NCEE Working Paper

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Working Paper 19-04
May, 2019

U.S. Environmental Protection Agency
National Center for Environmental Economics
https://www.epa.gov/environmental-economics

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There is consensus that early childhood lead exposure causes adverse cognitive and behavioral effects, even at blood lead levels (BLL) below 5 μg/dL. What has not been established is to what extent the effects of childhood lead exposure persist across grades. In this paper, we examine data from 538,493 children living in North Carolina between 2000-2012 with a BLL ≤ 10 μg/dL to estimate the effects of early childhood lead exposure on educational performance from grades 3-8, to determine if effects in lower grades persist as a child progresses through adolescence. We estimate fixed-effects models and use socio-economic and demographic information along with coarsened exact matching techniques to control for confounding effects to identify the causal effect of BLL on test performance. We find that the effects of early childhood exposure to low lead levels caused persistent deficits in educational performance across grades. In each grade (3-8), children with higher blood lead levels had, on average, lower percentile scores in both math and reading than children with lower blood lead levels. In our primary model, we find that children with BLL = 5 μg/dL in early childhood ranked 1.50 – 2.07 (1.94 – 2.43) percentiles lower than children with BLL ≤ 1 μg/dL on math (reading) tests during grades 3-8. As children progressed through school, the average percentile deficit in their test scores remained stable.

Key Words: Children; Education; Lead; Blood Lead Level; Cognitive Development

JEL classification: I18, I21, Q53

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Introduction

Children are exposed to lead through a variety of sources, including lead paint, consumer products, and contaminated soil and water. While environmental policy has drastically reduced lead emissions from 1970 levels (U.S. EPA (2013)), many children in the United States continue to exhibit elevated blood lead levels (BLLs). The Flint, Michigan, drinking water crisis of 2014 was a stark reminder that lead exposure poses an ongoing threat.

There is consensus that childhood lead exposure leads to adverse health outcomes, including cognitive and behavioral deficits (Aizer et al. (2018); Bellinger et al. (1992); US EPA (2013); Evens et al. (2015); Lanphear et al. (2005); Magzamen et al. (2015); NTP (2012); Pocock et al. (1994); Reyes (2015)). What is less well understood is the persistence of the adverse lead effects, particularly at low BLLs, and whether the effects attenuate (or amplify) as children age. The first recorded case of lead poisoning in children was in 1892. The prevailing wisdom at that time was that if "the child recovered from the acute phase [of poisoning], no lasting effects would occur" (Needleman (1989)). In the 1940s, it was shown that children who survived acute lead poisoning continued to have significantly elevated lead levels and damage to their central nervous systems (Needleman (1989)).

Early studies on the effects of lead on children focused on IQ and the Bayley Mental Development Index for infants. These are small-sample studies of populations exposed to much higher mean or peak lead levels than are typically observed in today's child population (BLL > 10 µg/dL). These studies uniformly found statistically significant, negative correlations between early childhood

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[1] The authors thank the Children's Environmental Health Initiative (CEHI) at Rice University, in particular, the CEHI Director, Marie Lynn Miranda, and Claire Osgood for their generosity in sharing their data and providing technical support, as well as Daniel Axelrad in EPA's National Center for Environmental Economics and Juleen Lam, Cal State – East Bay, for their comments on a draft version. The protocol for this study was approved by the Rice University Institutional Review Board. All results have been screened by the CEHI to ensure no confidential information, including any identifiable individual-level data, is disclosed.

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lead exposure and IQ (Pocock et al. (1994)). These studies did not address the issue of persistence in the effects of lead.

More recent literature has used individual-level blood lead surveillance data and public-school records to examine the relationship between BLL and achievement test scores. Achievement test scores reflect both intelligence and traits such as conscientiousness and neuroticism -- characteristics strongly associated with later-in-life outcomes (Borghans et al. (2016)). These studies found that higher BLLs led to significantly lower test scores in grades 3 or 4, but they did not examine the effects in later grades (Miranda et al. (2007, 2009); Magzamen et al. (2013, 2015), Evens et al. (2015); Aizer et al. (2018)). Zhang et al. (2013) and Elliot et al. (2015) found a positive relationship between less-than-proficient test scores and lead levels in grades 3, 5, and 8, but neither study examined the heterogeneity of lead's effect by grade.

