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County-Level Prevalence Estimates of ADHD in Children in the United States

Anja Zgodic, MS[1], **Alexander C. McLain, PhD**[1], **Jan M. Eberth, PhD**[1,2], **Alexis Federico**[3], **Jessica Bradshaw, PhD**[3], **Kate Flory, PhD**[3]

[1]Department of Epidemiology and Biostatistics, University of South Carolina, Columbia, SC.

[2]Rural and Minority Health Research Center, University of South Carolina, Columbia, SC.

[3]Department of Psychology, University of South Carolina, Columbia, SC.

Abstract

Background: Attention-deficit/hyperactivity disorder (ADHD) is a common childhood disorder often characterized by long-term impairments in family, academic, and social settings. Measuring the prevalence of ADHD is important as treatment options increase around the U.S. Prevalence data helps inform decisions by care providers, policy makers, and public health officials about allocating resources for ADHD. In addition, measuring geographic variation in prevalence estimates can facilitate hypothesis generation for future analytic work. Most U.S. studies of ADHD prevalence among children focus on national or demographic group rates.

Methods: Using a small area estimation approach and data from the 2016–2018 National Survey of Children's Health, we estimated childhood ADHD prevalence estimates at the census regional division, state, and county levels. The sample included approximately 70,000 children aged 5–17 years.

Results: The national ADHD rate was estimated to be 12.9% (95% Confidence Interval: 11.5%, 14.4%). Counties in the West South Central, East South Central, New England, and South Atlantic divisions had higher estimated rates of childhood ADHD (55.1%, 53.6%, 49.3%, and 46.2% of the counties had rates of 16% or greater, respectively) compared to counties in the Mountain, Mid Atlantic, West North Central, Pacific, and East North Central divisions (2.1%, 4.0%, 5.8%, 6.9%, and 11.7% of the counties had rates of 16% or greater, respectively).

Correspondence: Correspondence concerning this article should be addressed to: Anja Zgodic, Department of Epidemiology and Biostatistics, Arnold School of Public Health, University of South Carolina, Discovery Building, Office 419, 915 Green Street, Columbia, SC 29201, azgodic@email.sc.edu, Phone: 803 576 6054.

Author Contribution Statement

Drs. McLain and Eberth conceptualized and designed the study, and reviewed and revised the manuscript.

Dr. McLain, Dr. Eberth, and Ms. Zgodic conceptualized the data analysis plan and carried out the data analyses.

Dr. Flory, Dr. Bradshaw, and Ms. Federico contributed to data analytic design, critically reviewed the manuscript for important intellectual content, and reviewed and revised the manuscript.

Dr. Flory, Ms. Zgodic, and Ms. Federico drafted the initial manuscript, and reviewed and revised the manuscript.

All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

Conclusions: These local-level rates are useful for decision-makers to target programs and direct sufficient ADHD resources based upon communities' needs.

Keywords

Childhood Attention-Deficit/Hyperactivity Disorder; Prevalence; National Survey of Children's Health; County-Level; Small Area Estimation; Policy

Introduction

Attention-deficit/hyperactivity disorder (ADHD) is a common childhood disorder characterized by impairments in family, academic, and social settings (Visser SN et al., 2014; Hoare P, & Beattie T, 2003; Merrill R, Lyon J, Baker R, & Gren L, 2009). One-third of children with ADHD continue to face difficulties into adulthood (Barbaresi WJ et al., 2013). Adults with ADHD are at an increased risk for substance use disorder, reduced income, and unemployment (Fletcher JM, 2014; Groenman, AP, Janssen TWP, & Oosterlaan J, 2017). The economic impact of ADHD is large, costing the U.S. healthcare and education systems up to $69 billion annually (Doshi JA et al., 2012).

Prevalence data, along with other types of evidence, informs public awareness and decisions by care providers, policy makers, public health officials, and community and education administrators about allocating resources for ADHD (Wolraich ML et al., 2014; Holbrook JR, Bitsko RH, Danielson ML, & Visser SN, 2017). Measuring geographic variation in prevalence rates can also facilitate hypothesis generation for future analytic work. Most U.S. studies of ADHD prevalence among children focus on national rates, overall or stratified by sociodemographic group, and use robust population-based data sources such as the National Survey of Children's Health (NSCH). The most recent estimate of prevalence, measured in 2016 using the NSCH, indicated that 8.4% of U.S. children between 2 and 17 years of age had a parent-reported diagnosis of ADHD (Danielson ML et al., 2018).

