Environmental mercury release, special education rates, and autism disorder: an ecological study of Texas

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Accepted 1 November 2004

Abstract

The association between environmentally released mercury, special education and autism rates in Texas was investigated using data from the Texas Education Department and the United States Environmental Protection Agency. A Poisson regression analysis adjusted for school district population size, economic and demographic factors was used. There was a significant increase in the rates of special education students and autism rates associated with increases in environmentally released mercury. On average, for each 1000 lb of environmentally released mercury, there was a 43% increase in the rate of special education services and a 61% increase in the rate of autism. The association between environmentally released mercury and special education rates were fully mediated by increased autism rates. This ecological study suggests the need for further research regarding the association between environmentally released mercury and developmental disorders such as autism. These results have implications for policy planning and cost analysis.

Keywords: Mercury; Special education; Autism; Environmental toxins; Ecological

Introduction

Exposure to a variety of environmental neurotoxicants is known to affect normal child development, resulting in a spectrum of adverse outcomes, ranging from severe mental retardation and developmental disability to more subtle changes in functioning, depending in part on the timing and dose of the chemical agent (Landrigan and Garg, 2002; Mendola et al., 2002; Rice and Barone, 2000).
first and second) toxic substance in the United States (ATSDDR, 2001).

Symptoms of nervous system disruption associated with chronic exposure to mercury has been known since the 19th century, when mercury was widely used in the felt industry which led to the expression of “hatter’s disease” (Hu, 1998). Further epidemiological evidence of the neurotoxicity of mercury dates back to the 1950s, when it was ascertained that thousands of people in Minamata and Niigata Japan suffered various neurological impairments caused by consumption of mercury contaminated fish (Harada, 1978). However, the neurotoxicity of low-level mercury exposure has only recently been documented (NAS, 2000; EPA, 1997) and recent reports implicate mercury in the etiology of various developmental and learning disabilities (Ramirez et al., 2003; Grandjean et al., 2003) including autism (Bernard et al., 2001, 2002).

Recent evidence for mercury toxicity relevant to the biology of autism is compelling (Palomo et al., 2003; Aschner and Walker, 2002; Bernard et al., 2002; Vojdani et al., 2003) and Bradstreet et al. (2003) report that levels of urinary mercury after a 3-day treatment with an oral chelating agent, meso-2,3-dimercaptosuccinic acid (DMSA), in children with autistic spectrum disorders were three times those in a matched normal control sample.

Environmentally released mercury is a major source of mercury exposure. Mercury is released into the environment largely from fossil fuel (mainly coal) combustion by electrical utilities and from municipal and medical waste incinerators. This inorganic mercury becomes airborne and may be carried for miles before being deposited on soil or water. This inorganic form of mercury is then converted to a toxic form (methylmercury) by chemical reactions or by bacteria, which is absorbed by aquatic microorganisms that are eaten by fish, and in this manner accumulates up the aquatic food chain. Humans are primarily exposed through fish consumption (Myers et al., 2000) and transmission from mothers to infants is well documented in animal models (Newland et al., 1994) and human studies (Ramirez et al., 2000; Grandjean et al., 1995). Results from several studies show that maternal mercury exposure during pregnancy is associated with neuropsychological deficits in children and that this association is most evident in women with stable exposures throughout pregnancy (Ramirez et al., 2003; Grandjean et al., 2003).

Other than accidental poisoning at the population level, where developmental disabilities have been reported as the result of large mercury spills (Racz and Vandewater, 1982), there have been no published studies examining the risk of disability associated with mercury released into the environment within the current legal limits. The available information regarding exposure to toxic agents associated with developmental disorders is suggestive but inconclusive (Ostrowski et al., 2003). In a prior study, we report evidence for an association between environmentally released mercury and various developmental disorders, including autism, at the state level (n = 50) (unpublished manuscript). We considered the positive association between developmental disabilities and environmentally released mercury in that investigation as preliminary due to the relatively small number of large geological regions. In this study, we investigate the association between environmentally released mercury pollution and autism rates at the county (n = 254) and school district level (n = 1184) in Texas. The advantage of using county level data in this study allows an investigation using greater numbers of smaller geographic units in the analysis—this can potentially increase our power to detect an effect if in fact it present. Since Texas ranks 4th among states with the highest reported mercury releases (next to California, Oregon, and West Virginia) (USEPA-TRI, 2004), analysis of data from this state can be useful for further investigation of the association between environmental mercury release and developmental disorders. In this study, we investigate the association between total special education rates, autism, and environmental mercury release.

