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County-Level Prevalence Estimates of Autism Spectrum Disorder in Children in the United States

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Abstract

Prevalence estimates of autism spectrum disorder (ASD) point to geographic and socioeconomic disparities in identification and diagnosis. Estimating national prevalence rates can limit understanding of local disparities, especially in rural areas where disproportionately higher rates of poverty and decreased healthcare access exist. Using a small area estimation approach from the 2016–2018 National Survey of Children's Health (N = 70,913), we identified geographic differences in ASD prevalence, ranging from 4.38% in the MidAtlantic to 2.71% in the West South-Central region. Cluster analyses revealed "hot spots" in parts of the Southeast, East coast, and Northeast. This geographic clustering of prevalence estimates suggests that local or state-level differences in policies, service accessibility, and sociodemographics may play an important role in identification and diagnosis of ASD.

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Keywords

small area estimate; autism prevalence; national survey of children's health; geographic disparities

Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental disorder with a complex, multifactorial, and still largely unknown etiology. Accurate and early identification of ASD leads to earlier onset of intervention and better outcomes for individuals with ASD and their families (Koegel et al., 2014). Yet, chronic disparities in the prevalence of ASD exist across geographic regions and socioeconomic strata in the United States (Wiggins et al., 2020). Sociodemographic factors that have demonstrated an effect on ASD prevalence estimates include race/ethnicity, maternal education, income level, and geographic region (Durkin et

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al., 2010; Nevison & Zahorodny, 2019; Shaw et al., 2020; Shenouda et al., 2022; Zablotsky et al., 2019). State- and local-level ASD prevalence estimates reveal significant geographic variability (Shenouda et al., 2022; Xu et al., 2019) and some posit that prevalence of the disorder is directly related to awareness and access to services (Mazumdar et al., 2013). Advanced analytic techniques that produce small area, county-level prevalence estimates using nationally-representative samples may more precisely identify geographic disparities that can be linked to area-specific policy, environment, and sociodemographic features (Broder-Fingert et al., 2018; Shenouda et al., 2022).

Large population-based studies of ASD in the United States suggest a range of prevalence estimates between 1.85 and 2.76% (Maenner et al., 2021; Xu et al., 2018). Speculation about reasons for prevalence discrepancies across studies include different methods used in data acquisition (e.g., service agency records vs. national parent-report surveys) and estimation (direct vs. small area estimates) as well as differences in participant characteristics (e.g., age of the sample) (Fombonne, 2018). Co-occurring conditions can also influence the likelihood and timing of ASD diagnosis, with attention-deficit/hyperactivity/disorder (ADHD) being among the most common co-occurring conditions (Antshel & Russo, 2019). The national prevalence of ADHD is about 9.4% in the general population, but is four to five times higher (38.5%) in individuals with ASD (Danielson et al., 2018; Rong et al., 2021). Some evidence suggests that an initial diagnosis of ADHD can delay the subsequent diagnosis of ASD (Miodovnik et al., 2015).

Complex interactions between co-occurring conditions, race/ethnicity, geographic region, and poverty have become particular points of interest to understand gaps in ASD diagnosis and service utilization (Mandell et al., 2009; Shattuck et al., 2009; Zablotsky et al., 2019). For example, racial and ethnic minority groups have historically experienced significant barriers to care access, resulting in lower rates and later age of ASD diagnosis (Mandell et al., 2002; Zuckerman et al., 2017). In general, families who are from minoritized racial/ethnic groups, have lower maternal education, and are living in poverty are less likely to be diagnosed with ASD or experience a later age of diagnosis (Bickel et al., 2015; Durkin et al., 2017; Mandell et al., 2009; Shattuck et al., 2009; Shenouda et al., 2022; Wiggins et al., 2020). However, a shift toward reduced influence of SES gradient on diagnosis may be emerging in some states (Shenouda et al., 2022; Winter et al., 2020).

