) via optic fiber, we use the distance between a given municipality and the closest UGS - a good proxy for the investment required to connect the municipality - as a source of variation for the availability of high-speed internet. Since the pre-existing infrastructure was not randomly distributed, our identification strategy - which follows Campante et al. (2017) - relies on interacting that distance with the time variation between the period before and after broadband became available. This strategy relies on the assumption that the correlation between the distance and unobserved municipal characteristics did not change at that point in time, other than through the introduction of high-speed internet. The continuous and time-variant nature of our instrument strengthens our identification by allowing us to control not only for time-invariant municipal characteristics but also for differential trends related to key demographics.

Using this approach, we document no significant impact of the introduction of broadband internet on the overall occurrence of mental disorders. However, when differentiating between age groups, we find that internet access has a positive and significant impact on the occurrence of mental disorders among younger individuals, i.e., those born between 1985 and 1995 and aged 6 to 16 years old in 2001 when internet started to spread in Italy. In particular, access to internet is associated with higher occurrence of cases of depression/anxiety, drug abuse, and personality disorder for all individuals in this cohort and, for females only, also of eating and sleep disorders.

From a conceptual standpoint access to internet can influence mental health in various ways, both positively and negatively (Castellacci and Tveito, 2018). On the negative side, internet use can crowd out activities that are beneficial to mental health, such as spending time with family and friends, exercising, or sleeping (Twenge, 2017). Also, certain online activities, such as the use of social media or gambling, can lead to addictive behavior (Allcott et al., 2021; WHO, 2018). On the positive side, the internet makes it easier for individuals experiencing mental disorders to access information about these pathologies, learn about potential treatments, and seek the help of health professionals. Such increased awareness could, on the one hand, lead to a higher number of diagnoses even if the underlying prevalence of the disorders remains unchanged. On the other hand, better information can allow patients to treat their disorders earlier on, preventing more severe symptoms, and reducing the need for hospitalization.

Our rich data allow us to explore whether the effect we document is driven by a mere increase in awareness or also by an actual change in the prevalence of mental disorders. In this regard, we find that access to internet is also associated with an increase in the probability of i) suicide attempts and episodes of self-harm, and ii) compulsory hospitalizations due to mental health conditions posing a threat to the patient or others. Unlike for milder disorders, finding an effect on such extreme outcomes can hardly be explained by better access to mental health information. We also find a similar effect on both planned and urgent hospitalizations. Again, this result is inconsistent with an explanation based only on increased awareness, and supports the view that the prevalence of mental disorders in the population actually increased.

Our results are robust to several specification checks such as focusing only on the primary diagnosis (out of the three possible diagnoses coded by doctors) or exploiting the number of years of broadband coverage rather than contemporaneous coverage. Moreover, while our main specification concentrates on the extensive margin in mental health disorders, we also find economically and statistically significant increases along the intensive margin for the youngest cohort when we look at the total number of cases instead. Last but not least, we also investigate the extent to which the effect of broadband internet on mental well-being may depend on how people access it. For example, smartphones may increase addictive behaviors more due to the devices' designs. To explore this alternative channel, we explicitly look at the role of mobile internet (3G). The results suggest that the specific type of internet connection/device does not matter, as we find similar increases in mental disorder occurrences among the youngest cohort when using municipal data on 3G coverage (following a related identification approach). Finally, we show that our findings are not driven only by urban areas but also apply to rural ones.

It is worth noting that our analysis focuses on a period when the use of social media was still limited.[4] As such, our findings highlight that the deteriorating impact of the internet on mental health may be driven not only by social media such as Facebook, Instagram or Twitter, as it precedes the advent of these platforms. Indeed, information campaigns regarding the risks posed by the internet to the health of children and teenagers - such as the European Union's "Action Plan for Safe Internet" - started well before social media became popular.[5]

Our paper contributes to a growing literature in economics on the impact of the internet on mental health.[6] Looking at the UK, McDool et al. (2020) investigate the link between neighborhood broadband speed and children's emotional well-being. Using panel data on self-reported well-being and a fixed-effect specification, they find that faster internet connection is associated with children feeling worse about their appearance, an effect which is especially pronounced for

[4] For example, at the beginning of 2009, Facebook had less than 5 million users in Italy. At the end of our main sample period (end 2011), there were around 20 million users.

[5] Concerns about the role of the internet in promoting eating disorders such as bulimia and anorexia were voiced by European politicians as early as 2006. See for example: https://www.europarl.europa.eu/doceo/document/E-6-2006-5752-ASW_EN.html and https://www.europarl.europa.eu/doceo/document/E-6-2006-5752-ASW_EN.html.

