Tiktok or Treatment? The causal effect of high-speed internet on mental health medication

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Abstract

A recent, steep decline in the mental health of adolescents and young adults may, in part, be caused by increased digital media. However, little research estimates its effect on treatment of mental illnesses. We leverage the rollout of fiber optics to estimate the effect of high-speed internet on use of mental health medications for people ages 12-25 using rich administrative data from the Netherlands. Using a continuous difference-in-differences approach, we find that the rollout of fiber optics has had no effect on the prescriptions of mental health medications for adolescents and young adults. This result continues to hold when stratifying by age and gender, and holds for both new and existing prescriptions.

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I herewith declare that my thesis meets the above requirements
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Data Management Plan statement:

I, the undersigned Robin Verbeek, declare that I followed the Data Management Plan
Code and medication data are in the CBS environment and cannot be shared
Data on fiber-optics deployment can be found here:
https://github.com/RobinV1/Data-Master-Thesis-Robin

1 Introduction

There is an ongoing public debate on the rise of mental illness among youths, and the role the internet and social media play in it. In the past two decades, there has been a worrying decline in the mental health of youths and young adults in high-income countries. For example, between 1999 and 2019, persistent feelings of sadness or hopelessness increased 30% among 14 to 18-year olds in the US (CDC (2019)). Similarly for the Netherlands, the prevalence of having a mental disorder rose between 17.4% and 26.1% for the adult population (18-74) in 2019-2022 compared to only 12 year prior, but finding stronger effects for younger adults aged 18-34 (ten Have et al. (2023)).

This decline in mental health coincides with increase of digital media, arousing much debate about the relation between the two. Association studies indeed find a strong negative correlation between social media use and important mental health markers, such as self-esteem, life satisfaction, self-harm and loneliness (Kelly et al. (2018), O'Day and Heimberg (2021), Hartas (2021)). This correlation could result from effects in either or both directions however, as youths use social media to compensate for feelings of loneliness (O'Day and Heimberg (2021)). This raises questions on the extent to which this association reflects a causal relationship from social media to mental health.

To test for this causal relation, studies exploiting exogenous variation in internet infrastructure have been performed: Golin (2022) uses technological limitations of broadband in Germany, Donati et al. (2022) and Arenas-Arroyo et al. (2022) use the rollout of broadband in Italy and fiber optics in Spain respectively, and Braghieri et al. (2022) uses the staggered introduction of Facebook on US campuses. All these papers find negative effects on mental health, either for adolescent women or both genders.

However, to our knowledge there are no papers which explore the internet's effect on the use of medication in treatment of mental illness. We help fill this gap by investigating the rollout of fiber optics in the Netherlands to estimate its effect on the prescription of mental health medication to adolescents and young adults ages 12-25.

In this paper, we use a staggered continuous Difference-in-Difference approach to estimate the causal effect of having access to high-speed internet on the use of mental health medications for youths ages 12 to 25, For this, we make use of rich administrative data on the prescription of medications in the Netherlands. We find small and statistically insignificant effects for all medications: antidepressants, anti-anxiety medications, ADHD medications, and anti-addiction medications. This effect remain insignificant when separated by age, gender and when stratifying by new and existing prescriptions.

There are three ways in which increased internet access can affect the prescription of mental health medications: it can affect underlying mental health, whether and when people with mental illnesses seek treatment, and whether this treatment involves medication. It is thus unclear whether our null results reflect a lack of an effect or that there are multiple effects which cancel out. Additional research looking to isolate one of these effects could help give a full picture behind these driving mechanisms.

The rest of this paper is structured as follows: In Section 2 we discuss the background of the rollout of fiber optics in the Netherlands. We also discuss the current literature on the rise of mental illness and the internet's relation to declining mental health and describe the healthcare system of the Netherlands. In Section 3 we explain the data we use for our analysis and give descriptive statistics. Next, we discuss our methodology and perform balancing tests in Section 4. In Section 5 we present our results and perform robustness checks. Section 6 concludes.

2 Background

Below we discuss the current literature on mental health and how internet usage and social media affects it. Next we give background on the psychiatric healthcare systems in the Netherlands. Lastly, we discuss the workings of fiber optics, how it affects the internet access of users, and how it was rolled out in the Netherlands.

2.1 Mental health

In recent years, there has been much attention on the mental health of adolescents and young adults. In the US, the Youth Risk Surveillance Survey from the CDC (2019) finds that 36.8% of youths between 9th and 12th grade (ages 14-18) had suffered from persistent feelings of sadness or hopelessness in the past twelve months in 2019, an increase of 30% since this question was included in the survey in 1999. This increase is not specific to the US. ten Have et al. (2023) conduct face-to-face interviews in the Netherlands in 2019-2022 and find that the 12-month prevalence rate of having any DSM-IV disorder rose with 17.4%-26.1% compared to the previous survey in 2007-2009. This effect persisted when only including pre-Covid interviews, and notably, was stronger for young adults (ages 18-34).

There are many possible explanations proposed for this increase, including increases in income inequality (Foster et al. (2011)), which have been linked to mental health problems (Langton et al. (2011), Tibber et al. (2022), Wildman (2003)), climate change (Fritze et al. (2008), Albrecht et al. (2007)), and increases in educational expectations (Sweeting et al. (2010), West and Sweeting (2003)). One of the possible explanations which has been widely discussed is the rise of internet use and social media.

There are multiple ways in which internet usage and social media can lead to worsening mental health, such as loneliness, social comparison, cyberbullying, and crowding out of beneficial activities. Kraut et al. (1998) investigate households in the first one to two years of gaining access to the internet and finds that it leads to decreases in social contact with family members, smaller social circles, and increased depression and loneliness. On the parents side, Ante-Contreras (2016) discuss how parents engaging in excessive social media use are more likely to be distracted and have decreased levels of parental engagement. They also find that hours spend on social media correlates to engaging in authoritarian parenting techniques. Kelly et al. (2018) perform an association study on the UK millennium cohort and find that greater social media use relates to online harassment, poor sleep, low self-esteem and poor body image, with these effects being stronger for girls than boys. O'Day and Heimberg (2021) find that social anxiety and loneliness are associated with problematic social media usage, and Hartas (2021) finds lower life-satisfaction and increased self harm as social media usage goes up. Olorunsogo et al. (2024) perform a meta-analysis on studies between 2000 and 2023 and conclude that social media has positive effects on connectivity and community support, while worsening cyberbullying, addiction and mental health issues. Similarly, Weigle and Shafi (2024) review recent evidence and find that social media use impacts anxiety, depression, and suicidality in youths, but advise that future research should look into the causality of these findings.

