

# **Connected and Distracted: The Impact of High-Speed Internet on ADHD Outcomes in the U.S.**

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# Connected and Distracted: The Impact of High-Speed Internet on ADHD Outcomes in the U.S

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## Abstract

I analyze the impact of high-speed internet connectivity on ADHD outcomes in the United States using county-level data from 2008 to 2023. Exploiting variation in the timing of broadband adoption, I employ two-way fixed effects models to estimate the effect of high-speed internet penetration on the demand for ADHD treatment drugs. I estimate that when counties surpassed 40% high-speed internet connectivity, total demand for ADHD medications increased by 1.14 percent, with amphetamine-based medications showing the highest increase at 2.45 percent. These effects are more pronounced in smaller counties. I also find some evidence of increased special education enrollment, though these effects are less consistent across specifications. Using the American Time Use Survey to investigate possible mechanisms, I find suggestive evidence that youth, particularly boys, spend more time with computers as their areas gain high-speed connectivity, although small sample sizes yield imprecise estimates. These results suggest that the expansion of digital infrastructure may have contributed to the rise of ADHD diagnoses, with implications for public health policy regarding the broader health effects of increased high-speed internet connectivity.

# 1 Introduction

The proliferation of high-speed internet has fundamentally reshaped how we allocate our time and conduct daily activities, with internet-connected devices becoming increasingly omnipresent across schools, homes, and workplaces. This digital transformation has created a complex landscape of opportunities and challenges for human development. While research demonstrates that internet access can improve educational outcomes and enhance human capital formation (Dettling et al., 2018; Grimes & Townsend, 2018; Zuo, 2021), emerging evidence simultaneously reveals concerning negative impacts on health and human development (Arenas-Arroyo et al., 2025; Colombo & Failache, 2023; Jain & Stemper, 2025). Early medical studies have begun to associate increased screen exposure and hyperstimulation with difficulties in concentration and learning disabilities such as Attention Deficit Hyperactivity Disorder (ADHD), with children who have greater exposure to television and video games showing higher rates of attention problems (Swing et al., 2010). Additional research has documented negative effects, including increased sedentary behavior, disrupted sleep patterns, and reduced face-to-face social interactions (Braghieri et al., 2022; Geraci et al., 2022; Twenge et al., 2018). As societies continue to integrate digital technologies into virtually every aspect of daily life, understanding these dual effects and their underlying mechanisms becomes critical for informing evidence-based policies and interventions.

In this paper, I document how access to high-speed internet affects the demand for ADHD treatment drugs and special education enrollment. Specifically, I leverage the expansion of high-speed internet connections (equal or greater than 10 Mbps) across U.S. households as a quasi-natural experiment to evaluate its impact on ADHD medication distribution and special education enrollment at the county level. The analysis draws on comprehensive data covering all U.S. counties from 2008 to 2023, allowing for a robust examination of how the growth in high-speed internet connections affects both the prevalence of attention-related disorders and the corresponding allocation of educational resources.

Understanding the relationship between high-speed internet access and ADHD out-

comes is relevant given the long-term consequences of attention disorders on individual life trajectories and broader societal well-being. High-speed internet fundamentally reshaped how we interact with technology, enabling seamless streaming, video sharing, and instant content consumption that was impossible with dial-up connections. This transformation created a dramatically more stimulating digital environment that may particularly impact our ability to concentrate and sustain attention. Fletcher (2014) demonstrates that childhood ADHD significantly impairs adult labor market outcomes, with affected individuals experiencing reduced employment rates, lower wages, and decreased occupational attainment throughout their careers. Similarly, Colombo and Failache (2023) provide evidence that exposure to high-speed internet during early childhood development can have lasting negative effects on cognitive and behavioral outcomes, underscoring how early digital exposure may create developmental deficits that persist into adulthood. Arenas-Arroyo et al. (2025) find that high-speed internet availability significantly widened the gender gap in adolescent mental health outcomes in Spain, with particularly pronounced negative effects on female teenagers' hospital admissions for mental health disorders. These findings collectively highlight the importance of recognizing that the increased stimulus and constant availability of engaging content enabled by high-speed internet, particularly during early developmental stages, can have profoundly detrimental effects on children's long-term well-being, mental health, and economic prospects.

I draw on several publicly available data sources to comprehensively analyze the relationship between broadband connectivity and ADHD-related outcomes over the period from 2008 to 2023. First, I utilize broadband connection data from the Federal Communications Commission (FCC) to track high-speed internet connectivity across U.S. counties. To measure ADHD prevalence and treatment, I employ the Drug Enforcement Administration's Automation of Reports and Consolidated Ordering System (DEA-ARCOS) dataset to track substances commonly used to treat ADHD at the county level. Finally, I incorporate educational data from the Common Core of Data (CCD) maintained by the National Center for Education Statistics for special education funding distribution and enrollment patterns.

To identify the effects of high-speed internet expansion on the demand for ADHD medication and special education outcomes, I estimate two-way fixed effects models to assess the impact of high-speed internet penetration, using variation in the timing of broadband adoption across geographic units. I complement this analysis using difference-in-differences imputation as proposed by Borusyak et al. (2024), which accounts for heterogeneous treatment effects and potential violations of parallel trends assumptions in staggered adoption settings. These estimation methods enable me to separate the effects of broadband connectivity from potentially confounding factors such as local economic conditions or demographic characteristics that might simultaneously influence both internet adoption and the outcomes of interest.

I find that when counties surpassed 40% high-speed internet adoption, total demand for ADHD medications increased by 1.14 percent, with amphetamine-based medications showing the highest increase at 2.45 percent. These effects are more pronounced in smaller counties. I also find some evidence of increased special education enrollment, though these effects are less robust than those observed for ADHD medications. Additional robustness checks using alternative specifications suggest that these effects are not driven by pre-existing trends or confounding factors.

To explore potential mechanisms, I use data from the American Time Use Survey to show that high-speed internet adoption from 2008 to 2023 coincided with substantial increases in computer time among young males aged 5-20 years, whose weekly computing and gaming rose from approximately 7.5 hours in 2008 to 17.5 hours in 2023. In contrast, adult men aged 31-55 years exhibited relatively stable computer usage throughout this period. High-speed connectivity enabled very different forms of technology use—such as immersive multiplayer gaming and HD video streaming—that were not feasible with basic internet access during the earlier 2000s when information about ADHD was already widely available.

These findings contribute to the existing literature on technology's impact on human development and mental health in two main ways. First, I provide a large-scale analysis of high-speed internet exposure on ADHD outcomes and special education enrollment at

the county level across the United States, addressing a gap in the empirical literature that has primarily relied on small-scale studies or cross-sectional analyses (Andrisano Ruggieri et al., 2024; Swing et al., 2010). Second, while most ADHD studies rely on survey data (Morrill, 2018) or hospital records (Arenas-Arroyo et al., 2025), my research design utilizes pharmaceutical distribution data that overcomes survey credibility concerns and captures cases that may not be severe enough to require hospitalization. This provides a more comprehensive measure of ADHD incidence across all age groups. Additionally, I provide suggestive evidence of changes in recreational habits that may be contributing to the increased prevalence of attention deficit disorders.

From a policy perspective, this work has significant implications for federal broadband infrastructure programs and their unintended consequences. The Connect America Fund (CAF) has allocated over \$10 billion over seven years to expand broadband infrastructure to underserved rural areas through various programs (Connect America Fund Phase II, Rural Digital Opportunity Fund, Alternative Connect America Cost Model). My findings corroborate concerns documented in the medical and epidemiological literature (Danielson et al., 2022, 2024): smaller and rural counties—precisely those that received the most substantial CAF investments—exhibited more pronounced increases in ADHD-related healthcare demand, if expanded digital access disproportionately affected ADHD prevalence in these communities, this points to a need for more coordinated approaches to digital infrastructure development that account for potential developmental and health costs alongside connectivity benefits.

The remainder of this paper is organized as follows. Section 2 describes the data sources and outlines the empirical strategy and identification approach. Section 3 presents the main results, and Section 4 examines alternative specifications and explores heterogeneity in treatment effects. Section 5 discusses potential mechanisms driving the observed effects, and Section 6 concludes with a summary of findings and discussion.

## 2 Empirical Framework

### 2.1 Data

This study draws on several publicly available data sources to comprehensively analyze the relationship between broadband connections and ADHD-related outcomes over the main analysis period from 2008 to 2023. To measure broadband connectivity, I utilize connection data from the Federal Communications Commission (FCC) to track high-speed internet connections across U.S. counties over time. Connections are measured at the county level by tiers from 0 to 5, where tier 1 represents fewer than 200 connections per 1,000 households and tier 5 represents more than 800 connections per 1,000 households. I use connections of 10 Megabits per second or greater to designate an area as having high-speed connectivity. This represents the minimum reasonable speed that allows users to engage in online streaming and play online games, and also helps resolve compatibility issues with FCC data across different reporting periods.

To capture ADHD-related outcomes, I employ the Drug Enforcement Administration's Automation of Reports and Consolidated Ordering System (DEA-ARCOS) dataset, which registers all controlled substances dispensed since 2006 at the three-digit zip code level. Specifically, I track substances commonly used to treat ADHD: amphetamine (Adderall), methylphenidate (Ritalin, Concerta), and lisdexamfetamine (Vyvanse). I use the Department of Housing and Urban Development (HUD) Crosswalk files to transpose these pharmaceutical dispensing values to the county level, enabling me to track ADHD medication prescriptions as a proxy for ADHD cases per county and year.

From the Common Core of Data (CCD) maintained by the National Center for Education Statistics, I obtain information on special education enrollment (Individualized Education Program) across school districts, which I aggregate to the county level. There are 13 disability categories recognized under the Individuals with Disabilities Education Act (IDEA) for an Individualized Education Program (IEP) are: autism spectrum disorder, deaf-blindness, deafness, emotional disturbance, hearing impairment, intellectual disability, multiple disabilities, orthopedic impairment, other health impairment, specific

learning disability, speech or language impairment, traumatic brain injury, and visual impairment.