[6] Regarding the effect of the internet on physical health, DiNardi et al. (2019) find that the roll-out of broadband internet in the US was associated with an increase in body weight, while looking at Germany Billari et al. (2018) document a negative effect of internet on the number of hours slept. Relatedly, Amaral-Garcia et al. (2021) examine how access to (online) information affects health care choices in the UK and find it is associated with an increase in the number of c-sections.

girls. The authors attribute this result to the negative impact of social media, and to internet use crowding out more beneficial activities (e.g., exercising, face-to-face interactions with friends and family). Allcott et al. (2020) conduct a randomized experiment in which participants are paid to deactivate their Facebook account for a month. They find that individuals in the treatment group that disconnected from Facebook spent more time interacting with family and friends and experienced a small but significant increase in subjective well-being.[7] These findings suggest that the use of social media affects actual mental health conditions - and not just individuals' awareness of them - since being disconnected from Facebook translates into higher well-being. Braghieri et al. (2021) investigate the impact of Facebook on college students' mental health in the US exploiting the staggered introduction of the platform across US universities for identification and using survey data on self-reported mental conditions. Their results indicate that access to Facebook is associated with a deterioration in mental health status arguably due to Facebook facilitating unfavorable social comparisons. Another reason why social media use can be detrimental to mental health is its addictive nature. Allcott et al. (2021) develop a model of digital addiction and estimate that 31% of social media use is caused by self-control problems. Finally, Golin (2021) studies the effect of high-speed internet on mental health in Germany using survey data from the German Socio-Economic Panel and exploiting the relative position of municipalities in the pre-existing telephone networks (following Falck et al. (2014)). In line with our results, she finds that broadband access negatively affects self-reported mental well-being among female respondents only, and that this effect is larger for younger cohorts. In particular, internet use reduces the ability to socialize and cope with emotional problems, as well as sleep quality.

Our study contributes to this body of work in three important ways. First, our paper is the first one to provide systematic evidence of the causal impact of internet on mental health disorders diagnosed by health professionals. Medical diagnoses provide a more objective measure of mental health disorders than those based on self-reported data which are harder to compare across time and space and are more likely to "suffer from measurement error for reasons related to recall bias and lack of incentive" (Braghieri et al. 2021).[8] Second, the richness of our data allows us to estimate the effect of internet on specific mental disorders, on different types of hospitalizations, and for different segments of the population. This is crucial to identify which groups are most vulnerable to the changes brought about by new technologies (namely with respect to gender and age), and get a more precise picture of the potential costs of these changes to society. Moreover, our data - which cover the universe of mental health disorders diagnosed in Italian hospitals over

[7] Similar evidence is available from Mosquera et al. (2020).

[8] Doctors' assessment is itself not perfect and may be vulnerable to implicit biases related to the race, gender and sexuality of the patient (Snowden, 2003). Furthermore, doctors' evaluation of a given disorder may also be affected by medical information they can access online, though arguably less so than patients who have little or no medical training and are therefore more impressionable.

a 14-year period - allow us to assess the effect of internet on the entire population of children, teenagers, and young adults rather than focusing on a specific and potentially selected group (e.g., college students). Third, by looking at an early period when the use of social media was limited, our analysis shows that internet can influence mental well-being in ways other than through the use of social media platforms. In this regard, our findings complement nicely previous evidence on the effect of social media platforms, namely Facebook.

Finally, our paper contributes to a vast literature outside economics on the influence of internet on emotional well-being. In this context, several studies find a positive association between problematic internet use and suicidal behavior, depression/anxiety, personality disorders, and drug abuse (Kaess et al., 2014; Zadra et al., 2016; Ho et al., 2014). Similar findings have emerged regarding the use of mobile phones (Sohn et al., 2019). Evidence from psychology indicates that adolescents are especially susceptible to problematic internet and mobile phone use since they are developmentally more vulnerable (Sohn et al., 2019). Our results provide empirical support to this correlational evidence by showing a causal impact of broadband internet on mental health disorders. In particular, our evidence that such effect holds only for younger cohorts is consistent with existing studies suggesting that early-life circumstances are likely to affect behavior and mental health later in life (Adhvaryu et al., 2019; Almond and Currie, 2011).

The remainder of the paper is structured as follows. Section 2 provides background information on broadband technologies in Italy. Sections 3 and 4 describe the data sets used in our analysis and the empirical specification. Main results and robustness checks are reported in Sections 5, 6 and 7. Section 8 concludes.

2 Background and Study Setting

2.1 Fixed and Mobile Internet in Italy

Fixed-line broadband internet connection was first introduced in Italy in 1999 through Asymmetric Digital Subscriber Line (ADSL) technology.[9] Yet, the broadband infrastructure experienced a slow development in its early phase. By the end of 2000, only 117 out of 8,100 Italian municipalities had ADSL access. After 2001, the broadband roll-out experienced a more steady growth and by the end of 2005 ADSL was available in about half of Italian municipalities. As explained in detail by Campante et al. (2017), a key parameter driving the timing of the broadband infrastructure diffusion across Italian municipalities was constituted by the distance between the municipality and the closest higher-order telecommunication exchange: the Urban Group Stage (henceforth UGS) whose locations was pre-determined long before the advent of the internet.

[9]Alternative broadband technologies, such as cable and satellite, have been negligible in Italy (OECD, 2001; Between, 2008).

As such, all else equal, “the closer a municipality happened to be to a UGS when ADSL came into the picture, the more likely that that municipality would get ADSL access earlier on in the diffusion process" (Campante et al. 2017, page 1103).

Mobile internet connections arrived at a later stage. At the end of 2004, only 4% of mobile phones in Italy had a UMTS/3G technology (Between, 2008). By the end of 2006, this percentage increased to around 21%. As for the fixed-line broadband, also the mobile internet network had to be connected to the backbone of the telecommunication infrastructure (*core network*). As such, the distance of a municipality to the higher order nodes of the telecommunication network (urban group stages, UGS, or optical packet backbones, OPB) also was highly relevant in the timing of 3G coverage across Italian municipalities (Guerrieri, 2009; TIM, 2019).