The rollout of internet infrastructure has been commonly used to assess the causal effects of the internet. Akerman et al. (2015) estimate the effects of broadband internet on skill comprehension, Bhuller et al. (2013) estimate its effect on sex crime, and Amaral-Garcia et al. (2022) the effect on the demand for health care, specifically c-sections. Similarly, this approach has been used to investigate this causal effect of internet usage on mental health: Golin (2022) use a regression discontinuity design using the technological limitations of broadband in Germany and find that women, particularly women ages 17-30, with better access to broadband score lower on a mental health survey. As underlying mechanism, they find that broadband internet worsens socializing behaviors and the ability to cope with emotional distress. Arenas-Arroyo et al. (2022) use the laying of fiber optic in Spain and find increases of anxiety, drug abuse and self-harm in girls ages 15-19, but not boys. They show an underlying mechanism of reductions in sleep, homework, and socializing with family and friends. Donati et al. (2022) use a similar approach for broadband in Italy on hospital records and find increases in diagnoses of drug abuse, depression, anxiety and personality disorders in both genders, and increases in eating and sleeping disorders for females only. Zooming in on social media, Braghieri et al. (2022) use a generalized difference in difference approach using the staggered introduction of Facebook on US campuses and find that the rollout had a negative effect on student's mental health by facilitating unfavorable social comparisons.

Although the literature indicates a causal negative effect on both reported mental health and hospitalizations, to our knowledge, there are no papers on the its effects on utilization of mental health medications. We fill this gap by estimating the causal effect on increases in access to high-speed internet on the use of medication treating mental disorders in the Netherlands.

2.2 Healthcare in the Netherlands

In the Netherlands, it is mandatory to have a basic health insurance from age 18 onwards. Children are covered by the health insurance of their parents, such that everybody in the Netherlands has coverage. The Dutch government decides what is covered by this basis health insurance.[1] Notably, it covers all forms of mental health care and most mental health medications. An important exception to this are Benzodiazipines, a strong anxiolytic (O'Brien

[1]https://www.rijksoverheid.nl/onderwerpen/zorgverzekering/vraag-en-antwoord/wat-zit-er-in-het-basispakket-van-de-zorgverzekering

(2005)), which became significantly more restricted in attempt to stop misuse and can now only be prescribed for anxiety if there are no other viable alternatives.[2] Because of this, our analysis only looks at benzodiazipine use for extreme cases, on top of non-benzodiazipine anti-anxiety medications.

When someone seeks mental health treatment, the first step is to go to their General Practitioner (GP). The GP then evaluates the severity of the symptoms. If the symptoms are severe enough, the GP can prescribe medication or, if the GP cannot provide appropriate care, refer the patient to the Dutch mental health care (GGZ).[3] From there, the patient is treated by a psychologist and/or psychiatrist, who can prescribe medication if necessary. For children under 16 year old, parents are informed and have to agree with the prescribed treatment. In 2015, a law was passed that moved the duty of providing psychiatric healthcare for minors from the national to the municipality level, increasing wait times. Although longer wait times lead to patients having worse symptoms by the time they get treatment (Brown et al. (2002)), possibly leading to the prescription of more medication, we show in Section 4 these wait times are likely unrelated to the deployment of fiber optics and thus should not effect our results.

Nevertheless, the effect of social media and other digital media on this process of getting prescribed medications is multifaceted, as it can affect different steps differently. Firstly, as we have discussed above, it can affect mental health directly. This decrease in mental well-being could lead to an increase in the prescription of medications. Furthermore, it can provide information on mental health, and serve as an information treatment increasing the number of people seeking mental health care, increasing the number of mental health medications that are prescribed without necessarily increasing the prevalence of mental illness. For example, Amaral-Garcia et al. (2022) show that improved access to the internet raises demand for c-sections, implying that demand for health care is affected by the internet. However, this could also serve to have the opposite affect: if people seek mental health care earlier, they could receive help before their symptoms have progressed to the point where they need medication, reducing medication prescriptions. Conversely, Gorday and Bardeen (2022) show that problematic smartphone usage facilitates maladaptive coping strategies, engaging in overuse of technology to relieve emotional distress. Thus, individuals suffering from mental health problems might turn to digital media instead of seeking mental health care. Lastly, social media might affect the treatment people receive. A meta-analysis by Plackett et al. (2023) concludes that social media interventions are effective at improving mental well-being and reducing mental illness markers. If social media decreases mental health, but treatment for these cases does not involve medications, we will find no effect on medication usage. In short, as increased internet access might have a negative effect on mental health, an ambiguous effect on the seeking of treatment, and might push treatment to non-medication interventions, it is unclear in which direction it will affect the prescription of medication.

[2]https://www.npfo.nl/artikel/gevolgen-van-de-vergoedingsbeperking-van-benzodiazepinen-2009

[3]https://richtlijnen.nhg.org/standaarden/angst
https://www.rijksoverheid.nl/onderwerpen/geestelijke-gezondheidszorg/vraag-en-antwoord/waar-vind-ik-hulp-bij-psychische-problemen

2.3 fiber optics and social media

Fiber optic communication provides some of the fastest internet possible, being able to reach download speeds of up to 10 Gigabit per second (Gbps).[4] This is significantly faster than the current FCC benchmark of 100 Mbps (FCC (2024)) and is high enough to not be limited by download speeds for all practical purposes, such as the use of social media and playing online video games.[5]

Lower speeds have a negative impact on peoples ability to use digital services. Riddlesden and Singleton (2014) investigate the geographical differences of internet infrastructure in the UK between 2010-2013 and find that the heterogeneity in internet infrastructure affects access to and the performance of service provision. They conclude that rural areas suffer from worse quality services due to lower download speeds overall, while the quality in high density areas drops during peak hours as total demand increases. Similarly, Farrington et al. (2015) use a 2013 UK survey and find that over a million rural citizens have too slow internet to participate in common online behaviors. Additionally, they find that even in urban areas with high speeds available, only 65% of people rate their internet as "fast enough", leaving considerable room for improvement. Lastly, Singla et al. (2014) note that increased latency leads to decreases of usage.