A few longitudinal studies have examined the effects of lead on longer-term outcomes using small cohorts. These studies found negative correlations between early childhood lead levels and IQ or educational performance measured in later childhood or adulthood (Bellinger et al. 1992; Mazumdar et al. 2011, Needleman et al. 1990; Reuben et al. 2017). While these studies found that adverse effects of early childhood lead exposure persisted later in life, most did not quantitatively assess how the magnitude of those effects varied by age or grade. The exception is Reuben et al. (2017), who examined the change in IQ from childhood to adulthood among adults in New Zealand whose blood lead levels were measured as children. They observed that higher childhood BLL was associated with steeper declines in IQ from childhood to adulthood, but this analysis did not adjust for covariates.

In this study we estimate the effects of early childhood, low-level lead exposure on standardized test performance across grades in both math and reading. We study a cohort similar to that used by Miranda et al. (2007, 2009), but we follow those students every year from third through eighth grade, which allows us to estimate the change in trajectory of student performance across grades due to lead exposure. Our dependent variable is the student's percentile score on their achievement test, which allows us to compare a student's performance relative to their cohort. We focus our attention on two groups of children -- those with a maximum BLL ≤ 10 μg/dL and those with a maximum BLL ≤ 5 μg/dL. We use coarsened exact matching to construct "treatment" (children with BLL 2-5 μg/dL) and "control" (children with BLL ≤ 1 μg/dL) groups that have a better distributional balance across multiple covariates, improving our ability to identify the causal effect of BLL on test performance. Our research contributes to the literature in three ways: it adds to the understanding of how low-level BLL (≤ 5 μg/dL) affects a student's performance relative to their cohort; it addresses how BLL affects the educational trajectory as children age; and it helps to inform the development of public policies to minimize the adverse effects of lead exposure.

Methods

Data and Summary Statistics

This research was conducted under an agreement with the Children's Environmental Health Initiative (CEHI) at Rice University according to a research protocol approved by the University's Institutional Review Board.CEHI provided BLL data from the North Carolina Childhood Lead Poisoning Prevention Program surveillance registry. As in most other states, BLL testing in North Carolina is not universal. North Carolina state guidelines require screening for all children participating in Medicaid and recommend screening for other "at-risk" children (Dickman & Safer Chemicals, Healthy Families, 2017). Approximately 20 to 30 percent of one- and two-year old children were screened in North Carolina in the 1990s and 2000s (North Carolina Childhood Lead Poisoning Prevention Program, 2004). We do not formally address selection bias in this study, but it is an important caveat when interpreting our results.

Our sample begins with all children who were born between 1990 and 2004 and were screened for lead in North Carolina at least once during age 0–5. The dataset includes information about the child's birthdate, Medicaid enrollment status, BLL test date, blood sample method (capillary, venous), and the name of the laboratory responsible for the blood analysis. The majority of children in the registry were screened between the ages of 1-2 years using capillary ("finger prick") blood samples analyzed by the North Carolina State Laboratory of Public Health. While capillary samples are easier to collect than venous samples, they are also more susceptible to contamination (Caldwell et al. 2017) and therefore may be a potential source of measurement error in statistical analysis. While the majority of the children that we study had only a single blood lead test during childhood, for children with multiple BLL tests, we take the geometric mean over all tests to create a single BLL measure. Aizer et al. (2018) found that using the child's geometric mean BLL resulted in a larger estimated effect of BLL on test scores than a single random draw, suggesting that utilizing information from multiple tests can reduce attenuation bias coming from measurement error in a single BLL test result. North Carolina's Department of Health and Human Services recognizes a level of detection for blood lead at 1 µg/dL, so children with a reported BLL *below* the level of detection are assigned a value of 1 µg/dL in the state database. All other BLL values are rounded to the nearest integer.[2]