Several limitations of previous ASD prevalence studies exist, preventing a full understanding of sociodemographic disparities. Large, population-based studies are unable to estimate local disparities in small areas, especially in rural areas which are disproportionately characterized by lower maternal education and higher rates of poverty. Utilization of county-level data can help to overcome some of these limitations by isolating sociodemographic groups potentially experiencing diagnostic disparities. Moreover, advanced analytic approaches, such as small area estimation (SAE), can quantify geographic variability in prevalence rates at the local level. The goal of the current study was to apply SAE with post-stratification to data from the 2016–2018 National Survey of Children's Health (NSCH) to generate and map estimates of county- and state-level ASD prevalence among children aged 5–17 in the US. This is the first study, to our knowledge, to examine county-level estimates of ASD prevalence nationwide.

Methods

Data Sources

The NSCH, a US national survey sponsored by the Health Resources and Services Administration (HRSA), was used to collect data on child diagnosis and sociodemographic factors between 2016 and 2018. The NSCH asks parents to report on the physical and emotional health of their children aged 0–17 years. For this study, data for children aged 5–17 were included for two reasons. First, given that the average age of diagnosis for ASD is between 4 and 5 years old (Xu et al., 2018), we reasoned that the majority of children with ASD would have a diagnosis to report by age 5. Second, ADHD status was used as predictor in these models (see Child-Level Predictors below) and the ADHD dataset included children age 5 and above only.

The sampling design of the NSCH includes an equal number of randomly-selected households for each state, and within each household, a child is randomly selected, with an 80% oversampling probability for children with special needs (States, 2016). The US Census Bureau (USCB) carries out the survey using landline and cellular phones in all US states and the District of Columbia and parents or guardians of children answer survey questions (States, 2016). Analyses were conducted using this data at a participating USCB Research Data Center (RDC) in Raleigh, NC. Area-level variables included county, state, and regional division levels. These data were collected from publicly-available data sources such as governmental institutions and research centers (Table A1 in Appendix).

Variables

Primary Outcome: Autism Spectrum Disorder.—In the NSCH, parents were asked if a doctor or other health care provider had ever told them that their child has ASD, including Asperger's Syndrome or Pervasive Developmental Disorder–Not Otherwise Specified. Responses of 'yes, currently' and 'yes, not currently' were combined to represent ASD diagnosis for analysis.

Child-Level Predictors.—Keeping with the goal of providing county-level estimations from child-level outcomes and predictor variables, the pool of child-level predictors was determined based on (a) overall associations (not necessarily causal) with the ASD outcome as determined by the literature and availability of predictors in the NSCH, and (b) the availability of county-level population estimates for all child-level factor levels and cross-tabulations. After applying these criteria, we considered the following child-level demographic variables: race/ethnicity (Hispanic, Non-Hispanic white, Non-Hispanic Black, Multiracial/Other), biological sex (male, female), age, highest educational attainment of a child's either parent (less than high school, high school or General Educational Development [GED], some college, college or higher), and year of participation in the NSCH survey (2016, 2017, 2018). To increase the estimation ability of our model, we included the most common psychiatric comorbidity, ADHD status (Antshel & Russo, 2019). While population estimates and cross-tabulations of ADHD prevalence are not readily available, results from separate analyses were used (further information in the statistical

analysis section). In modeling, all two-way interactions were examined for the child-level predictors.

Area-Level Predictors.—Numerous area-level factors were considered in analytic models, including, but not limited to: census regional division (New England, Mid Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific [see Table A4 in Appendix]), state bullying laws, state Medicaid expansion status, state-level school wellness policy, federal/state/county school funding, county incarceration rates, county child insurance rates, county rate of children living in households with a single parent in 2015, number of primary care/pediatric providers per 100,000 residents in the county in 2016, presence of a school wellness policy at the state level in 2016, and county urban-rural designation based on 2013 Rural-Urban Continuum Code (RUCC). Table A1 of the Appendix shows all area-level variables considered in our analysis.

Statistical and Spatial Analysis

Per the disclosure process of the USCB, all descriptive statistics used the publicly-available NSCH surveys which do not contain county-level identifiers. The statistical models used the restricted NSCH surveys, and the output was approved by the Census Disclosure Monitoring Board. The public and restricted versions of our sample start from the same population, use the same exclusion criteria, and remove observations with missing values on the same individual-level variables. The difference between the two samples is that the restricted version excluded children from counties with missing area-level predictors while the public version did not. Overall, only two of 3,143 counties had missing area-level predictors, making the samples nearly identical.