ADHD is explicitly included as a condition that can make a child eligible for special education services under the "Other Health Impairment" (OHI) category of IDEA. However, not all children with ADHD qualify for special education services, as the condition must adversely affect educational performance. Children with ADHD may also qualify under other categories, including Specific Learning Disabilities (SLD) or Emotional Disturbance, depending on their unique characteristics and educational needs. Among students receiving special education services, specific learning disability is by far the most common category, representing approximately 32% of all students with IEPs, while other health impairments account for 15%. This distribution suggests that students with ADHD may be identified under multiple disability categories depending on their primary educational needs and the specific manifestation of their symptoms in the academic environment (CHADD, 2025; National Center for Education Statistics, 2023).

Additionally, I use data from the American Community Survey (ACS) at the county level for socio-demographic characteristics (population, income, education).

## 2.2 Background and National Trends

**A. High-Speed Internet Connections.** Figure 1 illustrates the dramatic expansion of high-speed internet access across U.S. counties from 2008 to 2023. The data shows a substantial increase in internet connectivity, with the population tier (representing the percentage of the population with access to high-speed internet) rising from approximately 1.2 (less than 20% coverage) in 2008 to 4.5 (80% or higher coverage) by 2023. The geographic distribution of this expansion is shown in the county-level maps presented in Figure 2, which reveal how internet access improved from sparse coverage in rural areas in 2008 to near-universal coverage by 2023. The internet evolution graph and maps demonstrate notable temporal and spatial variation in high-speed internet connections, supporting the use of an estimator with time and area fixed effects.

Figure 1: Evolution of High-Speed Internet Connectivity in the United States (2008-2023)

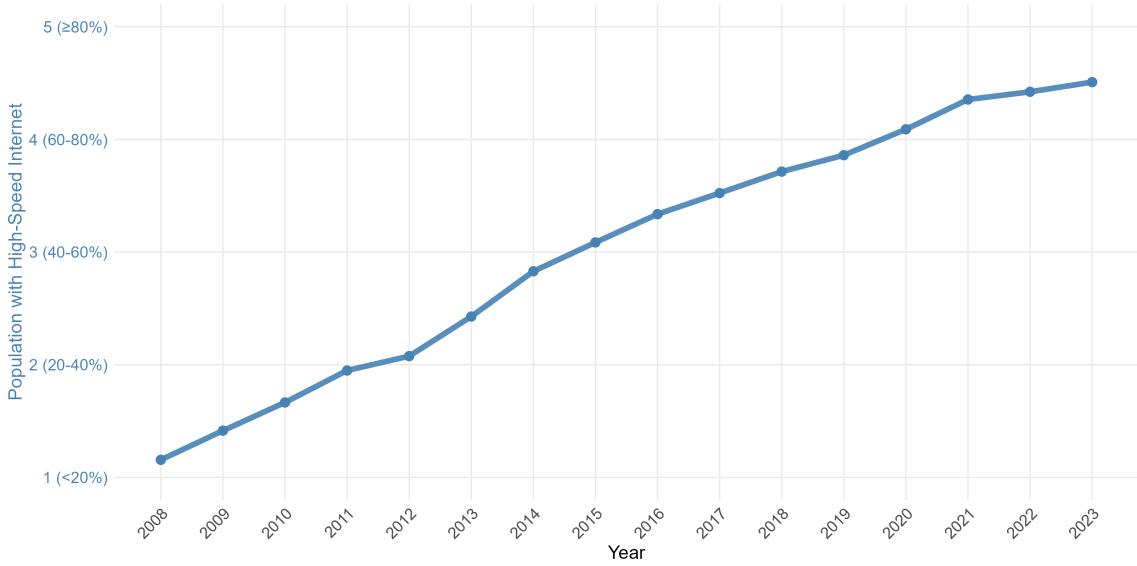
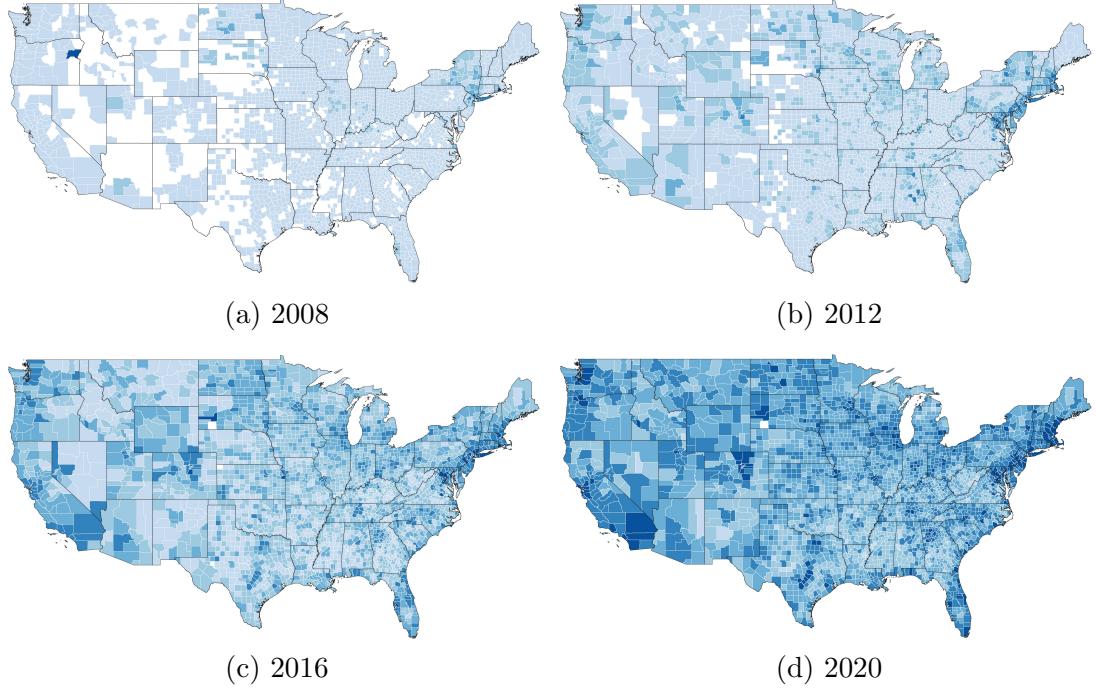


Figure 2: Geographic Distribution of High-Speed Internet Access by Year



*Note:* Darker blue shading indicates higher concentration of households with high-speed internet access.

**B. ADHD National Trends.** The prevalence of attention-deficit/hyperactivity disorder diagnoses among U.S. children has increased substantially over the past two decades. Data from the Centers for Disease Control and Prevention show that ADHD diagnoses among children aged 5-17 years rose from 6.9% in 1998-2000 to 11.4% in 2022

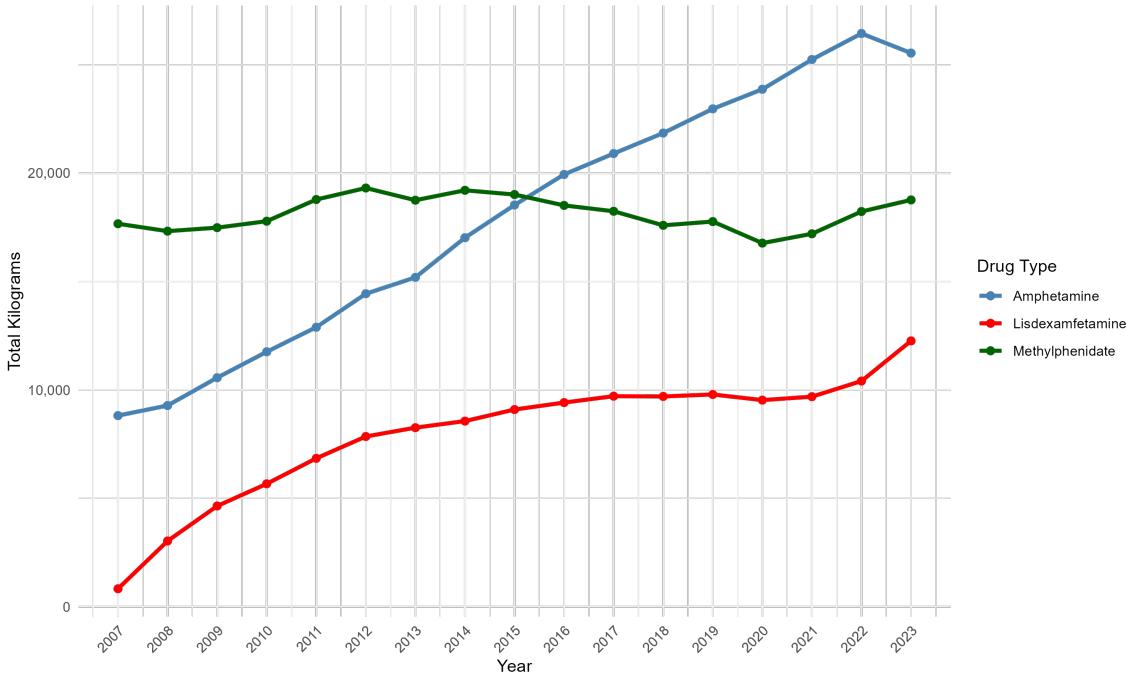
(Akinbami et al., 2011; Danielson et al., 2024), representing an approximate 65% increase. Rising ADHD diagnoses extend beyond childhood into young adulthood. Among adults aged 18-44 years, National Health Interview Survey data reveal that diagnosed ADHD prevalence increased from 0.9% in 1997-1998 to 4.0% in 2017-2018 (Chung et al., 2019). This fourfold increase was particularly pronounced among young adults aged 18-29, where prevalence rose from 0.7% to 4.3% over the same period. In addition, using the 2023 National Wellbeing Survey, London et al. (2025) show that among working-age adults (18-64 years), self-reported lifetime ADHD diagnosis prevalence has increased even more dramatically, rising from 4.25% in 2012 to an estimated 13.9% in 2023. This increase was evident across demographic groups, with particularly high rates among younger adults (20.9% among 18-29 year-olds).