While national rates are informative, there are several key benefits to estimating prevalence rates for smaller geographical areas. First, county-level prevalence estimates are particularly useful because they can reflect community-specific needs for ADHD resources, which can help guide resource allocation decisions along with other evidence. These resources can relate to ADHD identification, diagnosis, clinician training, and patient support or treatment. Second, local-level data are also beneficial to unmask differences that are not reflected through national or state-level prevalence statistics. Several studies have found higher ADHD prevalence for Black and Hispanic children (Fairman KA, Peckham AM, & Sclar DA, 2020) and that children facing socioeconomic hardship were more likely to have a diagnosis of ADHD (Russell AE, Ford T, & Russell G, 2015). Lower parental education has also been associated with increased risk of ADHD in children (Torvik FA et al., 2020). Accounting for differences in prevalence rates between diverse sociodemographic groups at the local level can provide more accurate information on within-community needs for ADHD services.

In nationally-representative surveys such as the NSCH, address and/or ZIP code data are often collected and can be used to label the geographic area of survey respondents

(United States Census Bureau, 2016). Sophisticated analytical approaches, such as small area estimation (SAE), can then be utilized to quantify geographic variability and to predict county-level prevalence rates (Cressie N, 1993; Banerjee S, Carlin B, & Gelfand A, 2004). The goal of an SAE model is to have an optimal mixture of flexibility, so that areas with large sample sizes can have predictions close to what one would estimate based on their data alone (i.e., direct estimates), and stability, so that predictions from areas with small sample sizes can borrow more heavily from the rest of the data. A drawback of national surveys is that they can reflect over- or underdiagnosis of health outcomes by providers. However, evidence reports that best practices in ADHD diagnosis are used by most providers and that prevalence estimates of parent-reported ADHD diagnosis align with estimates based on administrative claims data (Visser et al., 2013; Visser et al., 2015; Cree et al., 2022). Therefore, using large-scale survey data with SAE can approximate the true prevalence of ADHD.

The aim of this study is to use SAE to obtain updated prevalence rates of ADHD across all U.S. counties. Our predictions utilized NSCH data collected between 2016 and 2018 (n~70,000). We obtained county-level predictions using child-level covariate data, spatial information, and external county-level demographic data, analyzed using a spatial multilevel model with post-stratification (Eberth JM et al., 2018). To further understand the variability of ADHD rates, we also examined ADHD prevalence within various sociodemographic groups, nationally, and by regional division. In addition, through spatial clustering, we present the locations of areas with high or low prevalence (i.e., hot/cold spots) of ADHD.

Methods

Data Sources

The NSCH is a nationally representative survey focusing on the physical and emotional health of U.S. children. The survey, sponsored by the Health Resources and Services Administration (HRSA) and administered by the U.S. Census Bureau (USCB), targets households with children ages 0–17 years, and parents answer questions on behalf of their child. Within each state, households are randomly selected, and within each residence, one child is randomly selected (United States Census Bureau, 2016). The NSCH includes an 80% oversample of children with special needs (United States Census Bureau, 2016). The survey data is weighted to represent the population of non-institutionalized U.S. children aged 0 to 17 years, making study results generalizable nationally. For this study, we only included NSCH data for children aged 5–17 years to be consistent with most national prevalence studies of ADHD, and because ADHD is typically not diagnosed before children enter school (Centers for Disease Control and Prevention, 2013). We used the restricted 2016–2018 NSCH datasets to obtain geographic and child-level variables for our analyses.

For variables at the county, state, and regional division levels, we collected publicly available data from governmental institutions and research centers (Table A1 in Appendix). Our selection of child- and area-level variables was based on our research questions and a review of the existing literature (Russell AE, Ford T, & Russell G, 2015; Coker TR et al., 2016) pertaining to factors associated with ADHD.

Primary Outcome: ADHD Diagnosis

In the NSCH, parents were asked 'Has a doctor or other health care provider EVER told you that this child has Attention Deficit Disorder or Attention Deficit/Hyperactivity Disorder, that is, ADD or ADHD?' (Fairman KA, Peckham AM, & Sclar DA, 2020). We considered ADHD to be present if the parent indicated that the child had ever been diagnosed by a provider in the past, either currently or not currently.

Child-Level Predictors

The child-level variables considered were those where county-level populations and cross-tabulations were available. We tested race/ethnicity (Hispanic, Non-Hispanic white, Non-Hispanic Black, Multiracial/Other), biological sex (male, female), age, and highest educational attainment of a child's parent (less than high school, high school or General Educational Development [GED], some college, college or higher). We also identified if the child was part of the 2016, 2017, or 2018 NSCH dataset.

Area-Level Predictors

We included an extensive set of area-level variables in our analysis. These area-level variables included, but were not limited to: Census regional division, state bullying laws, state Medicaid expansion status, federal/state/county school funding, county child insurance rates, county rate of children living in single parent households (2015), number of primary care/pediatric providers per 100,000 residents in the county (2016), and county urban-rural designation based on 2013 Rural-Urban Continuum Codes [RUCC; indicator of urban (codes 1–3) or rural status (codes 4–9)]. Table A1 of the Appendix provides a complete list of area-level variables.

Statistical and Spatial Analysis

We calculated descriptive statistics for our sample using the public use data file, whereas the statistical models were performed on the restricted use dataset, in compliance with the USCB disclosure process. The two datasets were nearly identical; the only difference was the exclusion of two counties out of 3,143 with missing area-level covariate data. Data from children in these counties were included in the public use data but not in the models based on the restricted use data.