Throughout the past two decades, internet and social media have ubiquitous in daily life, especially for teens and young adults. According to CBS (2020), the number of 12 to 25-year-olds in the Netherlands who use social media daily has remained steady at around 96% between 2014 and 2019. Additionally, 99.8% of them had access to the internet in their households, which was most often accessed via their smartphone (CBS (2019)). Although the access and use of social media was near universal, the type of social medias did change over time. In a 2014-2015 survey, Anderson and Jiang (2018) find that Facebook was the most used social medium among youths at 71%. By 2018 however, this number had dropped to 52% and Facebook was overtaken by Youtube (85%), Instagram (72%) and Snapchat (69%), all of which are image and video based social media, requiring higher download speeds to use effectively.[6] This trend then continued with the rising popularity of TikTok, which by 2022 was used by 1.67 million, or around 60%, of 12 to 24-year olds in the Netherlands. (Newscom (2023))

To ensure that everyone can enjoy the benefits of digital services, the Dutch Government has made it an official goal that everyone has access to 100 Mbps broadband by the end of 2023, with most people having access to 1+ Gbps speeds. They have (mostly) reached this goal,[7] in large part through the rollout of fiber optics. Currently, around 88% of households in the Netherlands have access to a fiber optics connection (ACM (2024)), of which a third are activated (i.e. have a fiber optics plan with a provider).

In the Netherlands, rollout of optic fiber is done by commercial companies. The first fiber

[4] https://www.highspeedinternet.net/guide-to-internet-speed/
[5] https://nordvpn.com/blog/how-much-internet-speed-do-i-need/
[6] https://www.highspeedinternet.com/resources/best-internet-speed-for-social-media
[7] https://www.overalsnelinternet.nl/onderwerpen/kaart-vaste-internetverbindingen

optic connection was laid in 2005[8], and it is estimated that all households will have access to fiber optics in 2026. [9] This rollout is overseen by the Authority Consumers and Markets (ACM), who give advice on stimulating rollout and make sure there is enough competition in the market. Because of the commercial aspect of fiber optic rollout, it is subject to market forces, most notable of which is the different marginal cost between urban and rural areas and competition between firms (ACM (2024)). We discuss how we mitigate these market forces in Section 4, such that the variation in fiber optics is plausibly exogenous.

3 Data

3.1 Fiber-to-the-Home

We make use of publicly available data from Stratix, a Dutch consultancy firm specialized in internet infrastructure. They collect data on the laying of fiber optic cables from the responsible companies, which they aggregate to the municipality level. This gives us the Fiber-to-the-Home (FttH) of each municipality, which is the fraction of households which can have access to glass fiber. Here, a household is qualified as if they have fiber optic connection in their home or in their street, regardless of whether they have the subscription to use this connection.

The data spans 2011 to 2022, which we use to construct municipality-year panel data. Some years have observations for both the first and third quarter, in which case we take the average. As there is no data available for 2015, we linearly interpolate the 2014 and 2016 observations. We drop all municipalities which were either created or ceased existing in our observed time period. This leaves us with 309 municipalities with 12 yearly observations, giving us 3708 municipality-years.

As fiber optic cables are rarely removed, FttH in our panel data should (mostly)[10] only increase. Unfortunately, the data is quite noisy for some observations, with some municipality-year showing a decrease. Although our main results are presented using this noisy data, we show that our results still hold when we clean the data.

Figure 1 shows maps of the start and endpoints of fiber optic deployment and Table 1 we give descriptive statistics to show the evolution of FttH. In 2011, most municipalities had no fiber optics at all, although a few already had it and a few had fiber optics for every household. FttH then rose throughout the years, starting from 10.6% of households in 2011 to 64.4% in 2022. At that time, most municipalities had nearly full deployment, while for some deployment remained low. Thus, standard deviations remained high, providing necessary inter-municipality variation for our analysis.

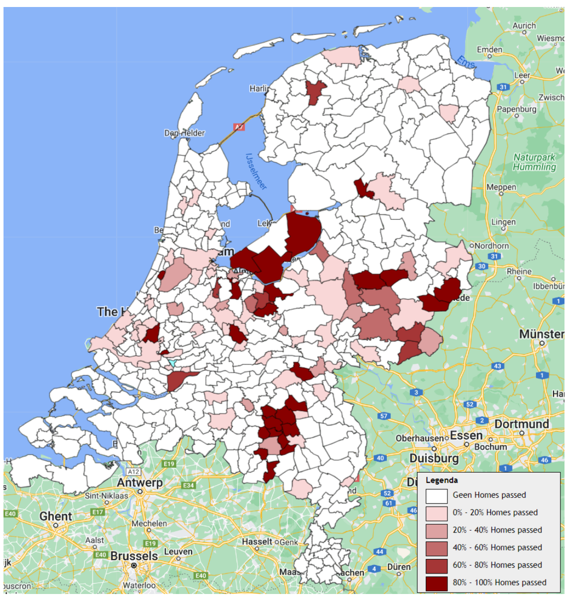
[8]https://www.solcon.nl/particulier/blog/waar-ligt-glasvezel-in-nederland-en-kunt-u-er-gebruik-van-maken/

[9]https://nos.nl/artikel/2518486-stoep-nog-een-keer-open-voor-glasvezel-100-000-woningen-met-dubbele-aansluiting