3 Data

3.1 Health Outcomes

Our first data source comes from Italian hospitals (both public and private) discharge reports (“Schede di dimissione ospedaliera" SDO) containing information on basic socio-demographic information of each individual (age, gender, municipality of residence) and the associated diagnosis. In particular, our dataset covers the universe of individuals born between 1974 and 1995 who were admitted to any Italian hospital between 2001 and 2013 and who were discharged with any mental health diagnosis by hospital doctors.[10] Starting from these individual data, we construct a balanced sample at the municipality-year level for each diagnosis. That is, we count—for example—the number of females born in 1974 resident in municipality m who were admitted to a hospital in year t and were later discharged with a diagnosis k related to mental health (e.g., eating disorders). We study the impact on depression/anxiety disorders, drug abuse/addiction, eating disorders, personality, and sleep disorders.[11]

[10] Hospital discharge reports in Italy typically contain up to three diagnosis codes. One of these is called “primary diagnosis", while the others are called “secondary or concomitant diagnoses". In Italy, the primary diagnosis is associated with the pathology that led to the greatest consumption of resources during the hospitalization episode, which does not necessarily coincide with the cause of hospitalization. Secondary or concomitant diagnoses, if present, specify further pathologies and contribute to providing a more complete clinical picture; some secondary diagnoses qualify as complicating diagnoses, i.e. specific pathologies that, together with the main diagnosis, lead to a greater burden of care. Source: http://www.salute.gov.it/portale/p5_1_2.jsp?lingua=italiano&id=126.

[11] Depression/anxiety groups together all discharges involving depression, anxieties, or neurotic disorders (ICD-10 codes: F32, F33, F40, F41, F43.21-23 (WHO, 2016)). Drug abuse/addiction aggregates all drug-related diagnoses (ICD-10 codes F10-F19). Eating disorders include anorexia, bulimia, and other eating disorders (ICD-10-CM code: F50). Personality disorders in our analysis include schizophrenia (ICD-10-CM codes: F20, F21, F25) and bipolar disorders (ICD-10-CM code F31), among other personality disorders (ICD-10-CM code: F60). Finally, sleep disorders correspond to code F51 in the ICD-10-CM classification.

3.2 Fixed and Mobile Internet

Our dataset on fixed broadband provides information on the percentage of households with access to ADSL in each Italian municipality for each year between 2005 and 2011. Specifically, the data covers an asymmetric six-point scale corresponding to the following brackets: 0%, 1-50%, 51-75%, 76-85%, 86-95%, and above 95%.[12] We linearize this scale (to make it more comparable with our 3G measures spanning the continuous interval 0-100%), by taking the midpoint of each interval. As explained in Section 2.1, the broadband coverage was still minimal in 2001 in Italy. Accordingly, we set our measure of ADSL equal zero for all municipalities in 2001. Moreover, as no data are available for the period 2002-2004, we drop this period from the analysis.[13]

In the robustness section, we consider alternative measures of ADSL access, such as "*Years Since Good Broadband*," defined as the number of years since at least 50% of households in a municipality have had ADSL access.[14] We also consider mobile internet as opposed to fixed broadband to assess whether our results might vary based on the type of device. Specifically, we use data on 3G coverage from the Collins Mobile Coverage Explorer,[15] covering the period 2007-2013. These data come in GIS vector format and assign value 1 to each 1×1km-cell that is reached by 3G signal. We use the spatial mean of these values to compute the average share of land covered by 3G for every municipality-year. The resulting measure spans the continuous interval 0-1, where 1 indicates that the entire area in the municipality is covered by 3G. Similarly to ADSL, we set 3G coverage equal to 0 for all municipalities in 2001 (as the technology was absent in that year) and drop the period 2002-2006 (as no data is available).

Finally, we gather information on municipal-level observables in census year 2001 as well as population estimates by age groups between 2002 and 2013 from the Italian national statistical office (ISTAT). Summary statistics on these variables are provided in Table 1.

4 Empirical Strategy

As explained in Section 2.1, a key variable in determining the cost of ADSL coverage of a municipality from the perspective of Telecom operators was the distance between a municipality and the closest Urban Group Stage (UGS). Accordingly, our identification strategy exploits the differences across Italian municipalities in such distance. In particular, to control for all fixed

[12] The dataset was provided by *"Osservatorio Banda Larga-Between"*, a joint venture between the main Italian telecommunications operators, the Italian Ministry for Telecommunications, and other private and public stakeholders.

[13] Results are robust to including the period 2002-2004 for municipalities with zero ADSL 2005, i.e., the ones for which we impute a zero ADSL also for the years 2002-2004 (see Table A.7).

[14] While this alternative measure has the advantage of looking at the cumulative effect of broadband internet, it may contain measurement error since we are forced to set 2005 as the first year of good broadband access for all municipalities with coverage 51% and above in 2005, as that is the first year for which data are available.

[15] http://www.collinsbartholomew.com/mobile-coverage-maps/mobile-coverage-explorer/

municipal characteristics—including the distance to the closest urban group stage, we follow Campante et al. (2017) and use the interaction between the distance of a municipality to the closest UGS and a dummy for the post-2001 period (i.e., after the introduction of broadband internet) as our instrument for ADSL coverage. The identification assumption is that, whatever correlation existed between the distance to the closest UGS and relevant municipality characteristics, this did not change at the time of the ADSL technology introduction. As such, we are identifying the effect of the change in the impact of distance on the outcomes of interest, under the assumption that any change in that impact occurs solely through the introduction of the internet.