Methods

Data source and sample data regarding environmentally released mercury for each county were obtained from the United States Environmental Protection Agency Toxics Release Inventory (TRI) (USEPA-TRI, 2004). TRI collects information about chemical releases and waste management reported by major industrial facilities in the US. The TRI database was established by Section 313 of the Emergency Planning and Community Right-To-Know Act of 1986 (EPCRA). Under EPCRA, industrial facilities in specific sectors are required to report their environmental releases and waste management practices annually to the EPA. Facilities covered by this act must disclose their releases to air, water, and land of approximately 650 toxic chemicals, as well as the quantities of chemicals they recycle, treat, burn, or otherwise dispose of on-site and off-site. The current analysis uses reports of pollution that industrial facilities provided to TRI for the calendar year 2001. The total number of pounds of environmentally released mercury was obtained for each county.

Administrative data from the Texas Education Agency (TEA) from school years 2000–2001 were analyzed. Data and data description are available at the TEA website at http://198.214.99.202. In compliance with the Texas Education Code, the Public Education Information Management System (PEIMS) contains
data necessary for the legislature and the TEA to perform their legally authorized functions in overseeing public education. The database consists of student demographic, personnel, financial, and organizational information. Autism counts per school district were obtained by special request from the TEA. Data were from 1184 school districts in 254 counties in Texas. These districts represented approximately 4 million children enrolled in grades K through 12.

Diagnosis of autistic disorder was abstracted from the school record for each year of the study period. Diagnoses were made by qualified special education psychologists employed by the TEA or from psychologists or medical doctors outside the TEA system. While diagnoses were not standardized, there is considerable evidence that diagnoses of autistic disorder are made with good reliability and specificity in the field (Eisenmayer et al., 1996; Hill et al., 2001, Mahoney et al., 1998).

District population wealth was calculated as a school district’s total taxable property value in 2001 as determined by the Comptroller’s Property Tax Division (CPTD), divided by the total number of students in the district in 2000–2001. Property value was determined by the CPTD as part of its annual study, which attempts to present uniformly appraised property valuations statewide. The CPTD value is calculated by applying ratios created from uniform independent appraisals to the district’s assessed valuations.

Racial composition was accounted for by the proportion of European-American children enrolled in schools within each district.

Total number of students was calculated as all enrolled students as of October 28, 2000 in grades kindergarten through twelve, who attended at least 1 day of school for that school year. Statewide, 6975 students, or 0.2% of all students, were enrolled but did not attend school.

Proportion of economically disadvantaged students was calculated as the percentage of students who were eligible for free meals under the National School Lunch and Child Nutrition Program, reduced-price meals under the National School Lunch and Child Nutrition Program, or other public assistance.

Total number of students enrolled in special education was calculated as the number of students receiving special education in each district.

Urbanicity. Eight separate demographic district regions were utilized in the analysis: (1) Major urban districts are the districts with the greatest membership in counties with populations of 650,000 or more, and more than 35% of the students are identified as economically disadvantaged. (2) Other central city—The major school districts in other large, but not major, Texas cities. Other central city districts are the largest districts in counties with populations between 100,000 and 650,000 and are not contiguous to any major urban districts. (3) Major suburban districts are contiguous to major urban districts. If the suburban district is not contiguous, it must have a student population that is at least 15% of the size of the district designated as major urban. (4) Other central city suburban—Other school districts in and around the other large, but not major, Texas cities. They are contiguous to other central city districts. If the suburban district is not contiguous, it must have a student population that is at least 15% of the size of the district designated as central city. (5) Independent town—The largest school districts in counties with populations of 25,000–100,000. (6) Non-metro: fast growing school districts that are not in any of the above categories and that exhibit a 5-year growth rate of at least 20%. These districts must have at least 300 students in membership. (7) Non-metro: stable school districts that are not in any of the above categories, yet have a number of students in membership that exceeds the state median. (8) Rural school districts that do not meet the criteria for placement into any of the above categories. These districts either have a growth rate less than 20% and the number of students in membership is between 300 and the state median, or the number of students in membership is less than 300.

In the analysis, the first two categories above were combined to form an “urban” dummy variable, categories three and four were combined to form a “suburban” dummy variable and categories five through seven formed an “other” category, with rural districts as the reference group.