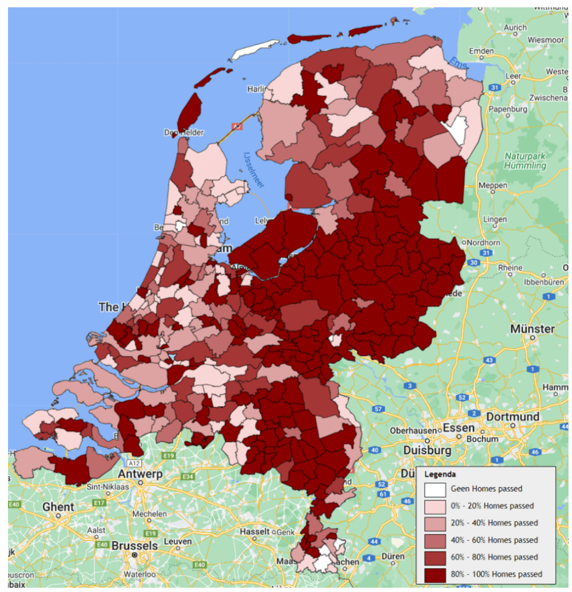
[10]It is possible for the FttH to drop slightly if new houses are build without fiber optics. As this could only cause very small drops, we do not think it would meaningfully affect our results

Year	Mean	Std. dev.	Min	Max
2011	.106	.269	0	1
2012	.167	.313	0	1
2013	.270	.379	0	1
2014	.335	.416	0	1
2015	.351	.388	0	1
2016	.373	.392	0	0.99
2017	.378	.395	0	0.99
2018	.401	.402	0	0.99
2019	.430	.410	0	1
2020	.479	.402	0	1
2021	.495	.400	0	1
2022	.644	.359	0	1

Table 1: Descriptive statistics of FttH of municipalities in fraction of houses by year



(a) Deployment of fiber optics in 2011



(b) Deployment of fiber optics in 2022

Figure 1: Deployment of fiber optics for the start and endpoint of our dataset. Colors go from white (No homes with fiber optics) to dark red (80% to 100% of homes have fiber optics). Source: https://www.stratix.nl/glaskaart

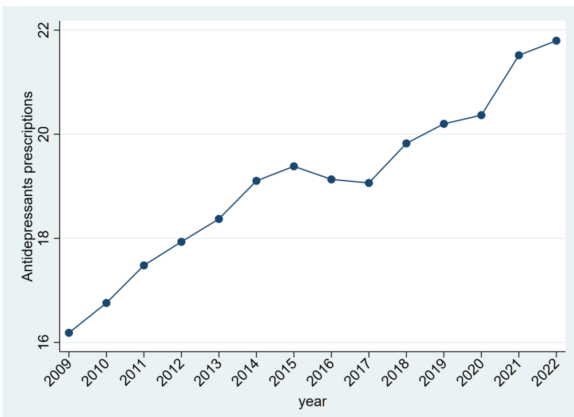
3.2 Medication usage

To assess the effect of FttH on mental health treatment, we make use of administrative data from all insurers to produce yearly data for all medications covered by basic insurance for the entire Dutch population. Using this data, we collect the medication usage of everyone ages 12 to 25 and aggregate this to the municipality level to obtain the fraction of the people ages 12-25 that take each medication for each municipality-year in our panel data. This data exists for the years 2009 to 2022, but we do not use the first two years for our analysis to match the fiber optics data.

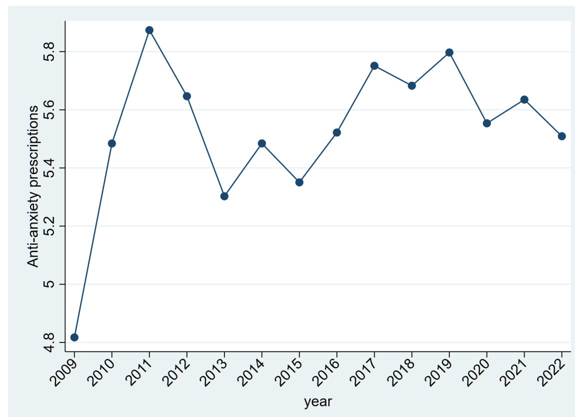
Medication data is given at the ATC4-level, meaning they are aggregated to the type of medication. In our analysis, we focus on four kinds of medication: Antidepressants

(N06A), Anti-anxiety medication (N05B), ADHD medications/Nootropics[11] (N06B), and anti-addiction medication (N07B). In addition to these mental health medications, we collect data on local antibiotics (D06A), beta blockers (C07A), single-corticosteroids (D07A), and general anesthetics (N01A) for placebo checks.

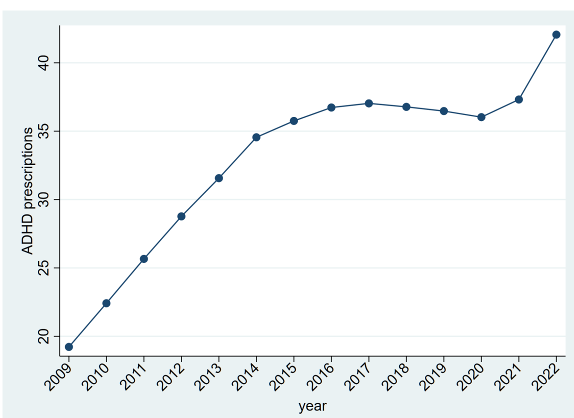
In Figure 2 we show the yearly means of the number of 12 to 25-year-olds of people being prescribed medication for our four mental health medications in Dutch municipalities. Values are given in use per 1000 people in our investigated age group. All medications show large increases, with antidepressant and anxiety medications going up by around 40% and 15% respectively between 2009 and 2022. ADHD prescriptions increase even more, more than doubling in this time period. Lastly, anti-addiction medications show significant increases, increasing almost threefold in our time period. However, this data is quite noisy, likely due to its low prevalence.