For our analysis, we study two overlapping groups of children. The first consists of children who had a maximum BLL ≤ 10 µg/dL between the ages of 0-5 (96 percent of the lead surveillance registry). This sample allows us to examine the effects of early childhood lead exposure by grade across a wide range of relevant exposure levels. We also consider a second, more restrictive sub-sample of children. It consists of children who had a maximum BLL ≤ 5 µg/dL (74 percent of the surveillance registry). This smaller sample allows us to examine the effects of low-level BLL on

[2] http://slph.ncpublichealth.com/hemachem/childhoodleadtesting.asp.

a more representative sample of children, as it is estimated that less than 1% of the US population age 1 through 5 has a BLL exceeding 5 µg/dL.[3]

Our focus on these two groups helps isolate the impact of lead exposure from the potentially confounding effect of medical interventions that may be implemented for children with an elevated BLL. During our study period, North Carolina guidelines indicated that children who presented a BLL > 10 µg/dL must be re-tested within 6 months. If their second test confirmed a BLL > 10 µg/dL then the child was eligible for a medical intervention (Billings and Schnepel 2018). During our sample period, children with a BLL ≥ 10 µg/dL simultaneously were considered by the Centers for Disease Control and Prevention (CDC) as having a blood lead "level of concern." For those children, the CDC recommended interventions such as conducting an environmental assessment and a detailed personal history to determine potential sources of lead exposure; providing nutritional counseling to increase calcium and iron intake to remove lead from the body; bowel decontamination if necessary; and oral chelation therapy in the case of dangerously high levels of lead. On the other hand, children having a BLL below the "level of concern," were not eligible for any medical intervention.[4] By examining samples of children with BLL values of 10 µg/dL and 5 µg/dL and below, we minimize this potentially confounding issue.

Every year, children living in North Carolina in grades 3 through 8 are administered end-of-grade standardized achievement tests in reading and mathematics. The North Carolina Education Research Data Center (NCERDC) maintains a database with records of those test scores. The NCERDC database also contains information on each student's school, grade, gender, race, age, and enrollment status in a free/reduced-price school lunch. (Students enrolled in free/reduced-price lunch are hereafter referred to as "economically disadvantaged.") We link students to their test results for each grade from 2000-2012, creating an unbalanced panel. We then merge the test-score panel data to the BLL dataset based on a common child identifier created by CEHI for matching purposes. CEHI created the common child identifier using 16 different combinations of social security number, date of birth, county federal information processing standards code, and first and last name. We augment the data with information from each child's birth certificate records provided by CEHI from the North Carolina Department of Health and Human Services. The birth certificate data includes the child's birthdate, mother's age and marital status at time of birth, and mother's smoking and alcohol use during pregnancy.

Table 1 presents summary statistics for the different samples we study. The primary sample of children (BLL ≤ 10 µg/dL) consists of 538,493 students from 2000-2012, which represents 57% of the lead surveillance registry with BLL ≤ 10 µg/dL, and 2,294,074 student-year observations. The average BLL in the sample is 3.68 µg/dL. The students in this sample are 51% non-Hispanic White, 36% non-Hispanic Black, and 13% all other races. Consistent with the focus on screening

[3] https://www.childstats.gov/americaschildren/tables/phy4a.asp.
[4] https://www.cdc.gov/nceh/lead/acclpp/blood_lead_levels.htm

at-risk children, 44% of the sample were eligible for Medicaid at the time of the blood test, 59% were considered economically disadvantaged, and 43% were born to single mothers. Our restricted sample of children with BLL ≤ 5 µg/dL includes 419,272 children with a mean BLL of 2.9 µg/dL.

In Figure 1 we plot average student performance in math and reading in grade 3 and grade 8 by BLL for our main sample (BLL ≤ 10 µg/dL). For our measure of performance, we transform raw test scores into percentile ranks relative to the population of all students in the state of North Carolina who took the exam in a given grade and year. The "percentile deficit" is the average percentile difference between the various "treatment" groups (students with an early childhood BLL = 2, 3, 4, …, 10 µg/dL) and the "control" group (students with an early childhood BLL ≤ 1 µg/dL). First, we observe that on average, children with higher BLLs rank lower than children with lower BLLs. In addition, between third and eighth grade, children with higher BLLs do not improve their performance relative to their cohort. In math, a child with a BLL of 5 µg/dL has an average score that is 6.89 percentiles lower than a student with a BLL ≤ 1 µg/dL in third grade. By eighth grade, this differential worsens; a student with a BLL of 5 µg/dL ranks 8.40 percentiles below a student with a BLL ≤ 1 µg/dL. A similar pattern exists for reading test scores. The data suggest a strong pattern of persistence in the effects of lead exposure on school performance. These associations, however, are not adjusted for any student, mother, or school characteristics that may confound the relationship between BLL and achievement test scores.