Multilevel SAE models typically use multilevel covariate data along with spatial random effects to allow areas with smaller sample sizes to borrow information from areas with larger sample sizes and stabilize predictions (Cressie N, 1993; Banerjee S, Carlin B, & Gelfand A, 2004). To this end, we fitted a multilevel mixed-effects logistic regression SAE model on child-level ADHD (yes/no) using child- and area-level covariate data. This model had a county-level random intercept that accounted for the spatial dependence between counties sharing a border using an Intrinsic Conditional Auto-Regressive (ICAR) structure (Cressie N, 1993; Banerjee S, Carlin B, & Gelfand A, 2004). Consistent with our goal of prediction, variable selection was based on forward selection using 5-fold cross-validated root mean squared prediction error (RMSPE) (Stone M, 1974, 1977; Allen DM, 1974). We accounted for the complex survey design by utilizing the survey weights (Carle AC, 2009; Goldstein H, 1991, 2010) provided by the NSCH, which we reweighted to have a mean of one within each survey year.

Since the SAE model is on the child level, it results in predicted ADHD prevalence rates for all 1,248 combinations (strata) of child-level predictors (4 race/ethnicity, 2 gender, 13 age, 4 parental education, and 3 survey years) for each county. We used post-stratification (Little RJ, 1993) to combine the strata-specific predictions for each county via a weighted sum; the weights correspond to the proportion of the county's population in a specific stratum. Strata population counts which were not publicly available were obtained using a multi-step approach where counts were modeled for available populations and adjusted based on the prevalence of the population of interest with missing counts (Zgodic *et al.*, 2021). Post-stratification ensures that the resulting estimates are consistent with each county's baseline demographics. Confidence intervals were estimated using the 2.5th and 97.5th percentiles of a sample of the county-predicted estimates obtained using a Monte Carlo parametric bootstrap (Efron B, & Tibshirani RJ, 1994; Buckland ST, 1984).

We also performed internal model validation by aggregating county-level estimates to the state level and comparing them to state-level direct estimates, which incorporated the NSCH complex sampling design. We compared the model-based and direct estimates using correlation and mean difference. Additionally, we compared state-level prevalence rates with the national prevalence rate within the bootstrap procedure by using t-tests with a False Discovery Rate correction applied to p-values. The model building was performed using SAS Software 9.4 (SAS Institute Inc, 2013) and the poststratification procedure using R 4.1.3 (R Core Team, 2014).

Choropleth maps were constructed to highlight county-level differences in parent-reported ADHD prevalence among children. We chose the natural breaks method (Jenks; De Smith MJ, Goodchild MF, & Longley P, 2007) with four cut-points: ≤11%, 12–15%, 16–19%, and ≥20%. To further explore spatial clustering of ADHD, optimized hot spot analysis was performed using ArcGIS Pro 2.0 (ESRI, 2011). The hot spot analysis performs statistical tests to identify concentrations of higher or lower parent-reported ADHD rates compared to neighboring areas.

Results

Table 1 shows the descriptive statistics of our sample. Out of 102,341 children in the 2016–2018 NSCH data, 70,913 were aged 5–17 years and had available covariate data. Less than 1% of excluded observations were due to missing covariate data. Over half of the children were non-Hispanic white (52.97%, weighted proportion), 24.15% were Hispanic, 12.68% were Non-Hispanic Black, and 10.20% were children of multiple or other races. Just over half (50.92%) of the sampled children were male and the average age was 11.65 years. Nearly half of the children (48.77%) had a parent with some college education, while approximately 20% of children had one parent who completed college (22.55%) or high school/GED (19.69%). Table A2 in the Appendix shows statistics by Census regional division.

Final model covariates included three county-level variables (number of primary care providers per 100,000 residents (2016), percent of single-parent households (2015), percentage of households speaking limited English (2016)), one state-level variable (presence of a state-mandated antibullying law (2018)), along with the child's age, main effects for child race/ethnicity, gender, highest parental education, and Census regional division, as well as several two-way interactions between the child-level predictors (Table A3 in the Appendix shows all model coefficients).

Table 2 shows the estimated parent-reported ADHD rates at the national and regional division levels, while Figure 1 shows a map of the estimated county-level ADHD rates. The national parent-reported ADHD rate was 12.9% (CI: 11.5%−14.4%). The South Atlantic division had the highest rate of 16.9% (CI: 14.5%−19.6%), while the Pacific division had the lowest with 9.5% (CI: 7.9%−11.5%). Counties in the West South Central, East South Central, New England, and South Atlantic divisions had higher estimated rates of childhood ADHD (55.1%, 53.6%, 49.3%, and 46.2% of the counties had rates of 16% or greater, respectively) compared to counties in the Mountain, Mid Atlantic, West North Central, Pacific, and East North Central divisions (2.1%, 4.0%, 5.8%, 6.9%, and 11.7% of the counties had rates of 16% or greater, respectively). Our model-based state-level ADHD estimates performed well compared to state-level direct estimates from the 2016–2018 NSCH public use files. The average (standard deviation) absolute difference between the estimates was 2.33% (1.38%) with high agreement (Pearson correlation = 0.88). On average, model-based estimates were higher than direct estimates.