This growth in ADHD prevalence appears to reflect substantial increases in diagnoses at the extensive margin of ADHD treatment, though this does not preclude concurrent changes at the intensive margin. Evidence from medication prescription data and national surveys indicates that the surge has been driven primarily by more children receiving initial diagnoses (Danielson et al., 2024). However, it is also worth noting that individuals with previously diagnosed mild ADHD symptoms who were not receiving pharmacological treatment may have initiated medication during this period due to aggravating circumstances or changing symptom severity, contributing to observed treatment increases.

An important limitation of existing ADHD surveillance data is that publicly available surveys of diagnosis trends are conducted at the national or state level. The most comprehensive data sources, the National Health Interview Survey and National Survey of Children's Health do not provide county-level estimates. This geographic aggregation prevents researchers from directly linking ADHD diagnosis patterns to local variation in high-speed internet adoption, in contrast to the county-level analysis possible with pharmaceutical distribution databases. Consequently, while I can document the temporal correlation between rising broadband and video technology and ADHD diagnoses nationally, establishing more granular geographic correspondence requires reliance on distribution data as a proxy for underlying trends in ADHD.

**C. ADHD medication distribution.** Figure 3 presents the national trends in ADHD medication distribution by drug type from 2007 to 2023. The data reveals distinct patterns across medication categories. Amphetamine-based medications show the most dramatic increase, rising from approximately 8,000 kilograms in 2007 to over 25,000 kilograms by 2022, representing more than a threefold increase. Lisdexamfetamine exhibits the steepest growth trajectory, starting from near zero in 2007 and reaching approximately 12,000 kilograms by 2023, reflecting its introduction to the market and subsequent rapid adoption. Methylphenidate distribution remained relatively stable throughout the period, fluctuating around 18,000-19,000 kilograms annually. These trends coincide with the period of internet expansion, providing the foundation for examining potential relationships between high-speed connectivity and medication demand patterns. Importantly, approximately half of diagnosed ADHD cases are treated with medication (Fletcher, 2014); therefore, the increase in real ADHD diagnoses due to internet use could be much higher than what medication distribution data alone suggests.

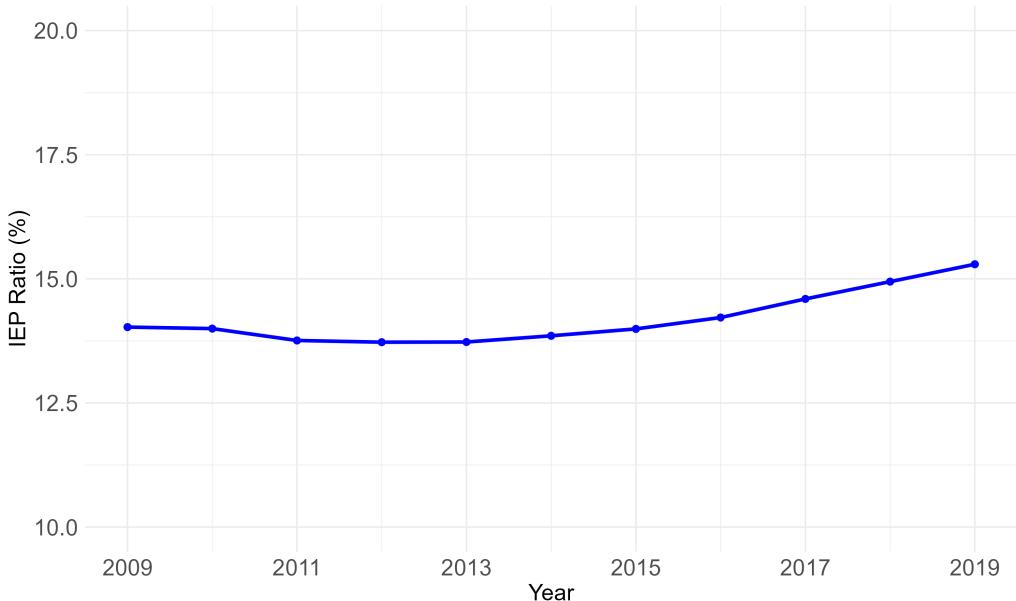
Figure 3: ADHD Medication Distribution Trends by Drug Type (2008-2023)



**D. Special Education Enrollment.** Although ADHD medication distribution increased significantly over the study period, the increase in special education identification

rates was less pronounced. Figure 4 shows the evolution of Individualized Education Program (IEP) ratios in the United States from 2009 to 2019, where IEP ratio represents the number of students receiving special education services divided by total enrollment. The data reveals a modestly increasing trend in special education identification rates over this period, with the national average rising from approximately 14.0% in 2009 to 15.2% in 2019. This U-shaped pattern may reflect policy changes, diagnostic improvements, or increased awareness of special education needs during this period. It is important to note that special education is a much broader umbrella category in which ADHD is included, and I do not have direct data on the number of ADHD-diagnosed students. However, Morrill (2018) indicates that a significant portion of special education needs stem from ADHD diagnoses. The analysis of special education outcomes covers a shorter time period than the ADHD medication analysis because publicly available data for special education ends in 2019.

Figure 4: Evolution of IEP Ratio in the United States (2009-2019)



To summarize, ADHD diagnoses grew concurrent with the expansion of high speed internet. These patterns are not evidence of a causal relationship on their own, so I turn to a two-way fixed effects approach to control for confounding trends and local characteristics that may be correlated with ADHD medications.

## 2.3 Econometric Approach

My baseline empirical strategy employs a two-way fixed effects (TWFE) model to estimate the effects of broadband expansion on ADHD and special education. The main specification is:

$$Y_{ct} = \alpha_c + \gamma_t + \beta \cdot HSI_{ct} + X'_{ct}\delta + \phi_1(f(t) \cdot \mathbf{Z}_c) + \epsilon_{ct} \quad (1)$$

where  $Y_{ct}$  represents the ADHD outcome variable for county  $c$  in year  $t$ . For medication demand,  $Y_{ct}$  is the natural logarithm of ADHD medication distribution from DEA-ARCOS data. For educational outcomes,  $Y_{ct}$  is the logarithm of special education enrollment from CCD.  $HSI_{ct}$  captures high-speed internet penetration ( $\geq 10$  Mbps) measured by the percent of connected households within each county.  $\alpha_c$  and  $\gamma_t$  are county and year fixed effects, respectively, and  $X_{ct}$  is a vector of time-varying county controls including demographic and socioeconomic measures (percent in poverty, median age, median income, percent with a college degree, and population for ADHD medication regressions or total enrollment for special education regressions). The vector  $\mathbf{Z}_c$  includes pre-adoption county-level characteristics measured at baseline (2007), and  $f(t)$  is a linear time trend.

This specification seeks to address threats to identification beyond time-invariant county characteristics and overall time trends (captured by county and year fixed effects) by including interactions between baseline county characteristics and linear time trends. This approach mitigates potential confounding from within-county time-varying factors that correlate with both internet expansion and ADHD outcomes, such as differential evolution of parenting behaviors or healthcare practices in counties with different socioeconomic profiles.(Caldarulo et al., 2023; Carruthers & Wanamaker, 2013; Hoynes & Schanzenbach, 2009).

I employ two estimation approaches to identify the effect of high-speed internet on the demand for ADHD treatment drugs. First, I use high-speed internet penetration as a discrete treatment measure in tiers from 0 to 5, where tier 1 represents less than 20%

of households with 10 Mbps connections, tier 2 represents between 20% and 40%, tier 3 between 40% and 60%, and so on. Second, I construct a binary treatment indicator for counties exceeding 40% high-speed penetration (tier 3 threshold).

The choice of tier 3 as the treatment threshold is motivated by theoretical and empirical considerations. First, when high-speed connection coverage approaches half of a county's housing units, the service has moved beyond early adopters to become broadly accessible to the general population, potentially creating network effects and widespread behavioral changes. Second, lower thresholds such as tier 1 may not provide sufficient time for internet connectivity to generate measurable effects on health outcomes. As the infrastructure and usage patterns may still be nascent at less than 20% coverage, and attention disorders require time to develop and manifest clinically. Achieving tier 3 penetration typically implies that high-speed internet has been present in that county for at least one to two years. Third, higher thresholds such as 80-100% coverage (tier 5) are fairly uncommon until late in the 2008 - 2023 panel. Additionally, the primary effects of high speed internet may have already been realized at that level of coverage, leaving little additional impact to detect.

To examine the dynamics of treatment effects of high-speed internet evolution on the outcomes of interest, I estimate an event study specification using the binary treatment measure. Given the staggered rollout of broadband infrastructure across counties and potential heterogeneous treatment effects, I use difference-in-differences imputation as proposed by Borusyak et al. (2024). This technique imputes weighted counterfactual outcomes for treated units using not-yet-treated or never-treated control units.

The approach offers several advantages over traditional two-way fixed effects event study designs. First, it avoids the negative weighting problems that can arise when treatment effects are heterogeneous across units or time (Goodman-Bacon, 2021; Sun & Abraham, 2021). Second, it provides more reliable inference by properly accounting for the uncertainty in the imputation process. Third, it allows for flexible modeling of treatment effect dynamics without imposing restrictive assumptions about parallel trends holding indefinitely into the future (Borusyak et al., 2024)

### 3 Results

Table 1 presents the baseline two-way fixed effects estimates examining the relationship between high-speed internet connectivity and total ADHD medication demand. The results reveal a small but positive and statistically significant relationship across both specifications.