Empirical Model

While Figure 1 suggests there may be a persistent pattern of educational deficit across grades resulting from early childhood lead exposure, it does not provide evidence of a causal relationship or rule out the possibility that the observed pattern is due to spurious correlation. To better understand the causal effect of lead exposure on school performance across grades, we start by estimating the following model:

$$Percentile\ Score_{igst} = \beta_0 + \boldsymbol{d}_{gst}\theta + \boldsymbol{X}_{it}\beta_1 + \boldsymbol{BLL}_i\boldsymbol{\gamma}_1 + \varepsilon_{igst} \qquad (1)$$

where $Percentile\ Score_{igst}$ is the math or reading percentile score for student *i*, in grade *g*, at school *s*, in year *t*, normalized based on the population of *all* North Carolina students in grade *g* and year *t*. Control variables include a vector of characteristics of both the student and the student's mother $(\boldsymbol{X}_{it})$, as well as a vector of dummy variables denoting individual grade-school-year combinations $(\boldsymbol{d}_{gst})$. $\boldsymbol{BLL}$ enters as a vector of dummy variables denoting each BLL above 1 µg/dL, and so the effect of BLL on percentile rank is allowed to vary non-linearly across BLLs.

To explore whether the educational trajectory of children across grades is affected differentially by early childhood lead exposure, we interact $\boldsymbol{BLL}_i$ with the variable G_g, where $G_g = 0$ if the student is in third grade, 1 if the student is in fourth grade, through $G_g = 5$ if the student is in eighth grade.

The model we estimate is:

$$Percentile\ Score_{igst} = \beta_0 + \boldsymbol{d}_{gst}\theta + \boldsymbol{X}_{it}\boldsymbol{\beta}_1 + (\boldsymbol{X}_{it} \times G_g)\boldsymbol{\beta}_2 + \boldsymbol{BLL}_i\boldsymbol{\gamma}_1 + \left(\boldsymbol{BLL}_i \times G_g\right)\boldsymbol{\gamma}_2 + \varepsilon_{igst} \qquad (2)$$

The parameter vector $\boldsymbol{\gamma}_2$ captures how educational outcomes change with grade at different levels of early childhood lead exposure. The interaction term $\boldsymbol{X}_{it} \times G_g$ is included to allow the impacts of other covariates to vary by grade, and thus identify $\boldsymbol{\gamma}_2$.

Finally, to consider whether the effects of early childhood lead exposure across grades vary by race or socioeconomic characteristics, we add interaction terms between a subset of variables found in $\boldsymbol{X}_{it}$, which we denote $\boldsymbol{Z}_{it}$, and $\boldsymbol{BLL}_i$ as well as G_g:

$$\begin{aligned} Percentile\ Score_{\ igst} = \beta_0 + d_{gst}\theta + \boldsymbol{X}_{it}\boldsymbol{\beta}_1 + (\boldsymbol{X}_{it} \times G_g)\boldsymbol{\beta}_2 + \boldsymbol{BLL}_i\boldsymbol{\gamma}_1 + \left(\boldsymbol{BLL}_i \times G_g\right)\boldsymbol{\gamma}_2 \\ + (\boldsymbol{BLL}_i \times \boldsymbol{Z}_{it})\gamma_3 + \left(\boldsymbol{BLL}_i \times \boldsymbol{Z}_{it} \times G_g\right)\gamma_4 + \varepsilon_{igst}. \qquad (3) \end{aligned}$$

β_1 captures the effect of various child and mother characteristics on percentile rank, and γ_3 allows the effect of BLL on percentile rank to differ across a subset of these characteristics. Of particular interest, estimates of γ_4 shed light on whether the effects of early childhood lead exposure by grade are consistent across different racial and socioeconomic groups.