Table 2 also shows parent-reported ADHD rates by various demographic groups for each regional division. Overall and by division, female children had lower ADHD rates than male children. Nationally and for all divisions except New England, South Atlantic, and East South Central, Non-Hispanic Black children had higher ADHD rates than white children. Similarly, Non-Hispanic white children had higher ADHD rates than Hispanic children and children of multiple/other races overall and for all divisions except Mid Atlantic. Finally, nationally as well as in more than half of the regional divisions (New England, East North Central, West North Central, South Atlantic, East South Central, Mountain), children who had a parent with a college degree had lower ADHD rates than children with parents in any other education group.

Figure 2 displays statistically significant clusters of high and low estimated parent-reported ADHD prevalence rates. The South Atlantic, East South Central, parts of West South Central, and New England regional divisions emerged as hot spots of ADHD. In contrast, nearly all the remaining regional divisions appeared as cold spots of ADHD. Table 3 shows state-level estimated ADHD rates for states with a rate significantly higher or lower than the national average. Mirroring Figure 2, all states with significantly higher rates than the national average were from the South Atlantic, East South Central, and West South-Central divisions. States with statistically lower rates were from the Pacific and Mid Atlantic divisions. Appendix Table A4 shows state-level estimated ADHD prevalence rates as well as direct estimates.

Discussion

In this study, we examined area-level parent-reported ADHD rates in U.S. children aged 5–17 years by applying small area estimation to data from the 2016–2018 National Survey of Child Health. SAE was combined with a post-stratification approach to ensure that predicted ADHD prevalence rates reflected the underlying distribution of children's sociodemographic characteristics within each county. To our knowledge, these are the most recent county-level estimates of parent-reported ADHD prevalence. In addition to area-level estimates, we produced ADHD rates for various sociodemographic groups of children, as previous studies identified disparities based on sociodemographic characteristics (Fairman KA, Peckham AM, & Sclar DA, 2020).

Our findings showed elevated parent-reported ADHD prevalence in non-metropolitan areas of the U.S. including the Mississippi Delta, the Appalachian region, and pockets throughout the Deep South, Texas, Florida, Maine, New Hampshire, and Vermont. Previous studies have also identified non-metropolitan areas as experiencing 18–30% higher odds of ADHD diagnosis than metropolitan areas (Danielson ML et al., 2018; Cuffe SP, Moore CG, & McKeown RE, 2005). These statistics align with previous findings that the risk for child mental health problems in general is higher in rural areas than in urban or suburban areas (Lenardson JD et al., 2010). One potential explanation is the higher burden of exposure to adverse childhood experiences (ACEs; e.g., child abuse and neglect) by youth living in rural areas (Calthorpe LM, & Pantell MS, 2021). Greater ACEs have been associated with a myriad of child and adolescent mental health problems and deleterious outcomes (Schilling EA, Aseltine RH, & Gore S, 2007). Lower socioeconomic status among individuals living in rural areas (Anderson MS et al., 2013) may also be related to higher ADHD prevalence This could be further compounded by the limited availability of behavioral health treatment resources and medical specialists in rural settings (Kelleher KJ, & Gardner W, 2017).Our analyses identified most of the Southeastern U.S., Maine, and most of New Hampshire and Vermont as parent-reported ADHD hot spots. In addition, all states identified as having rates statistically higher than the national parent-reported ADHD rate were in the Southeast. Others have also identified the Southeastern U.S. as an area where children have increased odds of receiving an ADHD diagnosis (Danielson ML et al., 2018). It is likely that socioeconomic risk factors may again help explain these regional disparities in ADHD prevalence. Also, the most recent prior research on national prevalence rates of parent-reported ADHD (Danielson ML et al., 2018) revealed that the proportion of Black children who received an ADHD diagnosis was higher than for white children, which may help to explain prevalence differences by geographic region. However, there is also research suggesting that Black children may be underdiagnosed with ADHD (Moody M, 2016).

Geographical differences may also originate from discrepancies between ratings of ADHD symptoms between parents and teachers, where teachers rated non-white children's ADHD symptoms higher than the symptoms of white children (Harvey AE et al., 2013; Lau AS et al., 2004; Kang S, & Harvey EA, 2020; DuPaul GJ et al., 2016). Another aspect of regional differences concerns access to a robust public health or healthcare system to diagnose ADHD in children. It has been hypothesized that the estimated prevalence of ADHD may be more closely aligned with the level of resources in a region than the underlying true prevalence of ADHD (Madsen, KB, et al., 2015). For example, one study (Fulton BD et al., 2009) found that a child having a diagnosis of ADHD or taking medications for ADHD was associated with the number, age, and type of physicians within a state, particularly pediatricians. This hypothesized alignment should be further investigated.