To accurately estimate ASD prevalence at the county level, we used SAE models with post-stratification, which result in robust estimations that incorporate multilevel covariate data and spatial random effects. Specifically, we used a multilevel mixed-effects logistic regression model where the outcome was child-level ASD (yes/no), and predictors were other child- and area-level factors. The random intercept for counties in the final model controls for spatial dependence between neighboring counties with an Intrinsic Conditional Auto-Regressive (ICAR) structure. We based our variable selection procedure on forward selection using 5-fold cross-validation that minimized the root mean squared prediction error (RMSPE) (Allen, 1974; Stone, 1977). To account for the NSCH's complex survey design, we used the survey weights (Carle, 2009; Goldstein, 1991) provided in the dataset, which we rescaled to have a mean of one for each survey year.

The final SAE model resulted in child-level estimation of prevalence for each county- and child-level predictor-variable combination. The child-by-county-level estimations were then aggregated to the county level using post-stratification (Little, 1993). In post-stratification procedures, a weighted average of all possible child-level predictor variable combinations is calculated where the weights reflect the proportion of a county's population in each predictor-variable combination. As a result, in SAE, the pool of child-level predictor variables was restricted to those where county-level population estimates, stratified by

all child-level predictor levels, were known. Usually, this means that variables like child-level ADHD status cannot be used (despite the strong co-occurrence) since estimates of county-level population counts for ADHD status are not available. As a result, this study's post-stratification procedure leveraged a model for county-level prevalence of ADHD (see MASKED, *under review*) also developed from the restricted NSCH data, to estimate ADHD prevalence, obtain estimated counts of children with ADHD within each county, and subsequently aggregate child-level ASD estimations to the county level (e.g., (Zgodic et al., 2021)). Post-stratification allowed the county-level ASD estimation to reflect each county's underlying demographic distribution and the incorporation of ADHD status, a strong child-level predictor.

To get confidence intervals for the county-level ASD prevalence rates, we sampled the estimated prevalence of each county using a parametric bootstrap. This procedure involved generating estimations 5,000 times by drawing from the estimated sampling distribution of all model parameters and calculating strata-specific prevalence estimates for each. Parallel samples of ADHD prevalence by strata were used to propagate post-stratification uncertainty. Then, the median, 2.5th, and 97.5th percentiles of the bootstrap sample of predicted rates give the county-level ASD rate and its 95% confidence interval.

To assess model validity, we aggregated county-level estimates to the state level and compared them to state-level direct estimates of the NSCH dataset, still accounting for the survey design. We then evaluated the correlation between the model-based and direct estimates and checked the mean and standard deviation of the differences between the two types of estimates. 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 (FDR) correction applied to p-values.

We developed choropleth maps to highlight geographic differences in ASD prevalence among children aged 5–17. The color categories were selected using the quantile method which results in relatively equal category sizes (De Smith et al., 2007) Specifically, there were four cut-points: ≤2.6%, 2.7–4.3%, 4.4–8.1%, and ≥ 8.2%. To explore the extent of spatial clustering of ASD among children in the US, optimized hot spot analysis was performed using ArcGIS Pro (ESRI, 2011). This tool uses the Getis-Ord Gi* statistic optimized by correcting for multiple testing and spatial dependence using the FDR. Statistically-significant hot spots (i.e., clusters of high values of ASD) are shown in orange and red, while cold spots are shown in shades of blue, with darker reds and blues indicating greater certainty (Getis & Ord, 1992).

Note that the authors acknowledge there was no community involvement in the reported study.

Results

Descriptive statistics of the overall sample are displayed in Table 1. Out of 102,341 children in the 2016–2018 NSCH data, 70,913 were aged 5–17 years and had available sociodemographic data. Over half of the children (52.97%) were non-Hispanic white,

24.15% were Hispanic, 12.68% were non-Hispanic Black, and 10.20% were children of multiple or other races. 50.92% of the sampled children were male and the average age was 11.03 years. Nearly half of the children (48.77%) had a parent with a college education, while approximately 20% of children had one parent with some college education (22.55%) or who completed high school/GED (19.69%). Table A2 in the Appendix shows descriptive statistics by Census regional division. The South Atlantic regional division (19.05%) had the most children sampled, followed by the Pacific division (16.38%).