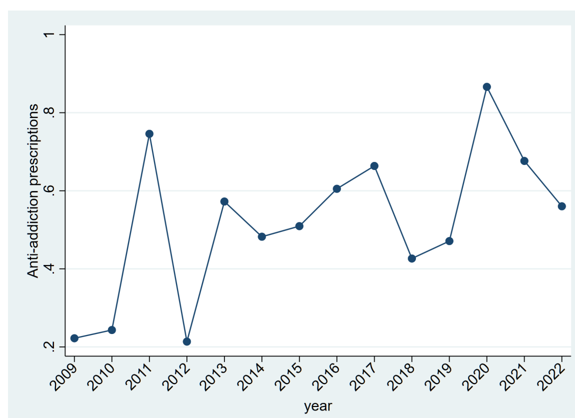
(a) Mean use of antidepressants



(b) Mean use of anti-anxiety medication



(c) Mean use of ADHD medication



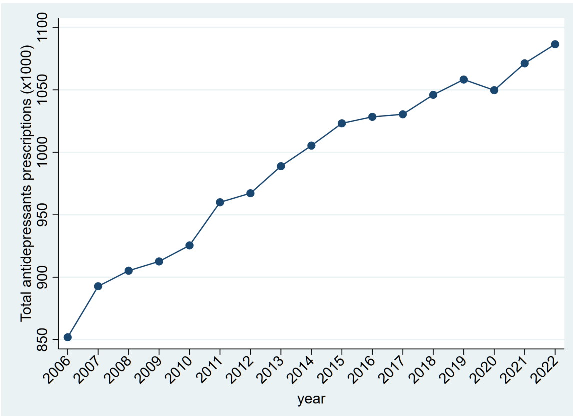
(d) Mean use of anti-addiction medication

Figure 2: Yearly mean of mental health medication use in Dutch municipalities per thousand in the sample.

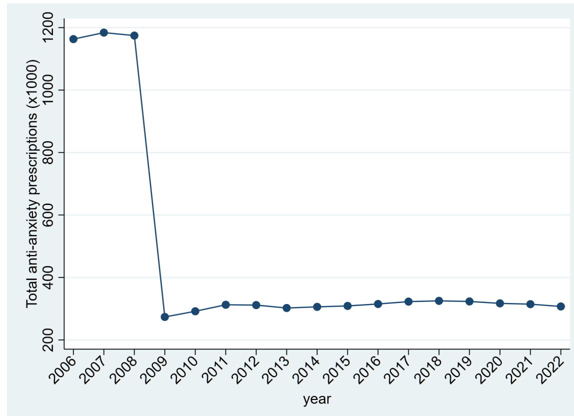
In Figure 3, we show the total number of prescriptions in the Netherlands from 2006 to 2022 for each medication. For anxiety medications, we see a large drop of 75% in 2009. In this

[11]Nootropics are also given for diseases causing cognitive decline, like dementia and Alzheimers. As these types of diseases are extremely rare for our sample of ages 12-25, we interpret this category as strictly use of ADHD medication.

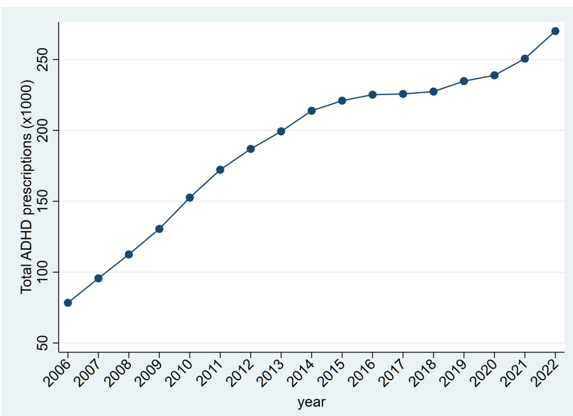
year, insurance of Benzodiazepines became significantly more restricted in attempt to stop misuse and can now only be prescribed for anxiety if there are no other viable alternatives. ADHD and anti-addiction medications, we see very similar trends to those of our 12-25 year old population. We also see a similar trend for antidepressants, with the exception that the growth is steeper for our population, only going by 19% between 2009 and 2022 compared to the 40% increase in our population, which is consistent with the literature discussed in Section 2.



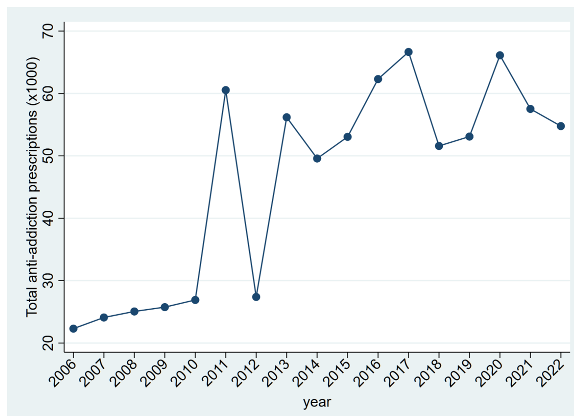
(a) Total prescriptions of antidepressants



(b) Total prescriptions of anti-anxiety medication



(c) Total prescriptions of ADHD medication



(d) Total prescriptions of addiction medication

Figure 3: Total prescriptions of mental health medications in the Netherlands

4 Methodology

In this Section we discuss the empirical strategy we use and the underlying assumptions. Next, we perform two balancing checks to assess these assumptions.

4.1 Medication use and fiber optics

We use a continuous staggered Difference-in-Difference approach to estimate the effect of access to fiber optics on usage of medication:

$$Y_{mt} = \beta FttH_{mt} + X'_{mt}\gamma + \pi_m t + \eta_m + \lambda_t + \epsilon_{mt} \tag{1}$$

Where m is the municipality and t the year. Y_{mt} is the fraction of peoples ages 12-25 to use the four mental health medications, $FttH_{mt}$ is the fraction of houses who have fiber optic connection. X_{mt} is a vector of covariates including variables on population (population density, total population, percentage of one person households or households with kids), income (average income, percentage of households earning near or below social minimum, number of households receiving disability or unemployment benefits) and availability of health care (average distance to a GP). It also includes age-gender bands containing the fraction of the sample for each combination of age and gender (e.g. fraction of our sample which are 12-year old males). $\pi_m t$ is the municipality specific linear trend, which compensates for possible differing trends in municipality specific unobservables. Lastly, η_m and λ_t are the municipality and time fixed effects and ϵ_{mt} is the error term clustered at the municipality level.

In our main specification, we consider the use of any mental health medication and for each of the four medications separately. In addition, we perform an heterogeneity analysis by running the regression separately for minors and adults and by gender. For these subsamples, the gender-age bands are adjusted to reflect to changing composition in the sample. We also run an heterogeneity analysis stratifying between new and existing prescriptions.