This basic assumption justifies the following two-stage specification:

$$Y^k_{m,t} = \gamma Broadband_{m,t} + \beta X_{m,t} + \alpha_m + \tau_t + \epsilon_{m,t} \tag{1}$$

$$Broadband_{m,t} = \phi Distance\_UGS_m \times Post\text{-}2001 + \sigma X_{m,t} + \zeta_m + \theta_t + \eta_{m,t} \tag{2}$$

where subscripts m and t indicate respectively municipality and year, $Y^k_{m,t}$ represents the outcome of interest (e.g., occurrence of at least one case of mental health pathology k in municipality m in year t), α and ζ are sets of municipality fixed effects, τ and θ are region-year fixed effects, and X encompasses a set of control variables that we discuss below. The inclusion of region-year fixed-effects allows controlling for any variation over time in health care policies and supply, which in Italy are set at the regional level. *Broadband* stands for one of the measures of broadband access described above, while *Distance_UGS* is the (time-invariant) distance between a municipality's centroid to the closest UGS. We interact this variable with a dummy (*Post-2001*) that takes the value of 1 for years after 2001.

Our basic identification assumption would be violated if there were subjacent trends in our outcomes of interest that happen to correlate with factors that were in turn correlated with $Distance\_UGS \times Post\text{-}2001$. To account for this possibility, we make use of a number of economic and socio-demographic municipal characteristics at the yearly level and from the 2001 Census. Specifically, we include in X the interaction of these characteristics with year dummies. Hence, our identification strategy requires that—once we account for those demographic-related trends— the correlation between the distance to the UGS and the outcomes of interest around the time of broadband introduction did not change, other than through the availability of the internet.

For what concerns the time-varying controls at the yearly level, we include log population and the shares of population below 20, between 20 and 39, 40-59, and between 60 and 79 (the share above 80 being the residual category). In terms of census 2001 variables, we include municipal characteristics that are likely to be related to the demand and supply of broadband internet.

Specifically, we include municipal population density, the log of municipality ruggedness, the distance of the municipality centroid to the closest provincial capital, the municipal unemployment rate, the share of university graduates, the number of firms per capita, and the number of non-profits organizations per capita.

It is important to note that, by including population, size of the municipality, and distance to the closest provincial capital, we are taking into account in multiple ways the possibility that small, isolated, rural towns, which are more likely to be far from a UGS, may have differential trends in our variables of interest, relative to larger urban centers. In all regressions, we account for possible serial correlation in the errors by clustering standard errors at the municipality level.

5 Results

We first present the results aggregating outcomes across all age groups (Table 2). In our main specification, our dependent variables are dummies indicating the occurrence of any case of a specific mental disorder in a given municipality-year. Panel A shows the second stage regression results of broadband coverage and occurrence for each type of mental disorder category. We can see no statistically significant relationship between internet availability and mental disorders when looking at all age groups and genders together. The first stage works in the expected direction: the distance to the UGS is negatively correlated with ADSL coverage. The picture changes substantially when we decompose the mental disorders by age-cohorts and gender. In Table 3, we split the sample into two birth cohorts and by gender.[16] Panel A shows the regression results for individuals born between 1974 and 1984, while Panel B displays the results for people born between 1985 and 1995. The results for the 1974-1984 birth cohort again show no consistent economically and statistically significant relationship between ADSL access and mental health disorders. For younger patients, a different picture emerges. The presence of broadband internet leads to a statistically significant increase in the likelihood of observing the occurrence of all types of mental health disorders for females born between 1985 and 1995, with the exception of depression/anxiety. For males in the 1985-1995 cohort, broadband internet increases the likelihood of observing cases of depression/anxiety, drug abuse/addiction, and personality disorders. In the 1985-1995 cohort, increasing the ADSL coverage from 0 to 100% increases the probability of observing at least one male with a depression/anxiety diagnosis by 37 percentage points, while for females this probability is positive although not statistically significant. Moreover, increasing ADSL coverage from 0 to 100% rises the probability of drug abuse/addiction of about 26 and 14 percentage points for males and females, respectively. Figure 1 provides a visual representation of our baseline estimates for the 1985-1995 cohorts. Such effects appear rather

[16]Unless indicated otherwise, all coefficients in the following Tables refer to the second stage coefficient γ on ADSL access from Equation 1.

sizeable when contrasted with the sample averages over the 2001-2013 period (see Table A.1). For example, the estimated impact of ADSL coverage on the probability of observing at least one young female hospitalized because of drug abuse/addiction in a municipality is almost three times the average probability in the 2001-2013 period or, alternatively, 0.66 standard deviation units.[17]

One way to interpret our results is that internet availability increases information access about mental health diagnoses and resources. Instead of causing these disorders, people could now be better equipped to define their problems and more likely to seek help.[18] While this may partially explain our results, three observations speak against this interpretation as the main driver. First, we only observe a detrimental effect on mental health for individuals born between 1985-1995 but not for the cohorts born before. This would imply that only the youngest make use of the additional information on mental health. Second, we observe increases in the likelihood of observing episodes that are hardly connected with a simple awareness mechanism. Specifically, Table 4 shows the impact of broadband internet on the likelihood of observing episodes of self-harm (column (1)) or compulsory hospitalization (column (2)) in the 1985-1995 cohort. Self-harm refers to cases where hospital doctors registered the presence of suicide attempts or self-inflicted trauma. Expanding the ADSL coverage from 0 to 100% increases the probability of observing a case of young male inflicting self-harm by 8.3 percentage points, while for females it increases by 4.6 percentage points. The observed increase in the likelihood of self-inflicted trauma episodes cannot be rationalized with better access to resources and mental health information only. Similarly, we observe an increase in the likelihood of the occurrence of compulsory hospitalizations (i.e., forced hospitalization due to the possible threat that a patient posed for herself or for others).[19] Here again, the coefficient is larger for young male patients (14.3 pp) than for young females (4.7 pp). As in the case of self-inflicted trauma, it is difficult to explain an increase in compulsory hospitalization simply based on an information mechanism.