Statistical methods. Since the 1184 school districts were nested within 254 counties, we modeled the data using a multilevel Poisson regression model to adjust estimates due to a potential county level clustering effect—which can bias estimated standard errors downward, thus leading to type I errors if not properly addressed (Barcikowski, 1981).

A multilevel Poisson regression model allowing for over-dispersion of the dependent variable was used in which the total number of children with autism and the number of special education students (excluding autism) was modeled separately as a function of the total pounds of environmentally released mercury. The model was adjusted for percent of the population of European-American descent, district population wealth, percent economically disadvantaged and urbanicity. Rates were offset by the total number of children served in a school district. For the model predicting autism rates, special education counts were included as a covariate in a subsequent model. For the model predicting special education rates, autism counts were also included as a covariate in a separate model. All models were estimated using MLwiN software with a log link function specified (Goldstein et al., 1998). The analysis yields adjusted relative rate estimates as a function of pounds of environmentally released mercury.
Results

Table 1 shows the descriptive statistics of the study variables. The standard deviation and the maximum and minimum values indicate considerable variation for all study variables. Table 2 shows the results of the regression model where autism rates were modeled as a function of pounds of mercury and sociodemographic covariates (model 1), plus adjustment for the number of special education students (excluding autism) (model 2).

Model 1 shows that for each 1000 lb of environmentally released mercury, the rate of autism increases by 61%. A small but significant rate increase is noted for districts with higher wealth, and a small but significant inverse association is observed for percentage of European American and economically disadvantaged students. A large effect is observed for community type. The highest rate increase is observed when comparing urban to rural school districts—relative to rural districts there is a 473% higher rate of autism. There is a 255%

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Table 1
Descriptive statistics for study variables (n = 1184 school districts in 254 counties)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autism count total</td>
<td>5.11</td>
<td>21.39</td>
<td>0</td>
<td>416</td>
</tr>
<tr>
<td>Total special education population count</td>
<td>414.12</td>
<td>1205.21</td>
<td>0</td>
<td>21,900</td>
</tr>
<tr>
<td>Pounds of environmental mercury release</td>
<td>203.99</td>
<td>522.84</td>
<td>0</td>
<td>2059</td>
</tr>
<tr>
<td>Total student population</td>
<td>3382.30</td>
<td>10908.99</td>
<td>6</td>
<td>209,916</td>
</tr>
<tr>
<td>Percent economically disadvantaged</td>
<td>47.28</td>
<td>21.70</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Percent European American</td>
<td>58.33</td>
<td>29.71</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>District wealth</td>
<td>$189,080</td>
<td>$262,290</td>
<td>0</td>
<td>$4,276,736</td>
</tr>
<tr>
<td>Community type</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>% Urban</td>
<td>4.1</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>% Suburban</td>
<td>13.2</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>% Rural</td>
<td>34.9</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>% Other</td>
<td>47.8</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

Table 2
Poisson regression estimates predicting relative rate of autism prevalence

<table>
<thead>
<tr>
<th></th>
<th>Estimate (SE)</th>
<th>Relative rate</th>
<th>Lower 95% CI</th>
<th>Upper 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1: Predicting autism prevalence rates as a function of mercury release with demographic covariate adjustments</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mercury (per 1000 pounds)</td>
<td>0.479 (0.041)</td>
<td>1.614</td>
<td>1.487</td>
<td>1.752</td>
</tr>
<tr>
<td>Percent European American</td>
<td>-0.023 (.001)</td>
<td>0.977</td>
<td>0.975</td>
<td>0.979</td>
</tr>
<tr>
<td>District wealth (per 100,000 dollars)</td>
<td>0.060 (0.010)</td>
<td>1.062</td>
<td>1.041</td>
<td>1.083</td>
</tr>
<tr>
<td>Percent economically disadvantaged</td>
<td>-0.029 (0.001)</td>
<td>0.971</td>
<td>0.969</td>
<td>0.973</td>
</tr>
<tr>
<td>Urban versus rural</td>
<td>1.553 (0.109)</td>
<td>4.726</td>
<td>3.800</td>
<td>5.877</td>
</tr>
<tr>
<td>Suburban versus rural</td>
<td>0.935 (0.108)</td>
<td>2.547</td>
<td>2.052</td>
<td>3.161</td>
</tr>
<tr>
<td>Other versus rural</td>
<td>0.027 (0.112)</td>
<td>1.027</td>
<td>0.821</td>
<td>1.285</td>
</tr>
</tbody>
</table>