Callaway et al. (2024) show that for Equation 1 to give causal estimates, we need that strong parallel trend assumption holds. As we include municipality-specific linear trends, we allow for trends which are not parallel, as long as the difference in trends is linear. As Johnson and Persico (2024) point out, the strong parallel trend assumption also requires that a 1% increase in FttH should have the same effect on a municipality regardless of the base FttH rate. As a 1% increase in FttH signifies the same amount of households gaining fiber optics regardless of what the base level of that municipality is, this should in theory hold. Problems could arise however, households containing different numbers of 12 to 25-year-olds receive fiber optics at different times. To investigate this, we test whether differences in types of households, i.e. percentage of one-person households and households with kids, affect the deployment of fiber optics, the results of which we discuss below.

Additionally, as discussed in Section 2, the rollout of fiber optics is done by commercial companies and is thus subject to market forces. Because of this, estimates of Equation 1 would be biased if there are unobservable market forces which are municipality-specific, time-varying, that are not captured by the municipality specific linear trends and are correlated with medication use. Although we cannot test for this assumption, we show that important observable characteristics have little to no explanatory power on the rollout of fiber optics.

We might also be concerned that changes in the supply of healthcare during the period would bias our results. Notably, the 2015 law which moved the responsibility of psychiatric care for youths to the municipalities caused long wait times, which can affect the prescribing of mental health medications. Due to the lack of data on the wait times of psychiatric youth care for our time period, we cannot assess this directly. However, we show below that the rollout of fiber optics is not correlated to sociodemographic variables such as income, population, welfare dependency or distance to a hospital. It thus seems unlikely that the changes to the healthcare systems are correlated with the fiber optics rollout and thus should not affect our results.

4.2 Balancing checks

To check for possible bias in the deployment of fiber optics, we perform two balancing tests in the vein of Akerman et al. (2015) and Arenas-Arroyo et al. (2022). First, we assess whether municipalities experiencing different shocks in FttH have differences in their baseline variables. To assess this, we estimate whether increases in FttH can be explained by baseline covariates of the municipalities by running Equation 2:

$$\Delta FttH_{mt} = X'_{m,2011}\beta + \epsilon_{mt} \tag{2}$$

Where $\Delta FttH_{mt} = FttH_{mt} - FttH_{mt-1}$ is the increase in FttH and X_{2011} is a vector with the baseline covariates at the start of our sample in 2011: surface area, average income, population density, total population, percentage of one person households, percentage of households with kids, distance to a hospital, percentage of households earning around or below social minimum, and the number of households receiving disability or unemployment benefits. This regression is run separately for each year, the results of which are shown in Figure 4. For most variables, we see that they have no explanatory power to explain the rollout of fiber optics. However, the percentage of one person households and households with kids both have a positive and statistically significant for 2015 and 2016. If the types of households are relevant for how much fiber optics are deployed, this could suggest that the types of households receiving fiber optics are different, violating the strong parallel trends assumption. As they are not significant for the rest of the period, we do not believe this invalidates our results, although additional caution should be taken when interpreting the results.

Secondly, we regress FttH on the same covariates as Equation 2 together with municipality and time fixed effects as in Equation 3:

$$FttH_{mt} = X'_{mt}\beta + \pi_m + \lambda_t + \epsilon_{mt} \tag{3}$$

and find that time-invariant municipality and time fixed effects explain 81.96% of the variation, while the covariates only explain 2.69%, suggesting that the deployment of fiber optics is exogenous with respect to these key observables. However, we cannot exclude the possibility that there are unobservables which explain the variation in FttH. If these unobservables also correlate to medication use, are municipality specific, and time varying, our causal estimates will be biased. In order to mitigate this risk, we run a robustness test using non-mental health medication in Section 5.