Final model fixed effect covariates included one state-level variable (proportion of school funding coming from counties) and the main effects for child race/ethnicity, ADHD status, gender, highest parental education, and Census regional division, as well as several two-way interactions between these child-level predictors (see Table A3 for all model coefficients). Final model random effects included a random intercept for counties with a spatial component. With this spatial random effect, adjusting for state effects did not improve our model fit criterion. Our model-based, state-level ASD estimates performed well compared to state-level direct estimates from the 2016–2018 NSCH public use files. The average absolute difference between the estimates was 0.45% (SD = 0.32%).

Estimated rates of ASD at the national and regional division levels are displayed in Table 2. Figure 1 shows a map of the estimated county-level ASD rates. The national rate of ASD was 3.29% (CI: 2.89–3.73%). The Mid Atlantic division had the highest rate of 4.38% (CI: 3.37–5.69%), while the West South Central division had the lowest with 2.71% (CI: 2.08–3.58%). Counties in the New England, South Atlantic, and Mid Atlantic divisions had higher estimated rates of childhood ASD (73.1%, 40.6%, and 34.7% had rates of 2.8% or greater, respectively) compared to counties in the West South Central, West North Central, Pacific, East North Central, Mountain, and East South Central divisions (5.7%, 7.1%, 8.9%, 17.2%, 22.4%, and 25.3% had rates of 2.8% or greater, respectively). Only Hawaii had an estimated ASD rate significantly lower (1.64%) than the national average ($p < 0.001$).

ASD rates by various sociodemographic groups for each regional division are presented in Table 2. Overall and by division, female children had lower rates than males (1.38% vs. 4.58%, respectively). Nationally, the ASD prevalence was 3.82% (CI: 3.14–4.68%) among Black children, 3.36% (CI: 2.93–3.84%) among Hispanic children, and 2.87% (CI: 2.42–3.44%) among white children. These relative patterns were consistent across all divisions. Also nationally, the ASD prevalence among children who had a parent with a college degree was 2.62% (2.24–3.10%), while the rate for children with parents who had not completed high school was 4.04% (CI: 3.29–4.90%). This pattern of results was similar across all divisions.

Results from the hot spot analysis of county-level ASD rates are illustrated in Fig. 2. Clusters of high ASD rates were observed along the East Coast (from northeast North Carolina to Maine) and the South and Southeast (most counties in Georgia, portions of South Carolina, north Florida and Alabama). Smaller clusters of high ASD prevalence appeared around the cities of Los Angeles, Las Vegas, and Chicago. The main cluster of low ASD rates was located in the Texas panhandle and Oklahoma. Other low ASD clusters included northern California and an area including North Dakota, Minnesota, and Iowa.

Darker shades of hot/cold spots show that the Getis-Ord Gi* test statistic was significant at lower significance levels (for instance, $\alpha = 0.01$ vs. $\alpha = 0.05$), indicating greater certainty that the highlighted areas have significantly increased or decreased estimated ASD prevalence rates compared to neighboring areas (Getis & Ord, 1992).

Discussion

The primary aims of this study were to generate small area estimates of county-level rates of ASD and describe prevalence rates across sociodemographic factors. Small area estimation model estimations resulted in an overall US prevalence of 3.29%, with significant regional variability ranging from 2.71% in the West South Central region to 4.38% in the Mid Atlantic. Consistent with previous studies using NSCH data, we found a slightly higher national prevalence rate using small area estimates of data collected in 2016–2018 compared to the rate of 2.27% recently reported by the CDC's Autism and Developmental Disabilities Monitoring (ADDM) Network from data collected in 2018 (Kogan et al., 2018; Maenner et al., 2021). Several studies have reported high concordance (96–98%) between parent/caregiver-reported diagnoses of ASD and clinical diagnoses from licensed professionals (e.g., Daniels et al., 2012; Lee et al., 2010; Warnell et al., 2015), suggesting that any overestimates from the NSCH dataset are likely due to misdiagnosis rather than reporter bias. This discrepancy is more likely due to vastly different approaches to sample ascertainment. The NSCH is a national parent-report survey for children aged 0–17 years (ages 5–17 included in this study) while the ADDM Network is an 11-site study of ASD prevalence among 8-year-olds that relies on medical or educational documentation of ASD. It is probable that this ascertainment strategy makes the ADDM Network data more exclusive (i.e., excluding children with no documented diagnosis in medical or educational records) and geographically restricted compared to NSCH data, possibly resulting in underestimates of ASD prevalence (Fombonne, 2018).