Table 1: Two-Way Fixed Effects: High-Speed Internet and ADHD Treatment Demand

Log(Total ADHD Treatment Drugs Demand):		
	Discrete-Steps (0-5)	Discrete Treatment
	(1)	(2)
High Speed Internet	0.0085*** (0.0018)	0.0114*** (0.0026)
Observations	49,902	49,902
Controls	Yes	Yes
County & Year FE	Yes	Yes
Trend Interactions	Yes	Yes

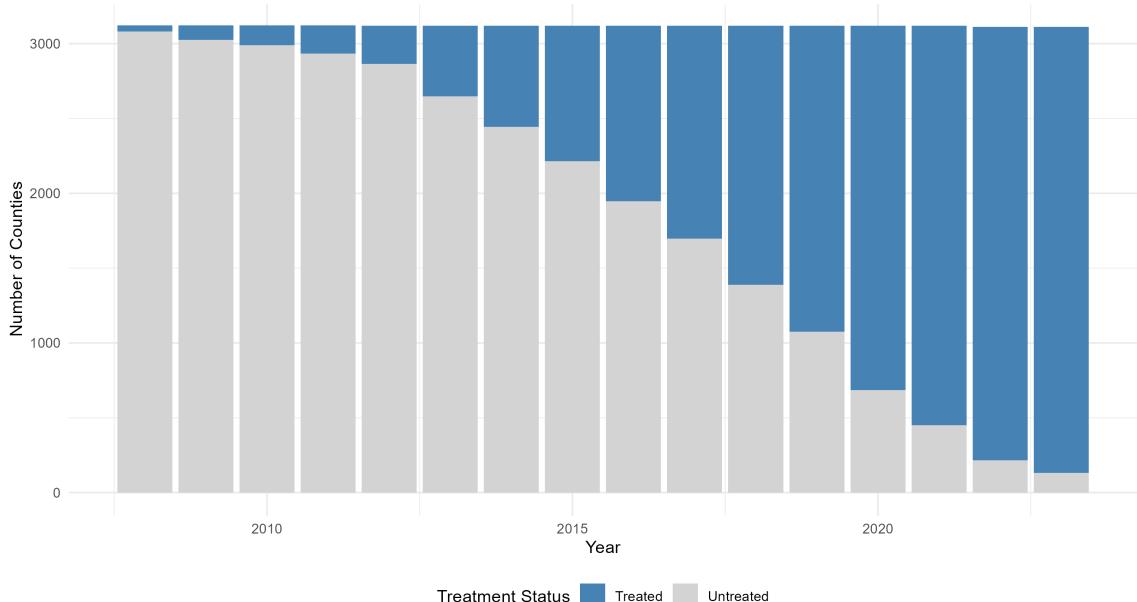
*Note:* Panel regressions with county and year fixed effects. Standard errors clustered at county level in parentheses. The dependent variable is log(ADHD drugs in grams) scaled by population. Trend interactions control for differential time trends based on 2007 baseline characteristics. Model 1: Multiple degrees of high-speed internet penetration (0-5 scale). Model 2: Binary treatment (1 if  $\text{internet10m} \geq 3$ , indicating  $>40\%$  of households in county  $i$  have 10 Mbps or greater internet connectivity). \*\*\*p<0.01

Model 1 employs a discrete-step measure of internet penetration using the FCC's tiered classification system (0-5 scale), where each tier represents progressively higher adoption rates ranging from fewer than 200 connections per 1,000 households (tier 1) to more than 800 connections per 1,000 households (tier 5). A one-unit increase in this penetration scale—representing approximately a 20% increase in connected households within a county—is associated with a 0.85 percent increase in the total ADHD medication demand. This graduated measure captures the incremental effects of expanding high-speed internet adoption as counties move through different adoption thresholds, suggesting that the relationship between connectivity and ADHD medication demand strengthens progressively with higher penetration rates. One potential explanation is that the tiered structure allows time for behavioral adaptations to take hold—as internet penetration increases gradually within a county, residents have extended exposure to new digital leisure

options, potentially allowing habits associated with online activities to form and intensify. The county-level measurement may also capture peer and network effects: as more households gain high-speed access and neighbors engage in online gaming, streaming, or social media, individuals may be increasingly drawn to adopt similar digital behaviors through social influence. This social diffusion of internet-based activities could amplify the observed relationship between connectivity and ADHD medication demand, as the shift in time allocation becomes reinforced through community-wide adoption patterns.

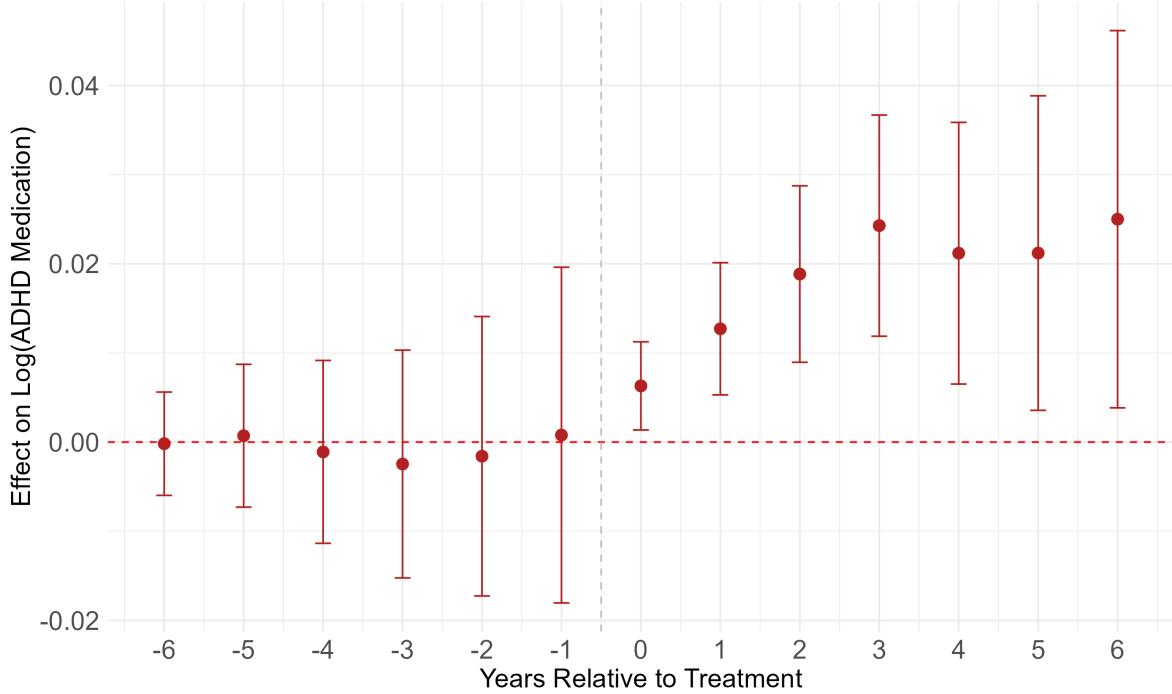
Model 2 employs a discrete-binary treatment approach, where the binary treatment indicator uses a threshold of tier 3 or higher, representing counties where at least 40% of housing units have access to high-speed internet connections (greater than 10Mbps). Figure 5 shows the evolution of treatment assignment over the study period, illustrating how the number of treated counties increased from 2008 to 2023. In 2008, most counties were classified as untreated (shown in gray), with only a small fraction meeting the high-speed internet threshold. The transition accelerated markedly around 2012-2016, with the majority of counties crossing the treatment threshold by 2020. The treatment effects in Model 2 show a significant increase in the demand for ADHD medications, with treatment associated with a 1.14 percent growth in medication distribution (also significant at the 1% level).

Figure 5: Number of Treated and Untreated Counties by Year



These findings may represent a lower bound of the true effect, as Fletcher (2014) states that for every medicated ADHD case, there is at least one additional case that was either not properly diagnosed or does not require medication, suggesting that the actual impact of high-speed internet on ADHD-related outcomes might be even larger than what medication distribution data alone captures. I continue to explore potential mechanisms underlying these effects in more detail in Section 5.

Figure 6: Event-Study Estimates - DID Imputation (Borusyak et al., 2024)



*Notes:* This figure displays event-study coefficients estimated using the Borusyak, Jaravel, and Spiess (2024) estimator. The dependent variable is  $\log(\text{ADHD prescription medication})$ . The x-axis represents years relative to treatment adoption, with period  $t = -1$  normalized to zero as the reference period. Point estimates are shown with 95% confidence intervals.

Figure 6 displays the dynamic effects of high-speed internet adoption using Borusyak et al. (2024) estimator. The pre-treatment coefficients are closely centered around zero, though some pre-treatment effects are imprecise but visible. As stated in the previous section, this is somewhat expected given that there is no clear-cut-off for high-speed internet adoption in this research design. I might start to see effects on the outcome before the county crosses the treated threshold, as internet penetration increases gradually rather than switching discretely from untreated to treated. The post-treatment effects show a clear upward trend, with treatment effects reaching its peak around year 3 after crossing

the threshold. Notably, the magnitude of the estimated effects using this estimator is approximately twice as large as those obtained from the standard TWFE estimation, suggesting that accounting for heterogeneous treatment effects and staggered adoption reveals stronger impacts.

This gradual increase suggests that the impact of high-speed internet on ADHD-related outcomes takes time to materialize, potentially reflecting behavioral and developmental mechanisms that compound over sustained exposure periods rather than generating purely contemporaneous effects. Changes in digital media consumption patterns, screen time exposure, and associated behavioral adaptations may require extended periods before manifesting in clinical diagnoses and measurable changes in medication demand.