Finally, we can use the information on whether a hospitalization in our dataset was planned or whether someone was hospitalized urgently. We repeat our main exercise from Table 3 but split the sample into urgent vs. planned hospitalizations. We hypothesize that if using the internet only improves information access and the matching between patients and providers only planned hospitalizations should be growing with early internet access. Instead, we can see in Table 5 that the increases are fairly similar in urgent compared to planned hospitalizations. These three findings together suggest a real increase in mental health crises and not only in detection rates.

[17] For the sake of comparison, Braghieri et al. (2021) estimate that the Facebook roll-out increased by 0.085 standard deviation units the index of poor mental health among US college students. One potential reason for the these differences is that our IV approach measures the LATE, which is usually larger than the ATE estimated via OLS.

[18] Similarly, doctors may now be better informed and more likely to diagnose a mental disorder.

[19] In Italy compulsory hospitalization are defined as TSO (“Trattamento Sanitario Obbligatorio") by Law 833/1978.

6 Robustness checks

We perform a variety of robustness checks to show that our results do not depend on our chosen specification. First, we study whether the increases in mental health conditions operate only on the extensive or also on the intensive margin. We repeat our main analysis for the youngest cohort but now use the natural log of total hospitalizations as our dependent variables.[20] Table A.2 shows that higher fixed internet coverage increases the number of mental health disorders for females across all categories. Also in the case of the intensive margin, the results point out the presence of sizeable effects. For example, increasing the ADSL coverage from 0 to 100% leads to 45.5% rise in the number of males diagnosed with depression/anxiety, and a 16.5% increase in the number of females with drug-addictive behavior. The results are qualitatively similar to what we see in the extensive margin specification of Table 3.

Our main specification assumes an immediate relationship between internet availability and mental health. Instead, we could assume that the detrimental effect on mental health needs time to materialize. In the next robustness check, we define our independent variable as the total number of years since the municipality has good coverage, which we set at more than 50%. Results are depicted in Table A.3. We observe that municipalities with an additional year of good internet coverage increase the probabilities of episodes of mental health disorders involving females (for all types of disorders, except depression/anxiety) and involving males with depression/anxiety, drug abuse/addiction, personality disorder, or self-harm. An additional year of good ADSL coverage increases the probability of observing at least one male with depression/anxiety by 10 percentage points, which corresponds to an increase of 0.33 standard deviation units.

Whether or not internet access influences well-being may depend on how people use it. For example, having access on smartphones rather than on fixed devices may increase addictive behaviors more due to the devices' designs. The arrival of 3G coverage may correlate with pre-existing telecommunication infrastructure and, therefore, with ADSL access. We investigate whether 3G usage in a municipality is related to increases in mental disorders in Table A.4. In this analysis, we use the minimum distance to the UGS or OPB network as an instrument (see Section 2). The first stage is strong (F-value: 107.91) and indicates the further a municipality centroid is from one of these networks, the lower is the municipality's 3G coverage. Despite investigating a different broadband technology and time-span (the 3G coverage data ranges from 2007-2013), the coefficients are fairly comparable to our main specification (Table 2).[21] The only differences from the results on fixed broadband are for the female subgroup, for which we find a positive effect of 3G on depression/anxiety but no significant effect on sleep disorders. We define our dependent variable using the presence of mental disorders in any of the three

[20]We use the natural log due to the skewed distribution in our dependent variable.

[21]The results remain unchanged when we harmonize the time-spans of the two analyses. Results are available upon request.

diagnoses present in the hospital records. As explained in Section 3.1, the first diagnosis does not need to coincide with the cause of hospitalization. The order in which diagnoses are reported reflects which pathology requires the highest resource consumption. Hence, as a robustness check, we investigate whether we observe similar patterns in the youngest cohort when we construct our outcome variables by focusing on the primary diagnosis only (i.e., including a case of mental disorder only if recorded as the primary diagnosis). Table A.5 indicates that the results focusing on the primary diagnosis are very similar to our main specification results.

Furthermore, as only one of the diagnoses needs to refer to a mental health condition, the reader may worry that individuals are generally more likely to be hospitalized in areas with early internet access and mechanically increase the mental disorder hospitalization rates. In the next robustness check, we drop from our sample all records where one of the diagnoses refers to a physical condition (i.e., we keep only cases where all the three diagnosis refer to mental disorders). Table A.6 shows that the results omitting any physical diagnosis from the sample are indistinguishable from the baseline coefficients depicted in Table 2.

Additionally, Table A.8 shows that our results are not driven by urban areas only. The table reports results when focusing only on the subset of rural municipalities.[22] The coefficient estimates are smaller compared to the baseline specification but qualitatively similar. The coefficient on ADSL coverage for female drug abuse/addiction is statistically insignificant in the rural sub-sample. These findings speaks against the interpretation that our results are driven by differential trends in urban areas, such as, for example, a higher supply of mental health treatments.