Model 2: Predicting autism prevalence rates as a function of mercury with demographic and special education count adjustment

<table>
<thead>
<tr>
<th></th>
<th>Estimate (SE)</th>
<th>Relative rate</th>
<th>Lower 95% CI</th>
<th>Upper 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mercury (per 1000 pounds)</td>
<td>0.160 (0.031)</td>
<td>1.174</td>
<td>1.103</td>
<td>1.249</td>
</tr>
<tr>
<td>Percent European American</td>
<td>-0.019 (0.001)</td>
<td>0.981</td>
<td>0.979</td>
<td>0.983</td>
</tr>
<tr>
<td>District wealth (per 100,000 dollars)</td>
<td>0.010 (0.010)</td>
<td>1.010</td>
<td>0.990</td>
<td>1.030</td>
</tr>
<tr>
<td>Percent economically disadvantaged</td>
<td>-0.034 (0.001)</td>
<td>0.967</td>
<td>0.965</td>
<td>0.969</td>
</tr>
<tr>
<td>Urban versus rural</td>
<td>0.953 (0.078)</td>
<td>2.593</td>
<td>2.219</td>
<td>3.031</td>
</tr>
<tr>
<td>Suburban versus rural</td>
<td>0.808 (0.074)</td>
<td>2.243</td>
<td>1.935</td>
<td>2.601</td>
</tr>
<tr>
<td>Other versus rural</td>
<td>-0.356 (0.087)</td>
<td>0.700</td>
<td>0.589</td>
<td>0.834</td>
</tr>
<tr>
<td>Special education count (per 1000)</td>
<td>0.172 (0.005)</td>
<td>1.188</td>
<td>1.176</td>
<td>1.200</td>
</tr>
</tbody>
</table>
higher rate of autism in suburban relative to rural districts.

In model 2, after adjustment for the number of special education students, mercury remained a significant predictor of autism rates, indicating a 17% increase in autism rates for every 1000 lb of mercury released in the environment. The number of special education students was a significant predictor of autism rates as well. Wealth was no longer a significant predictor and the other covariates showed decreases relative to model 1, but remained significant.

Table 3 shows the regression estimates where special education rates (excluding autism counts) were modeled as a function of pounds of mercury and sociodemographic covariates (model 3), plus adjustment for the number of autistic students (model 4).

Model 3 shows that each 1000 lb of reported mercury release is associated with a 43% increase in the rate of special education students. Small but significant increases were associated with the percentage of European Americans, economically disadvantaged and district wealth. Community type was strongly associated with special education rates. All community-type categories show a much higher percentage of special education students relative to rural communities.

In model 4, after adjusting for total autism counts, the association between pounds of mercury and special education rates was no longer statistically significant— with the other covariates in the model remaining significant. This indicates that increased rates in autism account for the association between environmentally released mercury and the rate of special education students.

Discussion

To the best of our knowledge, this is one of the first investigations to report an ecological association between developmental disorders and environmentally released mercury.

The results of this study demonstrate that school district autism and special education rates are significantly associated with environmentally released mercury. This association was independent of the number of children served in the educational system for that district, district wealth, ethnic make-up, and community type. Further, these results indicate that the association between mercury release and school district special education rates was completely accounted for by increased rates of autism. This indicates that, in Texas, the increase in special education rates attributable to environmental mercury can be explained by increases in autism. The results of this study are consistent with our prior nation-wide study where an association between various developmental disabilities and environmentally released mercury was observed at the state level.