Small area estimates revealed significant geographic variability of ASD prevalence. Higher rates of ASD were identified in the New England, South Atlantic, and MidAtlantic regions, consistent with previous studies of geographic variability in ASD prevalence (Baio, Wiggins, Christensen, Maenner, Daniels, Warren, Kurzius-Spencer, Zahorodny, Robinson, et al., 2018; Hoffman et al., 2017; Xu et al., 2019). These differences may be attributable to region-specific policies, service accessibility, state-specific insurance mandates, and educational and medical practices (Mandell et al., 2016; Sheldrick & Carter, 2018). Sociodemographic differences by region may also play an important role. Many state and nationwide studies of ASD prevalence report a racial/ethnic disparity in diagnosis, with Hispanic and, to a lesser extent, Black children receiving diagnoses at lower rates (Maenner et al., 2020; Shenouda et al., 2022). However, several recent reports suggest that the socioeconomic disparity in ASD diagnosis is narrowing (Kogan et al., 2018; Nevison & Parker, 2020; Nevison & Zahorodny, 2019; Shaw et al., 2020; Shenouda et al., 2022; Winter et al., 2020). These findings point to the need for comprehensive analytic models that more accurately represent complex social disparities across the US to guide future policy and service provision. For example, future studies that examine the ASD diagnostic classification, i.e., medical or educational diagnosis, may provide further insight into access

to resources, especially for families living in rural areas where doctors and psychologists specializing in ASD may not be accessible.

Hot spot analyses identified parts of the Southeast and Northeast as two geographic regions with higher-than-expected rates of ASD. Higher rates of ASD in the Northeast region, and New Jersey in particular, have been reported in previous research (Baio, Wiggins, Christensen, Maenner, Daniels, Warren, Kurzius-Spencer, Zahorodny, Robinson Rosenberg, et al., 2018; Hoffman et al., 2017). Smaller hot spots included the urban areas of Los Angeles, Las Vegas, and Chicago. In contrast, cold spots with outstandingly low rates of ASD were observed around the Texas panhandle, Oklahoma, northern California, and an area in the Midwest including North Dakota, Minnesota, and Iowa. Prevalence hot and cold spots may be linked to state-by-state insurance mandates for ASD treatment, an association that has been observed in previous research (Johnson et al., 2014; Mandell et al., 2016). States differ significantly in services covered by private insurance mandates, timing of adoption of insurance mandates, and availability of service providers, all unique factors that may impact whether and when parents seek an ASD diagnosis (Choi et al., 2020; Johnson et al., 2014). While statewide mandates certainly contribute to regional differences, county and neighborhood resource allocation and access play an important role in regional differences. Indeed, large variation exists even within small, relatively densely populated states (Shenouda et al., 2022). For example, regional hotspots observed in this study may be explained in part by clusters of high-resource areas within states, which can be examined using proximity to high-volume medical or autism centers. In the current study, this may be the case where some hotspots include areas with a high density of university-based medical research centers with autism diagnostic programs in the Northeast (including New York, NY, New Haven, CT, Providence, RI, Boston, MA), the Southeast (Atlanta, GA; Charleston, SC), and parts of Southern California (San Diego, Los Angeles). In addition, the observed contrast in ASD prevalence between hotspot regions in Southern California (San Diego/Los Angeles) and cold spot regions Northern California surrounding San Francisco (e.g., San Francisco, Marin) partially align with recent findings of increasing ASD diagnoses among white children in middle income counties, including San Diego, Los Angeles and decreasing ASD diagnoses among white children in wealthier counties surrounding San Francisco (e.g., Marin) (Nevison & Parker, 2020). These data highlight the importance of county- and region-specific examinations of ASD resources and suggest a combination of sociodemographic and geographic features that may serve as facilitators and barriers to ASD diagnosis. Future research should explore the intersection of ASD prevalence with neighborhood sociodemographics as well as the co-location of high or low ASD prevalence and the corresponding high or low density of healthcare providers (e.g., pediatricians, behavioral health providers, etc.) to determine the potential relationship with local access to care.