A state-level mandate for anti-bullying laws was predictive of parent-reported ADHD status in our model. This prompted our research team to conduct a search for state-level policies that could explain area-level differences in ADHD prevalence, but no consistent pattern of policies was identified. Related research (Fulton BD et al., 2009) found that state-level school accountability policies were not associated with ADHD diagnosis.

One strength of our SAE approach is that it incorporates additional sources of data as well as spatial components that provide more accurate predictions of parent-reported ADHD prevalence rates and thus can bridge the gap between prevalence estimates and case identification estimates, which are often difficult to reconcile (Song M, Dieckmann NF, & Nigg JT, 2019). In addition, SAE allows for robust estimates even for small counties, since it leverages information from neighboring counties with more data. The post-stratification procedure ensures that the prevalence estimates reflect each county’s underlying demographic distribution. Visualizations of the results highlight precise areas and groups of people which may need additional resources to combat ADHD.

A limitation of the current study is that ADHD diagnosis was parent-reported. It is important to recognize that some healthcare providers assign a diagnosis of ADHD and/or prescribe ADHD medications without conducting an evidence-based evaluation of the disorder following best-practice guidelines (Wolraich et al., 2019). This may lead to a parent reporting that an ADHD diagnosis is present when in fact it was not properly diagnosed, thus potentially resulting in an over-reporting of ADHD diagnosis. In addition, a parent may have difficulty recollecting if a child was previously diagnosed with ADHD, leading to the potential for recall bias (Miller CJ, Newcorn JH, & Halperin JM, 2010). However, studies have found a high agreement between parent-report ADHD status of children and the gold standard diagnostic procedure including a diagnostic interview conducted with parents along with teacher report of ADHD symptoms, specifically using the NSCH and the National Survey of the Diagnosis and Treatment of ADHD and Tourette Syndrome (NS-DATA; Cree et al., in press; Visser et al., 2013). Therefore, despite some potential limitations of using only parent-reported ADHD status, a data source such as NSCH combined with advanced analytic methods is expected to accurately reflect the prevalence of clinically diagnosed ADHD in U.S. children. A meta-analysis recently found a few studies reporting ADHD overdiagnosis (Kazda et al., 2021). For areas covered by these studies, our results can still inform resource allocation towards clinician training and education on best practices for ADHD diagnosis. An additional limitation of our study is the absence of some relevant ADHD-related predictors that may relate to prevalence rates of the disorder, for instance, additional comorbid conditions, adherence to medication regimens, and quality of providers in the area.

This research has important implications for public health practice and policy. Small area estimates of ADHD prevalence allow for more precise identification of areas in potential need of resources for ADHD diagnosis and treatment. In areas with suspected over/under diagnosis, resources may be allocated towards clinician training on the gold standard practices for ADHD diagnoses. In U.S. areas (e.g., rural areas, Southeast) and populations (e.g., individuals with lower socioeconomic status) with markedly higher rates of ADHD, resources may be allocated to support and treat children with ADHD. This information can be used by policymakers and public health officials to determine which geographic areas and sociodemographic groups need this additional programming, funding, or other resources. The results from this study can also be used by county- and state-level officials to create strategic plans, trainings, toolkits, and other resources to systematically assess and treat children with ADHD across the U.S.

Findings also highlight the importance of appropriate diagnosis of ADHD in youth. As noted, some healthcare providers assign an ADHD diagnosis without following best practices in evidence-based ADHD evaluation (Martel MM et al., 2015). It is possible that inaccurate diagnoses on the part of the provider led to a false positive report of parent-reported ADHD on this survey. Thus, widespread training of healthcare providers in the appropriate diagnosis of ADHD may reduce the number of children with inaccurate parent-reported ADHD diagnoses. In addition, state-wide policies to govern when ADHD medications can be prescribed (i.e., only after a diagnosis through an evidence-based evaluation) may also reduce ADHD diagnoses at the state level.

Future research includes sanalyzing the impact of symptoms or risk factors on the odds of ADHD diagnosis and considering additional predictors for inclusion in the statistical model. Additionally, conducting a similar analysis on data sources where ADHD diagnosis is established by gold standard diagnostic procedures and contrasting this with results obtained from using a large national database could provide more insights into communities that truly need additional resources and policies to support children with ADHD. A final area of research may concern underdiagnosis and the impact it has on the parent-reported ADHD prevalence estimates in counties where less resources or providers are available.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Competing Interests Statement

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Abbreviations:

ADHD	Attention-Deficit/Hyperactivity Disorder
NSCH	National Survey of Children's Health
SAE	Small Area Estimation
HRSA	Health Resources and Services Administration
ADD	Attention Deficit Disorder
GED	General Educational Development
RUCC	Rural-Urban Continuum Codes
ICAR	Intrinsic Conditional Auto-Regressive
RMSPE	root mean squared prediction error
ACEs	adverse childhood experiences

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Key points and relevance

What's known:

ADHD is a childhood disorder characterized by impairments in family, academic, and social settings. Most U.S. studies of childhood ADHD prevalence focus on national or subpopulation rates, but no recent studies provide U.S.-wide county-level prevalence estimates.