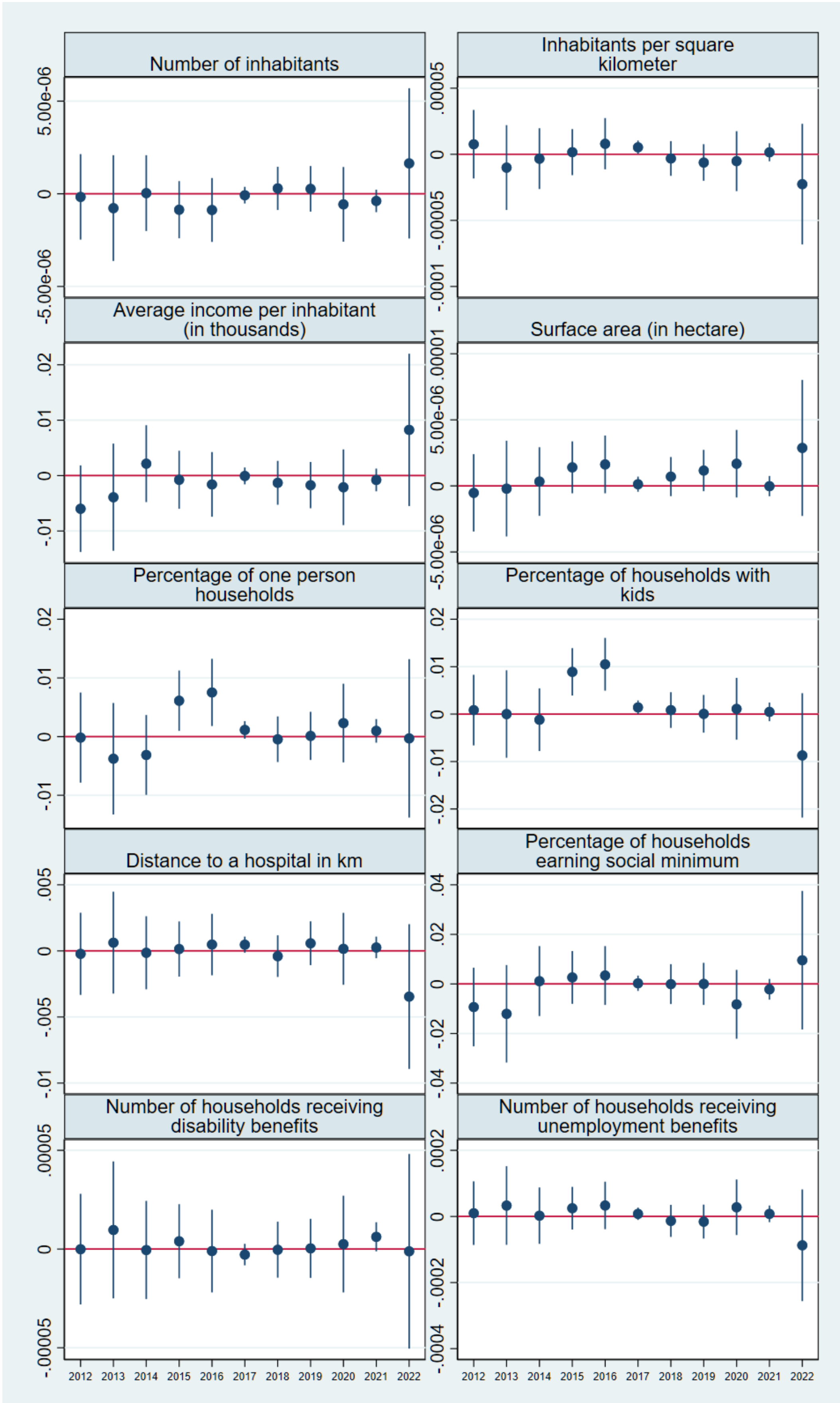


Figure 4: Box plots showing the effects with 95% confidence intervals of 2011 baseline covariates on the laying of fiber optics

5 Results

Here we present our main results and perform two heterogeneity analyses on both age and gender differences and differences between new and existing prescriptions. After this, we perform robustness checks on different ways of cleaning the data, a placebo test and the effect of the Covid-19 pandemic.

5.1 Main results

We present the results of our analysis in Table 5. The first column gives the effect on taking any mental health medication, where we see a positive but small and statistically insignificant effect. As the effect for the different kinds of illnesses, and thus medications, might be different, we also separate by types of medication. Doing this, we see positive effects for antidepressants and ADHD medications, and negative effects for anxiety and anti-addiction medications. However, none of them are statistically significant, suggesting that fiber optics have no effect on the prescription of mental health.

	Any medication	Antidepressants	Anxiety	ADHD	Addiction
FttH	0.308	0.438	-0.164	0.168	-0.071
	(0.637)	(0.363)	(0.205)	(0.511)	(0.076)
Mean	56.1	14.9	4.60	39.8	0.427
Relative effect	0.55%	2.94%	-3.57%	0.42%	-16.6%
N	3708	3708	3708	3708	3708

Table 2: Causal estimates of β in Equation 1, the effect of FttH on the number of people in the sample taking medication per thousand. Any medication gives the number of people taking any of the other four medications. Standard errors clustered at the municipality level in parentheses. Means and relevant effects of the dependant variable are given, with the relative effect showing the causal effect of going from no to full deployment of FttH.
* significant at 10%-level, ** significant at 5%-level, *** significant at 1%-level

As discussed in Section 2, males and females suffer from mental illnesses in different ways at different rates, and previous research finds that they are differently affected by access to internet. Similarly, there are medical and differences between minors and legal adults. For example, Jureidini et al. (2004) note that the side effects of antidepressants impose significant risk to minors, and recommend against prescribing it. Wender et al. (2001) discusses the differences in diagnosing and treating ADHD between children and adults.

We test whether these differences extend to medication usages by separating our data into four panels: males ages 18-25, females ages 18-25, males ages 12-17, and females ages 12-17, with our results presented in Table 3.

Looking at the differences between the groups, we see some expected differences. For example, we see that for antidepressants the effect on women is larger than those on men for both age categories. However, this is not the case for anti-anxiety and ADHD medications. Moreover, none of the effects are statistically significant, suggesting that there is not true effect for any age and gender group.

	Any medication	Antidepressants	Anxiety	ADHD	Addiction
Males 18-25					
FttH	-0.885	0.001	-0.024	-0.621	-0.114
	(1.058)	(0.623)	(0.339)	(0.749)	(0.153)
Females 18-25					
FttH	0.699	1.058	-0.551	-0.039	-0.073
	(1.139)	(1.02)	(0.454)	(0.72)	(0.18)
Males 12-17					
FttH	1.407	0.211	-0.329	1.738	0.003
	(1.617)	(0.329)	(0.417)	(1.745)	(0.036)
Females 12-17					
FttH	-0.026	0.468	0.089	-0.37	-0.032
	(1.21)	(0.606)	(0.264)	(0.892)	(0.047)

Table 3: Causal estimates of β in Equation 1, the effect of FttH on the number of people in each panel taking medication per thousand in the panel. Any medication gives the number of people taking any of the other four medications. Standard errors clustered at the municipality level in parentheses.
* significant at 10%-level, ** significant at 5%-level, *** significant at 1%-level

As discussed in Section 2, access to fiber optics can affect prescriptions in different ways. If access to fiber optics increases access to mental health information, we might expect different effects for first time prescriptions in contrast to continuation of existing prescriptions. We show our results separating new and existing prescriptions in Table 4. Here we see that the effect for new prescriptions is smaller than that for existing ones for all medications except anti-anxiety medications. All effects are still statistically insignificant however, suggesting that there is no difference between the two.

	Any medication	Antidepressants	Anxiety	ADHD	Addiction
New prescriptions	0.088	0.138	0.02	-0.07	-0.087
	(0.341)	(0.237)	(0.164)	(0.209)	(0.075)
Existing prescriptions	0.457	0.357	-0.089	0.264	0.006
	(0.642)	(0.287)	(0.113)	(0.54)	(0.022)

Table 4: Causal estimates of β in Equation 1, the effect of FttH on the number of people in the sample taking medication per thousand. Any medication gives the number of people taking any of the other four medications. Standard errors clustered at the municipality level in parentheses.
* significant at 10%-level, ** significant at 5%-level, *** significant at 1%-level

5.2 Robustness checks

5.2.1 Cleaning FttH data

One of the assumptions of our continuous DiD approach is monotonically increasing treatment. As discussed in Section 3, this does not strictly hold due to noise in our data, which could pose a treat to identification. To assess this threat, we rerun our main results using different ways of cleaning the data. In the first method, if a FttH drops, we set it to the previous value (upwards censoring). For the second method, we don't allow FttH to rise above the value of the coming year (downwards censoring). Additionally, we also try dropping all municipalities which have high noise, as defined by a drop of FttH by 10 percentage points or more, leaving us with 257 municipalities and 2844 municipality-years. We combine this with both upward and downward censoring for a total of five regressions, which we compare with our baseline in Table 5.