In the final specification checks, we cluster the standard errors at a higher geographic unit than municipalities. Results are displayed in Tables A.9 (province-level) and A.10 (region-year-level). We have 110 provinces and 220 region-year pairs. The partial F-values of the first stages are lower (28.71 and 21.23), but the qualitative conclusions remain unchanged. We do not lose statistical precision in the second stage despite clustering at a higher geographic unit.

7 Placebos

In the final set of empirical exercises, we seek to shed light on the identifying assumption. Although it is impossible to formally test for the exclusion restriction of our instrument, we conduct a series of placebo regressions to assess whether the instrument could directly affect the outcomes besides through the availability of the internet, thus violating the exclusion restriction. Particularly, we conduct reduced-form regressions of our outcomes on $Distance\_UGS \times Post\text{-}2001$, for all years between 2001 and 2005 and only in those municipalities without ADSL coverage as

[22] The urbanization index is provided by ISTAT. All municipalities with the highest urbanization index in 2001 (3) are excluded in this analysis.

of 2005. The results reported in Table A.11 speak in favor of the identifying assumption: we do not find a significant correlation between the instrument and the outcomes in the absence of ADSL coverage. These results provide important reassurance on the validity of our instrument and, therefore, of the identification approach used in the paper.

8 Conclusion

While the advantages of digital technologies are undisputed, studies providing causal evidence on the harmful effects on mental health remain rare. We provide the first causal estimation of the relationship between internet access and specific mental disorders diagnosed by doctors. We find economically and statistically significant increases in depression/anxiety disorders, drug abuse/addiction, and personality disorders among patients born after 1985. In addition, we find significant raises in eating and sleep disorders among female patients in the same cohort. We find no impact among the older cohort, born before 1984. The findings are in line with the interpretation that early-life circumstances are likely to affect behavior and mental health later in life (Adhvaryu et al., 2019; Almond and Currie, 2011).

Our results speak in favor of a true increase in mental disorder prevalence—rather than just increased awareness—as we also identify raises in self-inflicted harm, compulsory, and urgent mental health hospitalizations. Finally, as we focus on a period of early penetration of social media, our findings highlight that the deteriorating impact of the internet on mental health may be driven by several factors besides these specific digital platforms.

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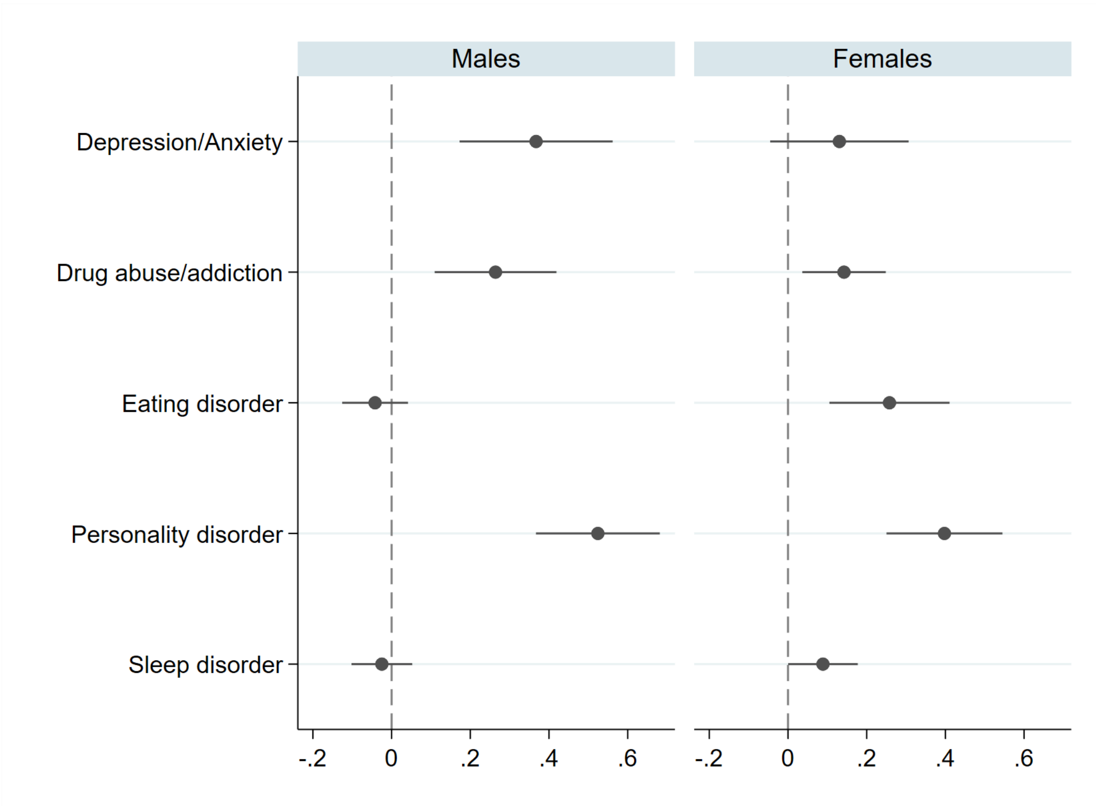
Figures and Tables

Figure 1: Internet and mental health hospitalizations (1985-1995)



Notes: The figure depicts the main regression results (coefficients and corresponding standard errors) of Table 3 for the birth cohort 1985-1995. We estimate equations 1 and 2. For a complete list of municipality controls, see the footnote in Table 2.