What's new:

We applied small area estimation to national survey data to estimate area-level ADHD rates in U.S. children. Findings showed elevated ADHD prevalence in the New England, South Atlantic, East South Central, and West South Central Census divisions.

What's relevant:

Study results can be used by policymakers and public health officials to determine which geographic areas and sociodemographic groups need additional programming, funding, or other resources (e.g., strategic plans, trainings, or toolkits) to systematically assess and treat children with ADHD.

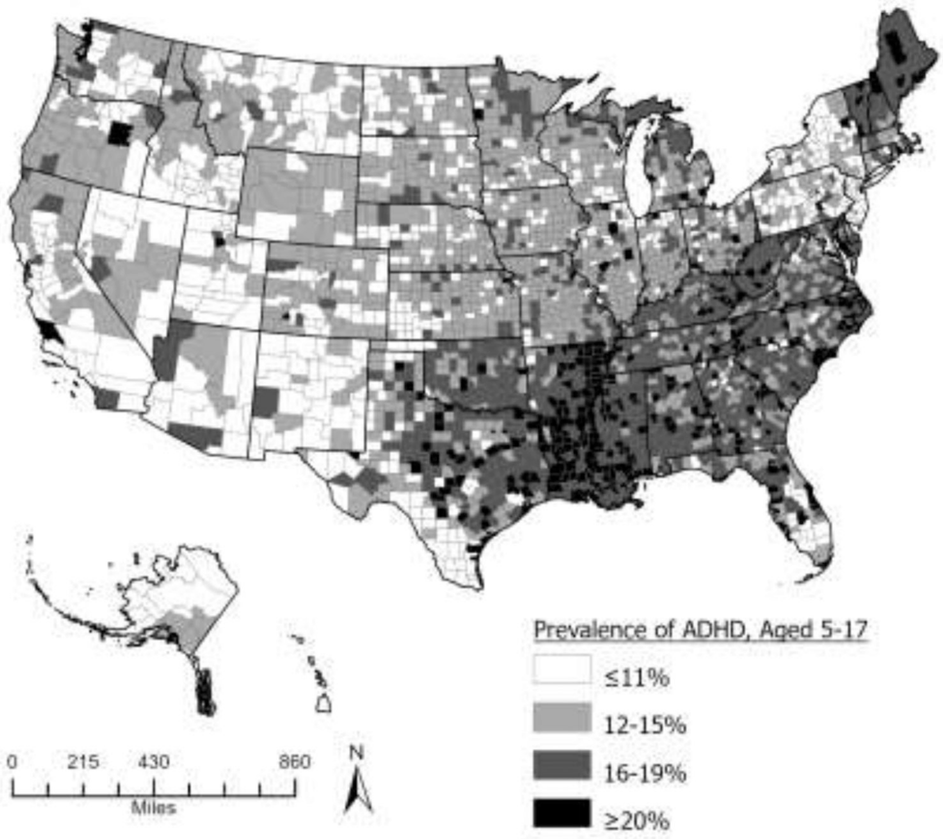

Figure 1. Estimated Proportion of Children Aged 5–17 Years with ADHD, County Level, 2016–2018

The lightest color represents counties with an ADHD estimate of 11% or lower. The second color in the gradient represents counties with an ADHD estimate between 12% and 15%. The third color in the gradient represents counties with an ADHD estimate between 16% and 19%. The darkest color represents counties with an ADHD estimate of 20% or higher. The lighter the color of the county, the lower the ADHD prevalence estimate. The darker the color of the county, the higher the ADHD prevalence estimate. For example, counties in the southern part of the U.S. have higher ADHD prevalence than counties in western states.