Table 2: Two-Way Fixed Effects: High-Speed Internet and IEP Students

	Log(IEP Students)	
	Discrete Steps (0-5) (1)	Discrete Binary (2)
High Speed Internet	0.0083** (0.0042)	0.0110 (0.0076)
Observations	34,226	34,226
Controls	Yes	Yes
County & Year FE	Yes	Yes
Trend Interactions	Yes	Yes

*Note:* Panel regression with county and year fixed effects. Standard errors clustered at county level in parentheses. Controls for total enrollment, demographics, and income included but not shown. Trend interactions control for differential time trends based on 2007 baseline characteristics. Model 1: Multiple degrees of internet access (0-5 scale). Model 2: Binary treatment (1 if  $\text{internet10m} \geq 3$ ). Years 2009-2019.

\* $p < 0.10$ , \*\* $p < 0.05$

When I estimate the effect of high speed internet adoption on special education enrollment, I still find positive but more imprecise coefficients compared to ADHD medication demand. Table 2 presents results for special education enrollment using IEP enrollment as the dependent variable. In contrast to the ADHD medication results, I observe less robust significance of high-speed internet connectivity on special education identification rates. The discrete-steps specification (0-5 scale) yields a positive and statistically significant coefficient: a 20% increase in connected households is associated with a 0.83%

increase in special education enrollment. However, the binary treatment specification shows a larger but statistically insignificant effect. These more limited and imprecise results may be partially explained by the more constrained data availability for special education enrollment, which covers only the period from 2009-2019, compared to the longer time series available for ADHD medication data.

## 4 Alternative Specifications

To understand the robustness of my main findings and explore potential heterogeneity in the relationship between high-speed internet adoption and ADHD-related outcomes, I estimate several alternative specifications. First, I test whether the results are sensitive to alternative controls for differential time trends, including state-specific linear trends and year-specific interactions with baseline characteristics. Second, I examine the sensitivity of the findings to different high-speed internet penetration thresholds, demonstrating that the relationship holds across multiple definitions of treatment intensity. Third, I investigate heterogeneity by county population size to assess whether effects vary between rural and urban areas. Finally, I explore whether the overall increase in ADHD medication demand reflects broad changes across all therapeutic classes or is concentrated in specific drug types. These specifications provide a comprehensive assessment of the robustness and generalizability of the main results.

**A. Alternative Time-Trend Controls.** Following the approach in my main analysis, I try two alternative time trend specifications to control for within-county time-varying omitted variable bias. First, I add state-specific time trends to the baseline estimation, specifically, I estimate:

$$Y_{ct} = \alpha_c + \gamma_t + \beta \cdot HSI_{ct} + X'_{ct} \delta + \phi_1(f(t) \cdot \mathbf{Z}_c) + \theta_s \cdot f(t) + \epsilon_{ct} \quad (2)$$

where  $Y_{ct}$  represents ADHD medication demand for county  $c$  in year  $t$ ,  $HSI_{ct}$  captures high-speed internet penetration ( $\geq 10$  Mbps), and  $\alpha_c$ ,  $\gamma_t$ , and  $X_{ct}$  are county fixed effects, year fixed effects, and time-varying county controls, respectively. The vector  $\mathbf{Z}_c$  includes

pre-adoption county-level characteristics measured at baseline (2007),  $f(t)$  is a linear time trend, and  $\theta_s$  is a vector of state-specific dummies that allows each state to have its own linear time trend.

Second, I modify the baseline specification by replacing the linear trend interaction  $f(t) \cdot \mathbf{Z}_c$  with year-specific interactions, where baseline characteristics  $\mathbf{Z}_c$  are interacted with a set of year dummy variables rather than a linear trend function.

Table 3: Alternative Time-Trend Controls

	Discrete-Steps (0-5)		Discrete Treatment	
	(1) Baseline	(2) + State Trends	(3) Baseline	(4) + State Trends
<b>Panel A: State-Specific Linear Trends</b>				
High-Speed Internet	0.0085*** (0.0018)	0.0059*** (0.0016)	0.0114*** (0.0026)	0.0130*** (0.0022)
<b>Panel B: Year Dummies Interacted with Baseline Characteristics</b>				
High-Speed Internet	0.0060*** (0.0019)	0.0035** (0.0016)	0.0057** (0.0028)	0.0083*** (0.0024)
County & Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
State-specific trends	No	Yes	No	Yes
Observations	49,902	49,886	49,902	49,886

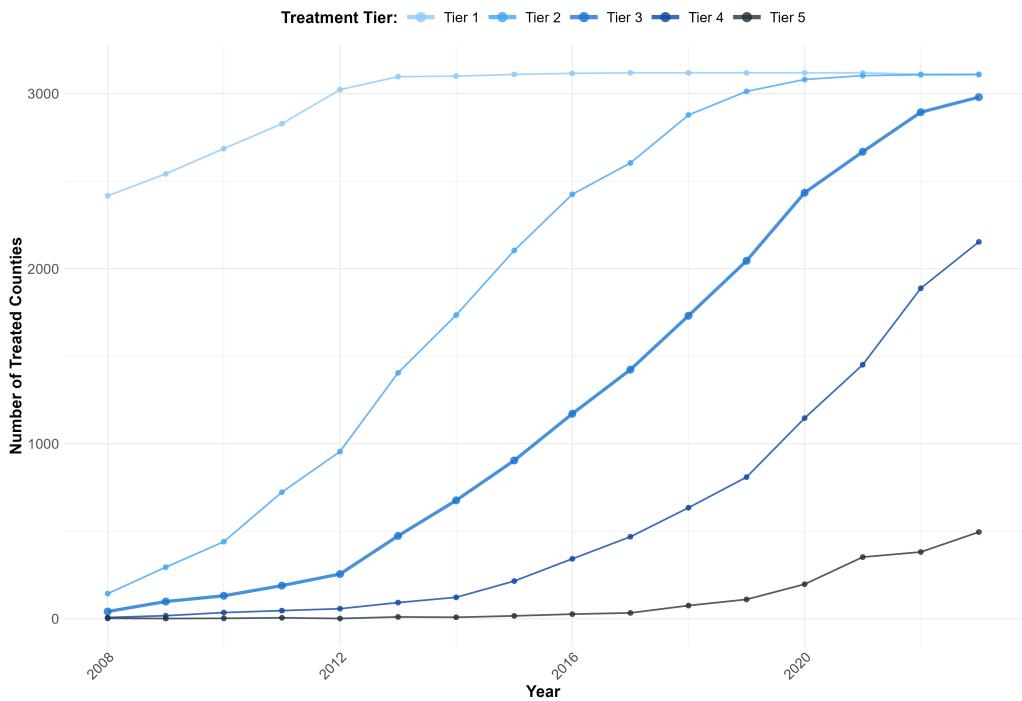
*Note:* Dependent variable is log(total ADHD drugs demand) at the county-year level. High-Speed Internet represents penetration of internet speeds  $\geq 10$  Mbps. In Panel A, discrete-steps (0-5) measures internet penetration on a 0-5 scale, while discrete treatment is an indicator equal to 1 if tier  $\geq 3$ , indicating  $>40\%$  of households in the county have 10 Mbps or greater internet connectivity. Panel B shows results when baseline county characteristics are interacted with year dummies instead of linear trends. All specifications include county and year fixed effects, plus time-varying county controls (median age, poverty rate, college degree rate, median income, log population). Standard errors clustered at the county level in parentheses. \* $p<0.10$ , \*\* $p<0.05$ , \*\*\* $p<0.01$ .

Table 3 demonstrates that the high-speed internet effects remain robust across both alternative specifications. In Panel A, when controlling for state-specific linear trends, the discrete-steps treatment effect decreases from 0.0085 to 0.0059, while the discrete treatment effect increases from 0.0114 to 0.0130. In Panel B, when using year dummies interacted with baseline characteristics instead of linear trends, the effects are smaller but still statistically significant: 0.0060 for the discrete specification and 0.0057 for the binary specification. The consistency of positive and significant coefficients across these

different trend specifications provides evidence that the main results are not driven by unobserved time-varying heterogeneity at the state or county level.

**B. Different High-Speed Internet Treatment Thresholds.** I also demonstrate the robustness of the main findings by examining treatment effects across various high-speed internet penetration thresholds, as shown in Figure 7 and Table 4. As previously discussed, tier 3 serves as the primary treatment threshold because it represents the point where high-speed internet transitions from early adoption to broad accessibility. The regression results reveal that the positive association between high-speed internet and ADHD drug demand is consistently observed across the middle-range thresholds (tiers 2, 3, and 4), all statistically significant and showing a monotonic increase in effect size as the threshold rises.

Figure 7: Counties Treatment Status per Tier-Threshold



**Notes:** Each line depicts the number of counties over time considered treated for the corresponding tier threshold. Tier 1 represents counties with 0–20% of households having 10+ Mbps connections, tier 2 represents 20–40%, tier 3 represents 40–60%, tier 4 represents 60–80%, and tier 5 represents counties with 80–100% of households having 10+ Mbps connections. Higher tiers indicate greater internet penetration ranges. The figure shows the temporal distribution of treatment adoption across different penetration levels, with tier 3 highlighted as the threshold used in the main specification.

The extreme thresholds provide limited analytical value due to variation constraints

Table 4: High-Speed Internet on ADHD Drug Demand by Different Thresholds

Treatment-Threshold	Log(Total County Grams of ADHD Treatment Drugs)					
	Tier $\geq 1$ (1)	Tier $\geq 2$ (2)	Tier $\geq 3$ (3)	Tier $\geq 4$ (4)	Tier $\geq 5$ (5)	Discrete-Steps (0-5) (6)
High-Speed Internet	-0.0141* (0.0062)	0.0067** (0.0025)	0.0114*** (0.0026)	0.0184*** (0.0031)	-0.0218*** (0.0065)	0.0085*** (0.0018)
County & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls & Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,902	49,902	49,902	49,902	49,902	49,902

Panel regressions with county and year fixed effects. Trend interactions control for differential time trends based on 2007 baseline characteristics. Standard errors clustered at county level in parentheses. Binary treatment models: 1 if  $\text{internet10m} \geq \text{threshold}$ , 0 otherwise. Continuous model: internet penetration on 0-5 scale. All models include controls for median age, poverty rate, college education rate, median income, log population, and their interactions with 2007 baseline characteristics. \* $p<0.05$ , \*\* $p<0.01$ , \*\*\* $p<0.001$ .