	Observations	Mean	SD	Min	Max
Hospitalizations					
Depression/anxiety	63496	0.43	0.49	0.00	1.00
Substance abuse/addiction	63496	0.30	0.46	0.00	1.00
Eating disorder	63496	0.17	0.38	0.00	1.00
Personality disorder	63496	0.35	0.48	0.00	1.00
Sleep disorder	63496	0.07	0.25	0.00	1.00
Self harm	63496	0.05	0.21	0.00	1.00
Compulsory hospitalization	63496	0.09	0.29	0.00	1.00
Municipality characteristics					
ADSL Internet (midpoints)	63496	0.65	0.45	0.00	0.98
Number of years with good ADSL (>50%)	63496	2.44	2.32	0.00	7.00
3G Internet Coverage	46882	0.62	0.43	0.00	1.00
Distance to closest capital city (km)	63496	23.39	13.24	0.00	209.80
Distance to closest SGU (km)	63496	14.03	8.89	0.00	212.02
Population aged 0-19	63496	0.18	0.04	0.00	1.00
Population aged 20-39	63496	0.26	0.03	0.00	0.45
Population aged 40-59	63496	0.28	0.02	0.00	0.57
Population aged 60-79	63496	0.22	0.04	0.00	0.55
Population aged 80 above	63496	0.06	0.03	0.00	0.31
Population	63496	7451	40933	33	2752637

Notes: information on 3G Internet Coverage is missing for years 2005 and 2006.

Table 1: Summary statistics (years covered: 2001, 2005-2011)

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Panel A: 2SLS					
ADSL	-0.085	0.105	0.051	0.021	-0.101
	(0.122)	(0.122)	(0.105)	(0.141)	(0.075)
Panel B: OLS					
ADSL	0.001	-0.001	-0.000	0.013*	0.008**
	(0.007)	(0.007)	(0.005)	(0.007)	(0.004)
Mean	0.414	0.287	0.170	0.340	0.062
Observations	63496	63496	63496	63496	63496
1st stage Wald F-stat	63.97	63.97	63.97	63.97	63.97
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: Contemporaneous municipality controls include: population size, share of age groups (0-19, 20-39, 40-59, 60-79, >80 residual category). Baseline characteristics at the municipal level (in census year 2001) interacted with year dummies are: population density, distance to closest provincial capital, ruggedness, unemployment rate, share of university graduates, number of firms per capita, and number of non-profits organizations per capita. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 2: IV and OLS estimates: internet and all mental health hospitalization

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Panel A: 1974-1984					
Males	-0.073	0.098	0.006	0.080	-0.046*
	(0.117)	(0.110)	(0.037)	(0.125)	(0.025)
Females	-0.061	-0.010	-0.090	0.143	-0.184***
	(0.132)	(0.086)	(0.092)	(0.123)	(0.060)
Panel B: 1985-1995					
Males	0.367***	0.264***	-0.042	0.524***	-0.025
	(0.099)	(0.079)	(0.043)	(0.080)	(0.039)
Females	0.131	0.142***	0.258***	0.398***	0.089**
	(0.090)	(0.054)	(0.078)	(0.075)	(0.045)
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 3: IV estimates: split by gender and cohort

	Self harm (1)	Compulsory hospitalization (2)
Males 1985-1995	0.083***	0.143***
	(0.016)	(0.029)
Females 1985-1995	0.046*	0.047***
	(0.024)	(0.018)
Observations	63496	63496
1st stage Wald F-stat	63.97	63.97
Municipality controls	Y	Y
Municipality FE	Y	Y
Region-Year FE	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 4: IV estimates: self-harm and compulsory hospitalizations

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Panel A: urgent hospitalizations					
Males 1985-1995	0.232***	0.230***	-0.002	0.390***	-0.044**
	(0.063)	(0.075)	(0.018)	(0.057)	(0.021)
Females 1985-1995	0.176**	0.097*	0.075*	0.368***	-0.012
	(0.073)	(0.050)	(0.044)	(0.056)	(0.023)
Panel B: planned hospitalizations					
Males 1985-1995	0.251***	0.095***	-0.046	0.300***	0.019
	(0.086)	(0.035)	(0.041)	(0.060)	(0.034)
Females 1985-1995	0.147*	0.072***	0.242***	0.211***	0.101**
	(0.076)	(0.026)	(0.073)	(0.057)	(0.042)
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 5: IV estimates: split by hospitalization type

Appendix Figures and Tables

	Depression or anxiety	Drug abuse or addiction	Eating disorder	Personality disorder	Sleep disorder	Self-harm	Compulsory hospitalization
N	105105	105105	105105	105105	105105	105105	105105
Males 1974-1984							
Mean	0.18	0.18	0.01	0.18	0.01	0.01	0.05
SD	0.39	0.38	0.10	0.39	0.08	0.12	0.22
Females 1974-1984							
Mean	0.25	0.09	0.09	0.17	0.03	0.02	0.03
SD	0.43	0.28	0.28	0.37	0.17	0.14	0.17
Males 1985-1995							
Mean	0.10	0.08	0.02	0.08	0.01	0.01	0.02
SD	0.30	0.27	0.13	0.28	0.10	0.08	0.13
Females 1985-1995							
Mean	0.14	0.05	0.10	0.08	0.03	0.01	0.01
SD	0.35	0.21	0.30	0.27	0.16	0.10	0.09