Strengths and Limitations

Our study benefited from the robustness of the SAE approach. Even for counties with low sample sizes, SAE produces estimates by leveraging information from neighboring counties, leading to robust predictors of ASD prevalence for all counties. In addition, our study includes ADHD status as a predictor of ASD using a novel statistical approach where a

co-occurring condition (i.e., ADHD) is accounted for in estimated rates. Specifically, we estimated county-level ADHD prevalence and used it alongside available population counts for various demographic groups to obtain the county-level ASD prevalence rates by group. This novel approach helps strengthen the power of our study and reduce prediction error, resulting in estimated prevalence rates with increased accuracy compared to methods that do not account for co-occurring conditions in modeling and post-stratification procedures. The use of a nationally representative sample with a wide age range of children across three cohorts (2016, 2017, and 2018) is also a strength of the current study. A limitation concerns the source of ASD diagnostic data: parent report of children with an existing diagnosis of ASD. It is possible that this survey missed children who may have been later diagnosed with ASD as well as children who were misdiagnosed as having ASD. In addition, while this study includes children who received a diagnosis earlier than age 5, the age inclusion criteria (age 5–17 years) limits our sample to children who were age 5 or older at the time of data collection. A second limitation is related to the constraint on child-level predictors included in our analyses. In order to complete the poststratification process for this analysis, only child-level predictors with available county-level population estimates for all factor levels could be used. Thus, many child-level predictors that may be associated with ASD, such as the presence of intellectual disability, were not included in this analysis. Inclusion of additional child-level predictors in future research may further refine small-area estimates of ASD prevalence.

Conclusion

Geographic disparities in the identification and diagnosis of ASD are complex. This study used small area estimation of ASD prevalence in a large, nationally representative sample to reveal nuanced geographic variability. Variable prevalence rates of ASD based on geographic region were identified and hot spots of ASD prevalence were apparent in the Southeast and Northeast regions of the US. Region-specific policies, service accessibility, routine screening guidelines, and insurance mandates may all play an important role in accurate and equitable identification and diagnosis. The county-level prevalence estimates and identification of hot spot regions in this study set a research agenda for investigation of critical factors associated geographic disparities in ASD identification and diagnosis. Further study of hot spot regions will be important to identify region-specific barriers and facilitators to diagnosis and services for families with ASD.

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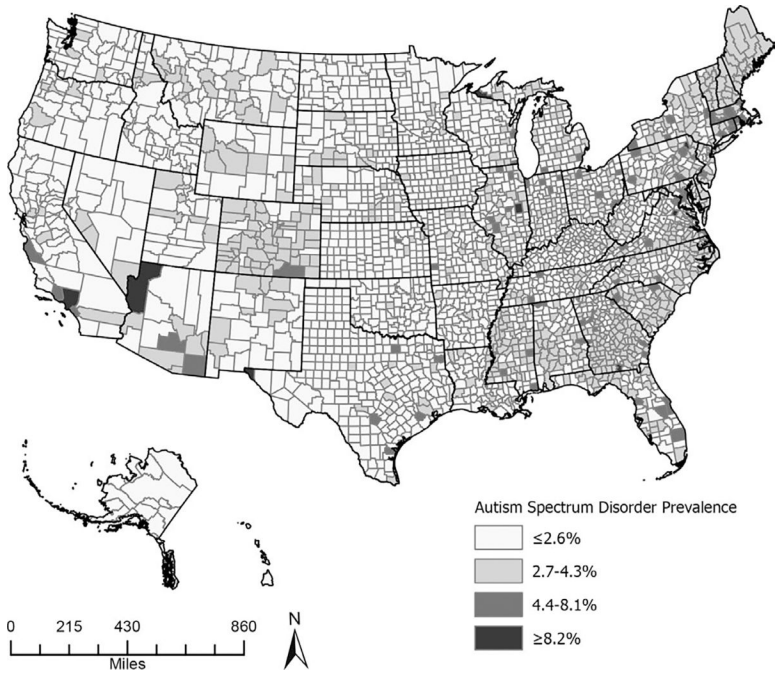