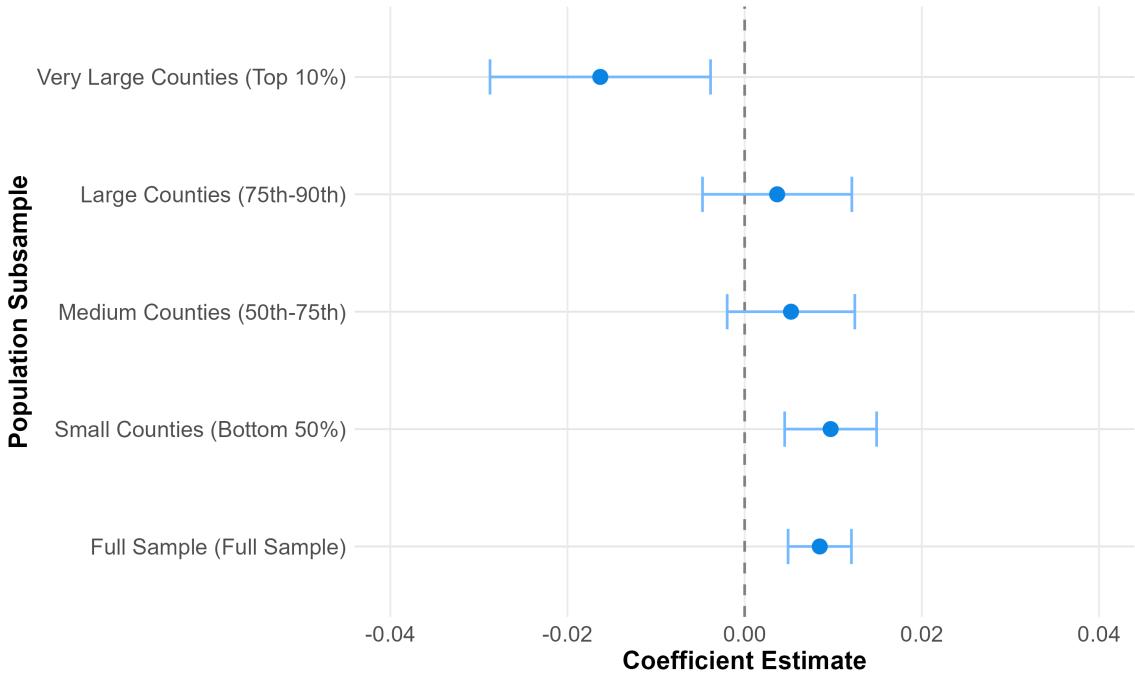
evident in the treatment distribution patterns. Tier 1 shows minimal variation early in the sample period, likely reflecting the nascent state of internet infrastructure, where effects have not yet materialized. Conversely, tier 5 demonstrates restricted variation throughout most of the observation period. The discrete-steps specification across all tiers confirms the overall positive relationship, supporting the choice of tier 3 as the optimal threshold that balances sufficient variation with meaningful treatment intensity.

**C. Heterogeneity by County Size.** To examine whether the effect of high-speed internet penetration on ADHD outcomes varies across counties of different sizes, I perform the same estimation exercise on mutually exclusive subsamples defined by county population. Small counties are defined as those below the median population, medium counties fall between the 50th and 75th percentiles, large counties span the 75th to 90th percentiles, and very large counties comprise the top 10% by population.

The estimates, presented in Figure 8, show that the estimated effect is larger for small counties, with the coefficient estimate centered around 0.015. As county size increases, the effect magnitude declines and becomes more imprecise. This pattern aligns with geographic variation in ADHD prevalence rates documented in the medical literature, where differences across rural and less densely populated areas have been observed (Danielson et al., 2022, 2024).

The variation documented here may reflect greater vulnerability to technology-related disruptions in rural and smaller counties following the expansion of high-speed internet.

Figure 8: Heterogeneity Analysis by County Population Size



One potential explanation is that youth in these areas may have had fewer recreational alternatives, leading to greater time allocation toward screen-based activities and gaming. I explore this mechanism in greater detail in the following section.

**D. Heterogeneity by ADHD Drug Type.** I investigate whether the increase in total ADHD medication demand was driven by a particular drug class or reflected broad changes across all medication types. To do so, I estimate separate models for: (i) amphetamine-based drugs (Adderall), (ii) lisdexamfetamine-based drugs (Vyvanse), and (iii) methylphenidate-based drugs (Ritalin, Concerta). Table 5 presents estimates for the discrete steps penetration measure (panel A) and binary treatment specification (panel B).

The results reveal heterogeneous effects across ADHD drug categories that reflect distinct patient populations for each drug class. Amphetamine-based medications (Adderall) show the largest response to internet penetration, with statistically significant coefficients of 0.0165 under the discrete steps specification and 0.0245 under the binary treatment specification (approximately 1.7 and 2.5 percent increases, respectively). This corresponds with Adderall's dominance among college students and young adults (Braghieri et al., 2022; IQVIA Institute for Human Data Science, 2024). Methylphenidate-based drugs

Table 5: High-Speed Internet and ADHD Medications by Drug Type

	Log(County-level ADHD Drug Grams)		
	Amphetamine (Adderall)	Lisdexamfetamine (Vyvanse)	Methylphenidate (Ritalin)
	(1)	(2)	(3)
<b>Panel A: Discrete Steps Specification</b>			
High-Speed Internet Penetration (0-5)	0.0165*** (0.0025)	0.0036 (0.0042)	0.0106*** (0.0020)
<b>Panel B: Binary Treatment Specification</b>			
High-Speed Internet Prevalence	0.0245*** (0.0036)	0.0019 (0.0063)	0.0150*** (0.0027)
County & Year FE	Yes	Yes	Yes
Controls & Time-Trends	Yes	Yes	Yes
Observations	49,902	49,902	49,902

*Note:* Panel regressions with county and year fixed effects. Standard errors clustered at county level in parentheses. Panel A uses continuous internet penetration measure (0-5 scale). Panel B uses binary treatment (Treatment = 1 if internet tier  $\geq 3$ , which means more than 40% of households have high-speed internet connectivity). Controls for demographics and time trends with baseline characteristics included but not shown. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1

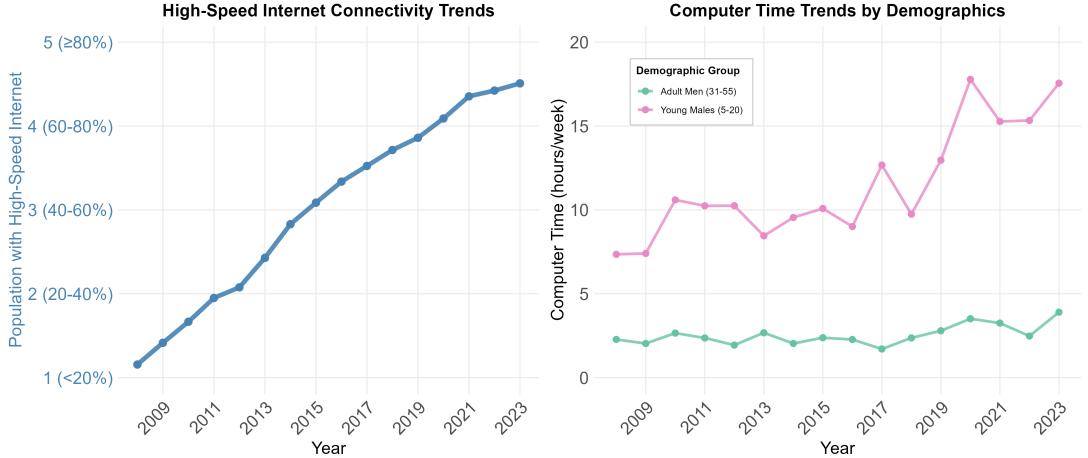
(Ritalin) also exhibit significant positive responses with coefficients of 0.0106 (discrete) and 0.0150 (binary), representing approximately 1.1 and 1.5 percent increases, respectively (Patel et al., 2024). This aligns with methylphenidate's continued widespread use in traditional pediatric populations aged 6 years and older. In contrast, lisdexamfetamine-based medications (Vyvanse) show smaller, statistically insignificant coefficients of 0.0036 (discrete) and 0.0019 (binary) across both specifications.

## 5 Suggestive Evidence on Mechanisms

**A. Leisure options and behavioral change.** Following the leisure-work research design proposed by Aguiar et al. (2021), I use the American Time Use Survey (ATUS) to display in Figure 9 a notable transformation in how young people allocate their time. High-speed internet adoption increased dramatically from 2008 to 2022, closely paralleling substantial increases in computer time among young males aged 5-20 years, whose weekly computing/gaming rose from approximately 7.5 hours in 2008 to 17.5 hours in 2023, an

increase of more than 130%. In contrast, adult men aged 31-55 years exhibited relatively stable and modest computer usage throughout the period, hovering around 2-3.5 hours per week with no clear upward trend.

Figure 9: High-Speed Internet Adoption and Computer Time by Age Group



*Notes:* High-speed internet adoption is tracked by the weighted tier index (blue line, left panel): tier 1 indicates less than 20% penetration, tier 2 indicates 20-40%, tier 3 indicates 40-60%, tier 4 indicates 60-80%, and tier 5 indicates greater than 80% penetration. Computer time (right panel) is measured in hours per week for young males aged 5-20 (pink line) and adult men aged 31-55 (green line).