Table A.1: Summary statistics hospitalizations by birth cohorts and gender (2001-2013)

Dep. var.: log	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995	0.455***	0.335***	-0.030	0.632***	-0.025
	(0.097)	(0.075)	(0.035)	(0.088)	(0.030)
Females 1985-1995	0.391***	0.165***	0.363***	0.540***	0.071**
	(0.099)	(0.046)	(0.088)	(0.086)	(0.035)
Observations	63496	63496	63496	63496	63496
1st stage Wald F-stat	63.97	63.97	63.97	63.97	63.97
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.2: IV estimates: total hospitalizations (log)

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995					
Number of years	0.100***	0.072***	-0.011	0.143***	-0.007
	(0.028)	(0.022)	(0.012)	(0.023)	(0.011)
Females 1985-1995					
Number of years	0.036	0.039***	0.071***	0.109***	0.024*
	(0.025)	(0.015)	(0.022)	(0.021)	(0.012)
Observations	63496	63496	63496	63496	63496
1st stage Wald F-stat	54.35	54.35	54.35	54.35	54.35
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.3: IV estimates: number of years since good coverage

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995					
3G	0.295***	0.269***	-0.051	0.528***	-0.046
	(0.079)	(0.064)	(0.034)	(0.065)	(0.032)
Females 1985-1995					
3G	0.152**	0.116***	0.183***	0.354***	0.030
	(0.075)	(0.043)	(0.062)	(0.064)	(0.035)
Observations	62312	62312	62312	62312	62312
1st stage Wald F-stat	107.97	107.97	107.97	107.97	107.97
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.4: 3G estimates (years covered: 2001, 2007-2013)

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995	0.313***	0.183**	-0.062	0.540***	-0.065*
	(0.073)	(0.074)	(0.041)	(0.078)	(0.036)
Females 1985-1995	0.181**	0.084*	0.210***	0.404***	0.084**
	(0.084)	(0.051)	(0.075)	(0.072)	(0.042)
Observations	63496	63496	63496	63496	63496
1st stage Wald F-stat	63.97	63.97	63.97	63.97	63.97
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.5: IV estimates: using primary diagnosis only

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995	0.368***	0.264***	-0.042	0.524***	-0.025
	(0.099)	(0.079)	(0.043)	(0.080)	(0.039)
Females 1985-1995	0.128	0.143***	0.258***	0.397***	0.089**
	(0.090)	(0.054)	(0.078)	(0.075)	(0.045)
Observations	63496	63496	63496	63496	63496
1st stage Wald F-stat	63.97	63.97	63.97	63.97	63.97
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.6: IV estimates: using hospitalizations with mental health diagnoses only

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995	0.409***	0.323***	-0.049	0.597***	-0.020
	(0.113)	(0.091)	(0.049)	(0.091)	(0.045)
Females 1985-1995	0.173*	0.169***	0.281***	0.459***	0.110**
	(0.103)	(0.0619)	(0.0886)	(0.0850)	(0.0518)
Observations	75451	75451	75451	75451	75451
1st stage Wald F-stat	62.86	62.86	62.86	62.86	62.86
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.7: IV estimates: impute zeros for missing years

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995	0.334**	0.186*	-0.065	0.481***	-0.057
	(0.138)	(0.109)	(0.055)	(0.112)	(0.054)
Females 1985-1995	0.052	0.048	0.215**	0.323***	0.121**
	(0.126)	(0.075)	(0.107)	(0.103)	(0.060)
Observations	56280	56280	56280	56280	56280
1st stage Wald F-stat	40.43	40.43	40.43	40.43	40.43
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.8: IV estimates: exclude urban areas

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995	0.367***	0.264***	-0.042	0.524***	-0.025
	(0.113)	(0.077)	(0.044)	(0.089)	(0.038)
Females 1985-1995	0.131	0.142**	0.258***	0.398***	0.089*
	(0.105)	(0.060)	(0.087)	(0.083)	(0.049)
Observations	63496	63496	63496	63496	63496
1st stage Wald F-stat	28.71	28.71	28.71	28.71	28.71
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.9: IV estimates: cluster province level

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Males 1985-1995	0.367***	0.264***	-0.042	0.524***	-0.025
	(0.109)	(0.061)	(0.052)	(0.116)	(0.033)
Females 1985-1995	0.131	0.142**	0.258***	0.398***	0.089**
	(0.107)	(0.070)	(0.096)	(0.088)	(0.045)
Observations	63496	63496	63496	63496	63496
1st stage Wald F-stat	21.23	21.23	21.23	21.23	21.23
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.10: IV estimates: cluster region-year level

	Depression or anxiety (1)	Drug abuse or addiction (2)	Eating disorder (3)	Personality disorder (4)	Sleep disorder (5)
Panel A: 1974-1984					
Males	0.001	0.000	0.000	-0.001*	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Females	-0.001	-0.000	0.000	-0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Panel B: 1985-1995					
Males	-0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Females	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	19925	19925	19925	19925	19925
Municipality controls	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Region-Year FE	Y	Y	Y	Y	Y

Notes: The independent variable is the distance to the closest SGU * Post2001 (i.e., the IV). Only municipalities with no ADLS penetration in 2005 are included. For a list of municipality controls, see the footnote in Table 2. Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table A.11: Placebo estimates. Municipalities without ADLS, years 2001 to 2005.