Fig. 1. Estimated Proportion of Children with ASD, County Level, 2016–2018

Note. The lightest color represents counties with an ASD estimate of 2.6% or lower. The second color in the gradient represents counties with an ASD estimate between 2.7% and 4.3%. The third color in the gradient represents counties with an ASD estimate between 4.4% and 8.1%. The darkest color represents counties with an ASD estimate of 8.2% or higher. The lighter the color of the county, the lower the ASD prevalence is. The darker the color of the county, the higher the ASD prevalence is. For example, counties in the southern part of the US have higher ASD prevalence than counties in western states.

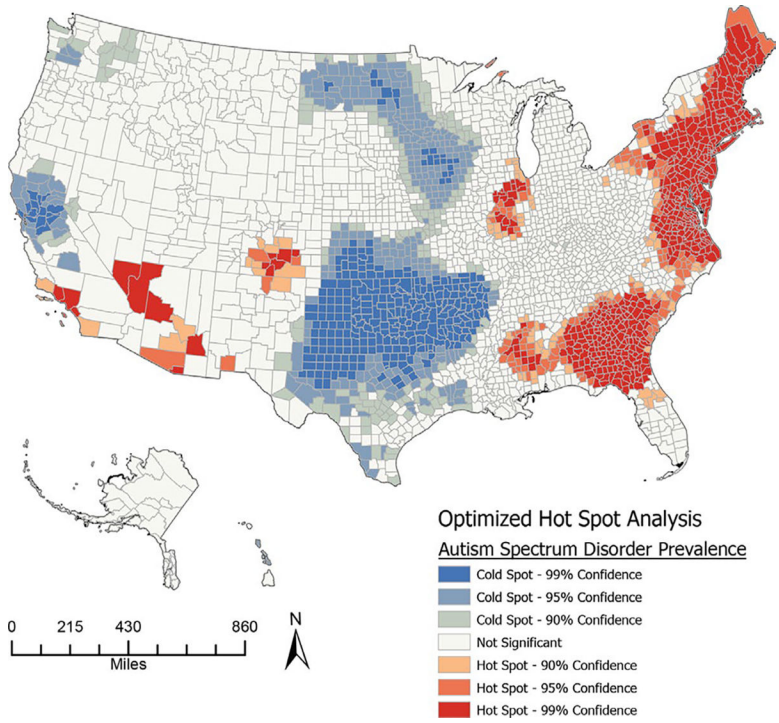

Fig. 2. Hot Spot Analysis for the Estimated Proportion of Children with ASD, County Level, 2016–2018

Note. Statistically significant clusters of high ASD rates (hot spots) are shown in orange and red. Significant clusters of low ASD rates (cold spots) are shown in shades of blue. Darker colors indicate greater certainty. The South Atlantic, Mid Atlantic, New England, and East South Central regional divisions are hot spots of ASD. West South Central appears as a cold spot of ASD.

Table 1

Descriptive Statistics of 2016–2018 NSCH Sample of US Children Aged 5–17 Years

Predictor	Unweighted *n* (Weighted %)
Child Race/Ethnicity	4,173 (12.7)
Non-Hispanic Black	7,722 (24.2)
Hispanic	8,676 (10.2)
Multiple/Other Race(s)	50,342 (53.0)
Non-Hispanic White	
Child Gender	36,634 (50.9)
Female	34,279 (49.1)
Male	
ADHD Status	62,366 (89.2)
No	8,547 (10.8)
Yes	
Parental Highest Educational Attainment	16,689 (22.6)
Less than High School	9,193 (19.7)
High School or GED	43,482 (48.8)
Some College	1,549 (9.0)
College Degree or higher	
Census Regional Division	7,316 (14.5)
East North Central	5,212 (5.8)
East South Central	4,274 (11.9)
Mid Atlantic	10,940 (7.8)
Mountain	8,751 (4.1)
New England	6,861 (16.4)
Pacific	12,050 (19.1)
South Atlantic	10,361 (6.8)
West North Central	5,148 (13.8)
West South Central	
Child Age (Weighted Mean, Weighted SD)	11.65 (3.77)