Table 3

<table>
<thead>
<tr>
<th>Estimate (SE)</th>
<th>Relative rate</th>
<th>Lower 95% CI</th>
<th>Upper 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mercury (per 1000 pounds)</td>
<td>0.360 (0.030)</td>
<td>1.433</td>
<td>1.350</td>
</tr>
<tr>
<td>Percent white</td>
<td>0.004 (0.001)</td>
<td>1.004</td>
<td>1.002</td>
</tr>
<tr>
<td>District wealth (per $100,000)</td>
<td>0.050 (0.010)</td>
<td>1.051</td>
<td>1.030</td>
</tr>
<tr>
<td>Percent economically disadvantaged</td>
<td>0.012 (0.001)</td>
<td>1.012</td>
<td>1.010</td>
</tr>
<tr>
<td>Urban versus rural</td>
<td>2.741 (0.104)</td>
<td>15.502</td>
<td>12.591</td>
</tr>
<tr>
<td>Suburban versus rural</td>
<td>2.110 (0.103)</td>
<td>8.248</td>
<td>6.713</td>
</tr>
<tr>
<td>Other versus rural</td>
<td>2.110 (0.110)</td>
<td>4.711</td>
<td>3.781</td>
</tr>
<tr>
<td>Autism count (per 100)</td>
<td>0.062 (0.032)</td>
<td>0.940</td>
<td>0.882</td>
</tr>
<tr>
<td>Percent white</td>
<td>0.008 (0.001)</td>
<td>1.008</td>
<td>1.006</td>
</tr>
<tr>
<td>District wealth (per $100,000)</td>
<td>0.030 (0.010)</td>
<td>1.030</td>
<td>1.010</td>
</tr>
<tr>
<td>Percent economically disadvantaged</td>
<td>0.014 (0.001)</td>
<td>1.014</td>
<td>1.012</td>
</tr>
<tr>
<td>Urban versus rural</td>
<td>2.240 (0.068)</td>
<td>9.393</td>
<td>8.199</td>
</tr>
<tr>
<td>Suburban versus rural</td>
<td>1.902 (0.066)</td>
<td>6.699</td>
<td>5.871</td>
</tr>
<tr>
<td>Other versus rural</td>
<td>1.174 (0.073)</td>
<td>3.235</td>
<td>2.795</td>
</tr>
<tr>
<td>Autism count (per 100)</td>
<td>0.689 (0.022)</td>
<td>1.992</td>
<td>1.906</td>
</tr>
</tbody>
</table>
(unpublished manuscript). However, the results of this report should be interpreted with caution for a number of reasons.

First, this is an ecological study that precludes interpretation at the individual level. We have used aggregate units in this analysis to investigate differential rates of autism as a function of pounds of mercury at the county level. While we properly addressed the potentially biasing effects of clustering (school districts nested within counties) by utilizing appropriate analytic methods (e.g. multilevel-analysis), individual data are required to make a better case for the observed associations and their interpretations. Nevertheless, ecological studies of this type are often an important first step in identifying subsequent areas of investigation.

Second, a causal association between environmentally released mercury and developmental disorders cannot be determined from this cross-sectional data. Data availability permitting, future studies could investigate this association by using longitudinal data where changes in mercury levels over time may be used as a predictor of the rate of change in developmental disorders over time.

Third, we should consider that school-based administrative autism data, such as these, are only a proxy for true community prevalence. However, these autism rates are most likely biased downward. For example, Yeargin-Allsopp et al. (2003) found that, in one metropolitan area, 18% of children who qualified for a diagnosis of autism according to their study criteria were receiving special education services but had not been categorized as having autism. The critical unknown issue is whether identification of children in the special education system is systematically biased in the same direction as reporting of environmental mercury release. For example, counties in which administrations are more aggressive regarding penalties for underreporting toxic release may also have educational policies that result in a greater number of children identified for special education services. Despite the limitations of these administrative data, as demonstrated, these data can be a useful component to preliminary epidemiological studies (Dales et al., 2001). By demonstrating an association between environmentally released mercury and developmental disorders, the results of this study provide a necessary first step in identifying plausible contributing factors of risk for developmental disabilities.

This line of research has implications for toxic substance regulation and prevention policies. The effects of differing state policies regarding toxic release of mercury on the incidence of developmental disorders should be investigated. For example, policies that have successfully limited exposures to lead have had direct effects on morbidity and have demonstrated reductions in health care costs related to lead exposure (Sargent et al., 1999; Galte et al., 2001; Brown, 2002). However, while federal efforts toward reducing mercury exposure through policy have been successful to some extent by signing bills into law, proportionally few have been enacted (Mercury Policy Project (MMP), 2004). Despite existing policy recommendations, debate concerning acceptable levels of safety still remains (Dourson et al., 2001; Kaiser, 2000), thus, limiting progress toward evaluating policies related to reducing exposure to mercury.

Conclusions

What is currently known about the low-level toxicity of mercury from behavioral toxicology and behavioral teratology studies are convincing enough to warrant further study. This study is among the first to demonstrate an association between environmentally released mercury at the county level and the rate of developmental disability. Given the limitations of this ecological association, future studies should investigate this association using other methodologies and samples. This line of research has important implications for public health policy and supports prior recommendations for reducing environmentally released mercury (Needleman, 1995; Landrigan et al., 1994).

References


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