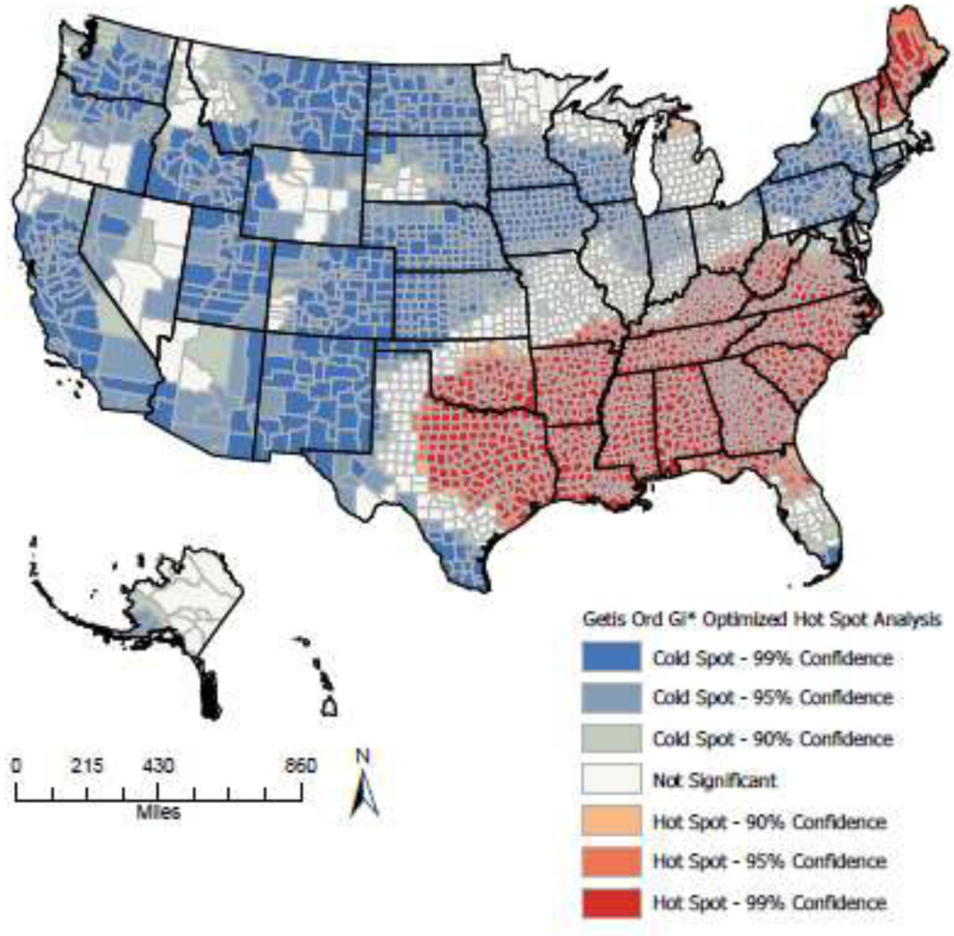

Figure 2. Hot and Cold Spots of ADHD Prevalence Estimates in U.S. Children Aged 5–17 Years, 2016–2018

The hot spot analysis uses the Getis-Ord Gi* statistic which is optimized by correcting for multiple testing and spatial dependence using the False Discovery Rates. Statistically significant clusters of high ADHD prevalence rates (hot spots) are shown in orange and red, while significant clusters of low ADHD prevalence rates (cold spots) are shown in shades of blue, with darker reds and blues indicating greater certainty. The South Atlantic, East South Central, parts of West South Central, and New England regional divisions are hot spots of ADHD. Nearly all the remaining regional divisions appear as cold spots of ADHD.

Table 1:

Descriptive Statistics of NSCH Sample of U.S. Children Aged 5–17 Years Between 2016–2018

Predictor	Unweighted *n* (Weighted Proportion)
Child Race/Ethnicity	
Non-Hispanic Black	4,173 (12.7)
Hispanic	7,722 (24.2)
Multiple/Other Race(s)	8,676 (10.2)
Non-Hispanic White	50,342 (53.0)
Child Gender	
Female	36,634 (50.9)
Male	34,279 (49.1)
Parental Highest Educational Attainment	
Less than High School	16,689 (22.6)
High School or GED	9,193 (19.7)
Some College	43,482 (48.8)
College Degree or higher	1,549 (9.0)
Census Regional Division [a]	
East North Central	7,316 (14.5)
East South Central	5,212 (5.8)
Mid Atlantic	4,274 (11.9)
Mountain	10,940 (7.8)
New England	8,751 (4.1)
Pacific	6,861 (16.4)
South Atlantic	12,050 (19.1)
West North Central	10,361 (6.8)
West South Central	5,148 (13.8)
	Weighted Mean (Weighted Standard Deviation)
Child Age	11.65 (3.77)

[a]East North Central = WI, MI, IL, IN, OH; East South Central = KY, TN, MS, AL; Mid Atlantic = NY, PA, NJ, Mountain = ID, MT, WY, NV, UT, CO, AZ, NM, New England = ME, NH, VT, MA, RI, CT, Pacific = AK, WA, OR, CA, HI, South Atlantic = DE, MD, DC, VA, WV, NC, SC, GA, FL, West North Central = ND, SD, NE, KS, MN, IA, MO, West South Central = OK, TX, AR, LA.