NSCH: National Survey of Children’s Health

Table 2

Predicted Rates of ASD in Children Aged 5–17 by Sociodemographic Characteristics and Census Regional Divisions

Group	US	New England	Mid Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
Overall	3.29, 2.89–3.73	4.10, 2.74–6.19	4.38, 3.37–5.69	3.17, 2.49–4.07	2.73, 1.97–3.80	3.28, 2.65–4.01	3.14, 2.32–4.28	2.71, 2.08–3.58	3.18, 2.32–4.33	3.91, 2.96–5.12
Sex										
Male	4.58, 4.03–5.25	5.73, 4.05–8.13	6.70, 5.30–8.35	4.96, 3.88–6.18	4.62, 3.59–6.00	4.65, 3.83–5.62	4.44, 3.44–5.94	3.38, 2.55–4.32	5.10, 3.77–6.82	3.86, 2.93–5.09
Female	1.38, 1.16–1.65	1.70, 1.17–2.51	2.15, 1.66–2.81	1.49, 1.14–1.92	1.42, 1.07–1.90	1.39, 1.10–1.71	1.36, 1.01–1.90	0.99, 0.74–1.34	1.54, 1.10–2.11	1.14, 0.83–1.54
Race/ Ethnicity										
White	2.87, 2.42–3.44	3.59, 2.49–5.27	4.08, 3.16–5.32	3.05, 2.32–3.91	2.87, 2.20–3.83	2.91, 2.35–3.59	2.75, 2.05–3.79	2.10, 1.54–2.75	3.17, 2.29–4.33	2.44, 1.78–3.27
Hispanic	3.36, 2.93–3.84	3.96, 2.62–5.98	4.65, 3.57–6.13	3.72, 2.85–4.73	3.54, 2.66–4.60	3.46, 2.83–4.29	3.34, 2.56–4.44	2.55, 1.92–3.33	3.98, 2.95–5.27	3.00, 2.21–4.06
Black	3.82, 3.14–4.68	5.15, 3.30–8.41	5.63, 4.27–7.46	4.21, 3.23–5.59	3.83, 2.86–5.18	3.95, 3.04–5.21	3.75, 2.77–5.19	2.77, 1.98–3.79	4.30, 3.00–5.85	3.49, 2.47–5.05
Other/ Mixed	2.66, 2.31–3.06	3.70, 2.36–5.88	3.76, 2.78–4.87	3.07, 2.38–4.02	2.88, 2.17–3.92	2.78, 2.25–3.52	2.56, 1.92–3.54	1.88, 1.35–2.65	3.16, 2.27–4.46	2.06, 1.41–3.02
Parental Education										
< High School	4.04, 3.29–4.90	4.57, 3.11–6.77	6.15, 4.67–8.06	4.85, 3.61–6.42	4.39, 3.26–5.81	4.11, 3.24–5.25	3.94, 2.94–5.37	2.39, 1.72–3.17	4.96, 3.57–6.76	3.34, 2.42–4.67
High School/GED	3.24, 2.80–3.84	4.28, 3.00–6.21	4.78, 3.72–6.15	3.52, 2.71–4.43	3.28, 2.51–4.38	3.30, 2.67–4.09	3.27, 2.49–4.42	2.52, 1.89–3.27	3.58, 2.56–4.95	2.83, 2.09–3.75
Some College	3.06, 2.61–3.57	3.91, 2.68–5.63	4.37, 3.37–5.63	3.33, 2.56–4.18	3.11, 2.34–4.12	3.08, 2.49–3.75	2.95, 2.23–4.03	2.30, 1.72–3.00	3.36, 2.47–4.56	2.59, 1.91–3.53
≥ College Degree	2.62, 2.24–3.1	3.22, 2.21–4.69	3.82, 2.93–4.98	2.8, 2.15–3.61	2.58, 1.96–3.41	2.65, 2.16–3.26	2.47, 1.84–3.36	1.92, 1.43–2.53	2.87, 2.10–3.97	2.21, 1.64–2.96

Note. Predicted rates with 95% confidence intervals calculated using small area estimate (SAE) models