I formalize this relationship in Table 6 using a TWFE regression of high-speed internet connectivity on computer time across demographic groups. Because ATUS does not provide county-level identifiers, I aggregate to the state level, controlling for state and year fixed effects and demographic characteristics. The coefficients on high-speed internet connectivity are positive across all groups, with point estimates for young males roughly double those for other demographic groups. While estimates are imprecise due to aggregation-induced sample size constraints, the pattern is consistent with high-speed internet primarily reshaping how young people spend their time.

This shift in recreational habits may have produced neurological and behavioral changes that could reduce capacity for sustained attention and concentration. Intensive exposure to the rapid-fire stimuli characteristic of online gaming, streaming video, and social media might alter neural pathways related to attention regulation and impulse control (Swing et al., 2010; Twenge et al., 2018). The developing brain's heightened neuroplasticity during childhood and adolescence makes this age group particularly sus-

Table 6: TWFE - High-Speed Internet and Computer Time Use

	Log(Avg Computer Time)		
	Young Males (5-20)	Adult Men (31-55)	All
	(1)	(2)	(3)
High Speed Internet Connectivity (0/5)	0.160 (0.202)	0.033 (0.108)	0.046 (0.060)
State & Year FE	Yes	Yes	Yes
Controls & Trends	Yes	Yes	Yes
Observations	699	810	812

*Note:* Panel regression with state and year fixed effects. Computer time averaged across demographic groups within each category. Computer time and total population are log-transformed. Trend interactions control for differential time trends by 2007 baseline characteristics. Standard errors clustered at state level in parentheses. Controls include: Median Age, Percent in Poverty, Percent College Degree, Median Income, and Log(Total Population).

ceptible to such environmental influences (Colombo & Failache, 2023). Consequently, the increased prevalence of ADHD diagnoses and medication demand may reflect, at least in part, changes in attention-related functioning potentially stemming from technology-mediated alterations in daily activities.

Building on this framework, I examine whether the effects of high-speed internet access vary across different time periods, recognizing that online gaming culture requires time to develop and depends on peer participation for sustained engagement. The hypothesis suggests that gaining high-speed internet access may have had progressively stronger effects on ADHD treatment demand in later periods, as gaming communities matured and online activities became more prevalent among youth. As Figure 9 illustrates, computing time among young people surged notably after 2016, suggesting that the behavioral impacts of internet access may have intensified over time as digital entertainment ecosystems became more sophisticated and engaging.

To test this temporal variation hypothesis, I estimate the following model that interacts high-speed internet access with distinct time periods:

$$\begin{aligned}
 \log(Y_{ct}) = & \alpha_c + \gamma_t + \beta_1 HSI_{ct} + \beta_2 HSI_{ct} \times \text{Period2}_t \\
 & + \beta_3 HSI_{ct} \times \text{Period3}_t + \beta_4 \text{Period2}_t + \beta_5 \text{Period3}_t \\
 & + \mathbf{X}'_{ct} \boldsymbol{\delta} + \mathbf{Z}'_{c,2007} \times t \boldsymbol{\phi} + \epsilon_{ct}
 \end{aligned} \tag{3}$$

where  $Y_{ct}$  represents total ADHD treatment drug demand in county  $c$  during year  $t$ ,  $HSI_{ct}$  is the high-speed internet access indicator,  $Period2_t$  and  $Period3_t$  are dummy variables for the periods 2014-2018 and 2019-2023 respectively (with 2008-2013 as the reference period),  $\mathbf{X}'_{ct}$  includes time-varying county controls,  $\mathbf{Z}'_{c,2007} \times t$  represents trend interactions based on 2007 baseline characteristics,  $\alpha_c$  and  $\gamma_t$  denote county and year fixed effects, and  $\epsilon_{ct}$  is the error term. The coefficients  $\beta_2$  and  $\beta_3$  capture the differential effects of high-speed internet access in the later periods relative to the baseline period.

Table 7: Time Period Sub Groups - Heterogeneous Treatment Effects

	Log(Total County ADHD Treatment Drugs Demand):	
	Discrete-Steps (0/5)	Discrete-Binary
	(1)	(2)
High-Speed Internet	0.0011 (0.0027)	-0.0011 (0.0052)
High-Speed Internet $\times$ Period 2 (2014-2018)	0.0097*** (0.0023)	0.0123** (0.0048)
High-Speed Internet $\times$ Period 3 (2019-2023)	0.0119*** (0.0036)	0.0188*** (0.0064)
Observations	49,902	49,902
Controls & Trends	Yes	Yes
County & Year FE	Yes	Yes

*Note:* Panel regression with county and year fixed effects using full sample. Standard errors clustered at county level in parentheses. Period 1: 2008-2013, Period 2: 2014-2018, Period 3: 2019-2023. Model 1 uses discrete-steps internet penetration (0-5 scale). Model 2 uses binary internet treatment indicator. Internet interactions show differential effects by time period. Time trends interactions control for differential trends based on 2007 baseline characteristics. \*\*p<0.05, \*\*\*p<0.01

The results in Table 7 support the temporal variation hypothesis. High-speed internet access had minimal effects during the initial period (2008-2013), with baseline coefficients close to zero and statistically insignificant. However, the interaction terms show progressively larger and more significant effects in later periods, with the strongest impacts emerging during 2019-2023. This temporal pattern aligns with the hypothesis that the behavioral impacts of high-speed internet connectivity strengthened as online gaming ecosystems matured and digital entertainment became more immersive among youth populations.

**B. Awareness/Information channel.** An alternative explanation for rising ADHD diagnoses might emphasize increased awareness and information access rather than gen-

uine behavioral changes. By 2008, major search engines and basic internet connectivity were widely available, enabling parents, teachers, and healthcare providers to research ADHD symptoms and treatment options. During this period, ADHD diagnoses had already increased substantially among children, coinciding with growing knowledge about the condition.

To examine whether the relationship between internet access and ADHD medication demand varies by connection speed, I estimate the same regression specifications using low-speed internet (200Kbps instead of 10Mbps) penetration as the treatment variable. This analysis uses low-speed internet connectivity as a proxy for information access provided by the internet to parents and healthcare providers, as these connections already allowed users to look up medical information and research ADHD symptoms. This approach addresses whether basic internet connectivity and information access alone drive changes in ADHD medication demand, or whether the relationship depends on high-speed connections that enable different types of digital engagement.

Table 8 presents regression results examining these differential effects across two analytical frameworks. Panel A estimate the effect of low-speed internet connectivity penetration on ADHD medication demand (instead of high-speed internet), while Panel B includes both high-speed and low-speed internet variables simultaneously. The results demonstrate that high-speed internet reveals a greater impact on ADHD medication demand in both magnitude and statistical precision compared to low-speed internet across both specifications, regardless of whether we include one or both internet treatment variables. For instance, high-speed internet coefficients (0.0077 and 0.0113) consistently exceed those of low-speed internet and maintain strong statistical significance, while low-speed internet shows smaller effects with weaker precision.

The differential effects between panels suggest that when accounting for high-speed internet availability, the additional contribution of low-speed connections becomes substantially diminished. While the evidence presented in this section cannot completely pin down all mechanisms, and both behavioral change and awareness channels might have played a role in the increased medication demand, the results provide suggestive

Table 8: Low-Speed Internet Penetration and ADHD Treatment Drug Demand

	Log(Total County ADHD Treatment Drugs Demand)	
	Discrete-Steps (0-5)	Discrete-Binary
	(1)	(2)
<b>Panel A: Low-Speed Internet Only</b>		
Low-Speed Internet	0.0060*** (0.0019)	-0.0027 (0.0033)
<b>Panel B: Both High-Speed and Low-Speed Internet</b>		
High-Speed Internet	0.0077*** (0.0018)	0.0113*** (0.0026)
Low-Speed Internet	0.0042** (0.0018)	-0.0019 (0.0033)
Observations	49,902	49,902
County & Year FE	Yes	Yes
Time-Trend & Controls	Yes	Yes

*Notes:* Panel regressions with county and year fixed effects. Trend interactions control for differential time trends based on 2007 baseline characteristics. Standard errors clustered at county level in parentheses. Column 1 shows continuous internet penetration (0-5 scale). Column 2 shows binary treatment indicators (1 if  $\geq 3$ ). High-speed internet refers to 10M+ connections; low-speed internet refers to 200k+ connections. All regressions include controls for median age, percent in poverty, percent college degree, median income, and log population. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

evidence that the behavioral change channel appears to have a heavier weight in driving this outcome compared to the information access channel alone.

## 6 Conclusion

I investigate the relationship between high-speed internet expansion and ADHD-related outcomes in the United States from 2008 to 2023, using comprehensive county-level data on pharmaceutical distribution, special education enrollment, and broadband connectivity. This research provides the first large-scale quasi-experimental analysis of how high-speed internet development may inadvertently impact attention-related disorders across diverse geographic contexts.

Using two-way fixed effects models with county and year fixed effects, I find that when counties surpassed 40% high-speed internet adoption, total demand for ADHD

medications increased by 1.14%. A multiple-discrete measure of internet penetration yields similar conclusions, with each tier increase associated with a 0.85 percent increase in medication demand. These estimates remain robust across alternative specifications, with coefficients ranging from 0.59% to 1.30%. Difference-in-differences Imputation estimator (Borusyak et al., 2024) that accounts for heterogeneous treatment effects yield effect magnitudes approximately twice as large, reinforcing the main findings.

When applying the same framework to special education enrollment, I observe a positive and statistically significant coefficient of 0.83% under the discrete-steps specification, while the binary treatment yields a larger but insignificant effect of 1.10%. These more limited results likely reflect the broader diagnostic scope of special education beyond ADHD, shorter data availability (2009-2019), and complex institutional factors, including state financial incentives and bureaucratic processes that distinguish educational classification from pharmaceutical records.