Table 2:

Childhood ADHD Rates in the U.S. and in Census Regional Divisions using SAE Model Predictions based on 2016–2018 NSCH Dataset Including Children Aged 5–17 Years, with 95% Confidence Interval

Group	U.S.	New England	Mid Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
Overall	12.9, 11.5–14.4	14.5, 11.6–18.0	10.4, 8.7–12.2	13.6, 11.7–15.6	13.3, 11.1–15.8	14.7, 12.9–16.7	16.9, 14.5–19.6	14.4, 12.6–16.5	11.5, 9.4–14.0	9.5, 7.9–11.5
Male	19.3, 17.7–21.1	21.5, 16.6–27.8	15.1, 12.6–17.8	18.9, 16.4–21.6	17.9, 14.9–21.4	20.3, 18.2–22.7	20.8, 17.7–24.4	20.7, 18.3–23.4	16.1, 12.6–20.3	16.4, 13.4–19.9
Female	9.6, 8.7–10.6	11.0, 8.1–15	7.2, 5.9–8.8	9.4, 7.9–11.1	8.8, 7.1–10.9	10.2, 8.9–11.7	10.5, 8.6–12.6	10.5, 9.0–12.1	7.9, 6.0–10.4	8.1, 6.5–10.2
Hispanic	9.6, 8.5–10.9	16.2, 11.3–22.4	12.4, 10.0–15.5	9.7, 7.5–12.6	9.1, 6.1–12.9	13.2, 11.1–15.7	12.8, 8.7–18.2	10.9, 9.1–13.1	7.8, 5.9–9.9	10.1, 8.2–12.4
Non-Hispanic White	15.1, 13.7–16.6	21.2, 16.4–27.1	11.7, 9.7–14.0	15.1, 12.9–17.5	14.7, 12.2–17.6	19.6, 17.1–22.2	19.5, 16.4–22.7	18.1, 15.8–20.9	13.8, 11.1–17	14.3, 11.6–17.5
Non-Hispanic Black	17.8, 16–19.8	14.3, 7.9–23.3	13.3, 9.9–17.4	18.6, 15.2–22.5	16.6, 11.8–22.4	15.9, 13.8–18.5	16.6, 13.5–20.6	20.0, 17–23.9	18.2, 11.4–26.7	15.6, 10.6–22.0
Multiple or Other Races	12.0, 10.0–14.7	13.3, 7.5–21.4	6.9, 4.8–10.0	12.7, 9.6–16.5	13.0, 8.9–18.2	12.8, 10.1–16.2	13.1, 8.4–19.7	11.9, 8.7–15.5	8.0, 5.2–12.4	8.7, 6.5–11.7
Parent with Less than High School	15.4, 13.7–17.3	20.6, 12.5–32.4	10.0, 6.9–14.0	16.0, 12.3–20.0	14.7, 10.1–20.8	16.8, 13.8–20.2	17.6, 13.2–23.1	11.6, 8.8–14.9	12.8, 8.0–19.4	16.9, 12.7–22.4
Parent with High School or GED	16.6, 15.0–18.4	20.1, 14.9–27	11.5, 9.2–14.3	13.4, 11.0–16.1	13.8, 10.5–17.5	14.6, 12.4–17.1	14.7, 11.5–18.4	18.2, 15.6–21.5	12.6, 9.3–16.6	8.1, 6.1–11.2
Parent with Some College	15.8, 14.3–17.5	13.1, 8.9–18.7	12.5, 9.8–15.6	13.4, 11.1–16.1	14.7, 11.5–18.7	15.8, 13.5–18.2	15.7, 12.6–19.9	17.1, 14.6–20.1	12.1, 9.0–15.4	11.6, 9.0–14.5
Parent with College Degree or Higher	12.3, 11.2–13.6	11.3, 8.3–15.4	10.2, 8.4–12.5	13.1, 10.9–15.5	10.4, 8.0–13.2	12.2, 10.5–14.0	14.4, 11.7–17.8	16.2, 14.0–18.9	10.1, 7.6–12.9	12.2, 9.9–14.9

Table 3:

Childhood ADHD Rates in States with Rates Significantly Lower or Higher than U.S. Overall Rate, using SAE Model Predictions based on 2016–2018 NSCH Dataset Including Children Aged 5–17 Years, with 95% Confidence Intervals

State	ADHD Rate, CI[a]	P-Value[b]
Significantly higher		
AL	16.00, 13.45–19.12	0.041
AR	18.23, 15.22–21.7	0.001
KY	17.27, 14.49–20.51	0.003
LA	20.07, 16.83–23.66	<0.001
MS	18.87, 15.83–22.39	0.001
NC	15.59, 13.17–18.26	0.041
OK	16.18, 13.37–19.39	0.042
SC	16.34, 13.85–19.15	0.006
TN	16.22, 13.52–19.47	0.028
VA	15.86, 13.5–18.54	0.006
WV	18.49, 15.27–22.06	<0.001
Significantly lower		
CA	8.79, 7.24–10.68	<0.001
NJ	9.73, 7.84–11.99	0.003
NY	9.29, 7.62–11.16	<0.001

[a] 95% confidence intervals defined as the 2.5th and 97.5th percentiles of the bootstrap sample;

[b] Corrected p-values for t-tests comparing state-level prevalence rates with the national prevalence rate.