Effect sizes increase when the data is censored, but for downwards and upwards censoring. Additionally, effect size also increases when we drop the outliers. Effects remain statistically insignificant however, providing evidence that our results are not due to the noise in the data.

	Any medication	Antidepressants	Anxiety	ADHD	Addiction
Baseline	0.308	0.438	-0.164	0.168	-0.071
	(0.637)	(0.363)	(0.205)	(0.511)	(0.076)
(1)	0.441	0.506	-0.133	0.227	-0.036
	(0.758)	(0.414)	(0.229)	(0.63)	(0.077)
(2)	0.538	0.632	-0.281	0.302	-0.04
	(0.858)	(0.453)	(0.247)	(0.697)	(0.082)
(3)	0.889	0.695	-0.396	0.677	-0.031
	(0.933)	(0.524)	(0.274)	(0.778)	(0.093)
(4)	0.892	0.734	-0.375	0.631	-0.034
	(0.934)	(0.526)	(0.275)	(0.781)	(0.093)
(5)	0.994	0.726	-0.436	0.772	-0.037
	(0.998)	(0.557)	(0.291)	(0.825)	(0.096)

Table 5: Causal estimates of β in Equation 1, the effect of FttH on the number of people in the sample taking medication per thousand. Baseline gives the estimates from Table 2. Following rows are: (1) upwards censoring, (2) downward censoring, (3) dropping outliers, (4) Upward censoring and dropping outliers, (5) Downward censoring and dropping outliers. Any medication gives the number of people taking any of the other four medications. Standard errors clustered at the municipality level in parentheses. Means and relevant effects of the dependant variable are given, with the relative effect showing the causal effect of going from no to full deployment of FttH.
* significant at 10%-level, ** significant at 5%-level, *** significant at 1%-level

5.2.2 Placebos: other medications

To assess whether our estimates reflect true causal effects, we run our regression using four different medications for physical health: local antibiotics, beta blockers, single-corticosteroids, and general anesthetics. Care should be taken when considering results. As Amaral-Garcia et al. (2022) find that improved access to internet affects demand of physical care through information treatments, there are no medications for which we can be sure that there is no effect. However, demand for mental health care is not only influenced by the internet through an information treatment, but also has effects on the underlying mental health as discussed in Section 2. Thus, if we find an effect on non-mental health medications, while there is no effect for mental health medications, this could suggest there is an opposite effect on the underlying mental health which gets cancelled by the information treatment. Looking at the table however, we see very similar results as for our main analysis, with statistically insignificant effects for both the any of the medications and the medications individually. Thus, it seems unlikely that an underlying mental health effect is cancelled out.

	Any medication	Antibiotics	Beta blockers	Corticosteroids	Anesthetics
FttH	-1.237	0.068	-0.359	-1.311	-0.015
	(1.118)	(0.621)	(0.228)	(0.81)	(0.012)
N	3708	3708	3708	3708	3708

Table 6: Causal estimates of β in Equation 1, the effect of FttH on the number of people in the sample taking medication per thousand. Any medication gives the number of people taking any of the other four medications. Standard errors clustered at the municipality level in parentheses.
* significant at 10%-level, ** significant at 5%-level, *** significant at 1%-level

5.2.3 Dropping Covid

Fruehwirth et al. (2024) finds that social media had a negative effect the mental health of college students during the Covid-19 pandemic. As the pandemic caused a large shock in mental health and decreased possibilities for social contact, the effect of high-speed internet might be different during this time than before, which would affect our estimates. To assess this, we rerun our analysis dropping years 2020 to 2022 from our sample and present our results in Table 7. Dropping this period, we see that the effect of fiber optics increases somewhat, but the effect stays insignificant. Thus, our results are robust to the Covid-19 pandemic.

	Any medication	Antidepressants	Anxiety	ADHD	Addiction
FttH	-0.056	0.72	0.137	-0.565	-0.016
	(0.791)	(0.511)	(0.233)	(0.53)	(0.107)
N	2781	2781	2781	2781	2781

Table 7: Causal estimates of β in Equation 1, the effect of FttH on the number of people in the 2011-2019 subsample taking medication per thousand. Any medication gives the number of people taking any of the other four medications. Standard errors clustered at the municipality level in parentheses.
* significant at 10%-level, ** significant at 5%-level, *** significant at 1%-level

6 Conclusion

Mental health among youths and young adolescents has worsened substantially in the past two decades. Although evidence points to the internet and social media as contributing to this decline, little is known on how it affects treatment. In this study, we estimate the effect the roll-out of high-speed fiber optic internet has on the use of mental health medications among teens and adolescents. We find small and statistically insignificant effects, suggesting that the high-speed internet has no effect on the number of people who are prescribed mental health medications. This result continues to hold when separating by age gender groups, and when stratified by new and existing medications.

Research into the role of the internet on the mental health of youths is rapidly evolving area of research, which we contribute to in two important ways. Firstly, we add to the still limited body of research estimating causal effects on mental health outcomes. Secondly, we make use of administrative data from the Netherlands, allowing us to be the first to estimate the causal effect of high-speed internet on the use of mental health medications.

As there are multiple steps between having access to fiber optic internet and the prescription of mental health medications, there are two possible explanations for our results. Firstly, it could be that fiber optic access has no effect on any step of the process, which would imply that the association between social media usage and mental illnesses has not causal or only has reverse causality. Secondly, it could be that high-speed internet access does have a negative effect on mental health, but that is effect is cancelled out by either a reduction of people with mental health problems seeking professional treatment, or that these mental health problems are not treated with medication.

For future research, testing the effect of these steps in isolation, such as by testing the effect of fiber optic access on non-medication treatments, could provide valuable insights for how and whether fiber optics affect teens and adolescents. Additionally, our analysis only looks at the contemporaneous effects of fiber optics on medication use. Investigating the effect of having faster internet when growing up on one's mental health later in life could prove a fruitful and, to our knowledge, unexplored avenue of research.

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