The effects are not driven by substitution between drug classes but reflect broad increases across therapeutic categories, with amphetamine-based medications (Adderall) showing the largest response (2.45%) and methylphenidate-based drugs exhibiting a 1.50% increase. The pronounced effect on Adderall aligns with its widespread adoption among college students and young adults, corroborating descriptive evidence from the National Health Interview Survey showing that youth populations experienced the greatest increases in new ADHD diagnoses during this period. Heterogeneity analysis reveals more pronounced effects in smaller counties.

Supplemental evidence from the American Time Use Survey reveals substantial increases in computer time among young males aged 5-20 years during the high-speed internet expansion period, with weekly computing and gaming rising from approximately 7.5 hours in 2008 to 17.5 hours in 2023—an increase exceeding 130%. TWFE regressions at the state level show that high-speed internet connectivity correlates positively with computer time across all demographic groups, with point estimates for young males roughly double those for other groups. However, given the imprecision in these estimates, this suggests that high-speed internet's effects may have operated primarily through changing

how young people allocate their time rather than through mechanisms affecting all age groups equally.

While increased awareness and information access represent potential explanatory mechanisms, several factors point toward behavioral and neurological changes as important contributors. The technological specificity of the observed effects—with high-speed connectivity showing distinct impacts compared to basic internet access—suggests qualitatively different patterns of use enabled by bandwidth-intensive applications. Supporting evidence from Uruguay (Colombo & Failache, 2023) and Spain (Arenas-Arroyo et al., 2025) indicates that high-speed internet exposure can adversely affect child development and adolescent mental health when parental supervision is limited. The gradual emergence of treatment effects over time, combined with dramatic increases in youth screen time, suggests that sustained behavioral changes drive a substantial portion of the documented increase in ADHD-related healthcare demand. Importantly, even if awareness plays a partial role, there are insufficient grounds to believe that awareness-driven diagnostic changes would systematically correlate with the timing and geographic pattern of high-speed internet adoption in ways that would confound the identification strategy.

These findings carry important policy implications for ongoing federal broadband expansion initiatives. While high-speed internet generates substantial benefits for education, economic opportunity, and social connectivity (Caldarulo et al., 2023; Dettling et al., 2018; Grimes & Townsend, 2018), this research highlights potential developmental costs that merit consideration in policy design. The Connect America Fund has allocated over \$10 billion to expand broadband to underserved rural areas—precisely the smaller counties where this study documents more pronounced increases in ADHD-related healthcare demand. Future broadband expansion policies might benefit from incorporating targeted interventions such as digital literacy education, parental guidance resources, and community programs that promote balanced technology use, particularly in areas with limited recreational alternatives for youth populations.

The study acknowledges some limitations that suggest directions for future research. County-level aggregation may mask important household and individual heterogeneity in

responses to internet connectivity. Administrative pharmaceutical data, while comprehensive, cannot capture undiagnosed cases or non-pharmaceutical treatment approaches. The observational research design, despite robust identification strategies, cannot definitively establish causal mechanisms. Future research employing individual-level longitudinal data could further illuminate these relationships and inform more targeted policy responses.

## References

Aguiar, M., Bils, M., Charles, K. K., & Hurst, E. (2021). Leisure luxuries and the labor supply of young men. *Journal of Political Economy*, 129(2), 337–382. <https://doi.org/10.1086/711916>

Akinbami, L. J., Liu, X., Pastor, P. N., & Reuben, C. A. (2011). Attention deficit hyperactivity disorder among children aged 5–17 years in the united states, 1998–2009. *NCHS Data Brief*, (70). <https://www.cdc.gov/nchs/products/databriefs/db70.htm>

Andrisano Ruggieri, R., Mollo, M., & Marra, G. (2024). Smartphone and tablet as digital babysitter. *Social Sciences (2076-0760)*, 13(8).

Arenas-Arroyo, E., Fernandez-Kranz, D., & Nollenberger, N. (2025). High speed internet and the widening gender gap in adolescent mental health: Evidence from spanish hospital records [Forthcoming]. *Journal of Health Economics*. <https://doi.org/10.1016/j.jhealeco.2025.103014>

Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting event study designs: Robust and efficient estimation. *Review of Economic Studies*, 91(5), 3253–3285. <https://doi.org/10.1093/restud/rdae007>

Braghieri, L., Levy, R., & Makarin, A. (2022). Social media and mental health. *American Economic Review*, 112(11), 3660–3693. <https://doi.org/10.1257/aer.20211218>

Caldarulo, M., Mossberger, K., & Howell, A. (2023). Community-wide broadband adoption and student academic achievement. *Telecommunications Policy*, 47, 102445. <https://doi.org/10.1016/j.telpol.2022.102445>

Carruthers, C. K., & Wanamaker, M. H. (2013). Closing the gap? the effect of private philanthropy on the provision of african-american schooling in the us south. *Journal of Public Economics*, 101, 53–67.

CHADD. (2025). *Individuals with disabilities education act*. Children and Adults with Attention-Deficit/Hyperactivity Disorder. Retrieved January 24, 2025, from <https://chadd.org/for-parents/individuals-with-disabilities-education-act/>

Chung, W., Jiang, S.-F., Paksarian, D., Nikolaidis, A., Castellanos, F. X., Merikangas, K. R., & Milham, M. P. (2019). Trends in the prevalence and incidence of attention-deficit/hyperactivity disorder among adults and children of different racial and ethnic groups. *JAMA Network Open*, 2(11), e1914344. <https://doi.org/10.1001/jamanetworkopen.2019.14344>

Colombo, K., & Failache, E. (2023, November). *Exposure to high-speed internet and early childhood development: Evidence from a countrywide program* (Working Paper No. 2023-01) (First version: January 19, 2023. This version: November 1, 2023). GEAR - Graduate Program in Applied Economic Research, Universitat Autònoma de Barcelona.

Danielson, M. L., Claussen, A. H., Bitsko, R. H., Holbrook, J. R., Charania, S. N., Haynie, D., Rohan, J. M., Rast, J. E., & Kaminski, J. W. (2024). Adhd prevalence among u.s. children and adolescents in 2022: Diagnosis, severity, co-occurring disorders, and treatment [Published online May 22, 2024]. *Journal of Clinical Child & Adolescent Psychology*. <https://doi.org/10.1080/15374416.2024.2335625>

Danielson, M. L., Holbrook, J. R., Bitsko, R. H., Newsome, K., Charania, S. N., McCord, R. F., Kogan, M. D., & Blumberg, S. J. (2022). State-level estimates of the prevalence of parent-reported adhd diagnosis and treatment among us children and adolescents, 2016 to 2019. *Journal of Attention Disorders*, 26(13), 1685–1697.

Dettling, L. J., Goodman, S., & Smith, J. (2018). Every little bit counts: The impact of high-speed internet on the transition to college. *The Review of Economics and Statistics*, 100(2), 260–273. [https://doi.org/10.1162/rest\\_a\\_00712](https://doi.org/10.1162/rest_a_00712)

Fletcher, J. M. (2014). The effects of childhood adhd on adult labor market outcomes. *Health Economics*, 23(2), 159–181. <https://doi.org/10.1002/hec.2907>

Geraci, A., Nardotto, M., Reggiani, T., & Sabatini, F. (2022). Broadband internet and social capital. *Journal of Public Economics*, 206, 104578.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277.

Grimes, A., & Townsend, W. (2018). Effects of (ultra-fast) fibre broadband on student achievement. *Information Economics and Policy*, 44, 8–15. <https://doi.org/10.1016/j.infoecopol.2018.06.001>

Hoynes, H. W., & Schanzenbach, D. W. (2009). Consumption responses to in-kind transfers: Evidence from the introduction of the food stamp program. *American Economic Journal: Applied Economics*, 1(4), 109–139. <https://doi.org/10.1257/app.1.4.109>

IQVIA Institute for Human Data Science. (2024). *Stimulant prescription trends in the united states from 2012–2023*. U.S. Drug Enforcement Administration. <https://www.deadiversion.usdoj.gov/pubs/docs/IQVIA-Report-on-Stimulant-Trends-2024.pdf>

Jain, R., & Stemper, S. (2025). 3g internet and human development. *Working Paper*.

London, A. S., Monnat, S. M., & Gutin, I. (2025). Self-reported ADHD diagnosis status among working-age adults in the United States: Evidence from the 2023 National Wellbeing Survey. *Journal of Attention Disorders*, 29(6), 399–410. <https://doi.org/10.1177/10870547251319861>

Morrill, M. S. (2018). Special education financing and adhd medications: A bitter pill to swallow. *Journal of Policy Analysis and Management*, 37(2), 384–402. <https://doi.org/10.1002/pam.22055>

National Center for Education Statistics. (2023). *Students with disabilities*. U.S. Department of Education. Retrieved October 13, 2023, from <https://nces.ed.gov/programs/coe/indicator/cgg/students-with-disabilities>

Patel, P., et al. (2024). Methylphenidate [Updated October 29, 2024]. In *Statpearls*. StatPearls Publishing. <https://www.ncbi.nlm.nih.gov/books/NBK482451/>

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199.

Swing, E. L., Gentile, D. A., Anderson, C. A., & Walsh, D. A. (2010). Television and video game exposure and the development of attention problems. *Pediatrics*, 126(2), 214–221. <https://doi.org/10.1542/peds.2009-1508>

Twenge, J. M., Martin, G. N., & Campbell, W. K. (2018). Decreases in psychological well-being among american adolescents after 2012 and links to screen time during the rise of smartphone technology. *Emotion, 18*(6), 765.

Zuo, G. W. (2021). Wired and hired: Employment effects of subsidized broadband internet for low-income americans. *American Economic Journal: Economic Policy, 13*(3), 447–482.