We estimate equations (1), (2), and (3) controlling parametrically for several potential confounders. These variables include the child's sex, race, economically disadvantaged status, Medicaid enrollment, birth month, and age upon entry to grade 3. We also include the mother's age, marital status, and self-reported alcohol and tobacco use at the time of the child's birth. Mother's age enters our model as a set of three categorical variables to allow for a potential nonlinear relationship between mother's age and school performance. Several studies examining educational outcomes also control for parental education. This variable exists in the NCERDC dataset, but CEHI no longer recommends using it out of concern over the quality of the self-reported variable, so we do not include it in our models. That said, our model results are not sensitive to the inclusion of the parent education variable. Finally, the use of grade-school-year dummy variables allow us to capture the effects of BLL on a student's percentile rank relative to other students in the same grade, same school, and during that same year, further minimizing the effect of potential confounders.

Coarsened Exact Matching

To interpret the coefficients on BLL as the causal effect on student test performance, the coefficient estimators must be unbiased. For this to be the case, there cannot be unobserved factors that directly affect percentile rank that are both correlated with early childhood BLL and are omitted from equations (1), (2), and (3). Such unobserved factors could include innate student ability, wellness, educational or medical interventions, and a supportive household.

To minimize the possibility of bias, we pre-process our data using a many-to-one coarsened exact matching (CEM) algorithm that is designed to better balance the distributions between the "treated" and "control" groups simultaneously for a set of observables that may affect percentile rank (Iacus, King & Porro, 2012). One motivation for this matching procedure is that if these two sub-samples are more balanced in terms of observed characteristics, then they may be more comparable in terms of unobserved characteristics as well. In addition, CEM provides a way to control non-parametrically for the observed characteristics.

CEM allows us to focus our analysis only on students who are similar in terms of key observed characteristics that may affect school outcomes (other than the variable of interest, BLL), thereby isolating the effect of BLL on percentile rank from that of other characteristics which may, themselves, be correlated with BLL. Balance is achieved by "pruning" observations in the control and treatment groups that cannot be matched and by using weights to balance the number of observations in each stratum across the groups. We define the "treated" group as students who had a geometric mean BLL > 1 μg/dL in early childhood. The "control" group consists of children with a BLL ≤ 1 μg/dL. We use 1 μg/dL as our cutoff as this is the stated minimum level of detection by the State Laboratory (Miranda et al. 2007). Because the treatment variable is dichotomous, we focus on the ≤ 5 μg/dL sample for the CEM analysis. Children with higher BLLs become increasingly less comparable to the control group of children with BLL ≤ 1 μg/dL.[5]

The covariates we use for exact matching are race/ethnicity (non-Hispanic White, non-Hispanic Black, and all other categories); economically disadvantaged status; mother's marital status at the time of birth (married or unmarried); enrollment in Medicaid at the time of the blood lead test; and school-grade-year indicators. We also match on mother's age at the time of the child's birth coarsened into three bins (less than 20 years, 20-29 years, and 30 years and above). For example, CEM allows us to compare the average percentile rank of Black eighth graders in 2012, attending a particular middle school, whose mothers were married, did not receive Medicaid, were not economically disadvantaged, and had an early childhood mean BLL ≤ 1 μg/dL, against students with those exact characteristics except that they had an early childhood mean BLL > 1 μg/dL. If the treatment and control groups are exactly balanced on the covariates, the causal effect can be estimated as the difference in the sample means across the two groups.

[5] Our results remain consistent when we use CEM matching on the full sample, but are not as precisely estimated due to pruning of observations at higher levels of BLL. Results are available from the authors, on request.

A measure of multidimensional imbalance, L1, is given by the rectilinear distance between the k-dimensional histogram, where k is determined by the number of covariates used in the matching algorithm (Iacus, King and Porro, 2012). The L1 parameter is bounded by 0 and 1 where an L1 value of 0 indicates perfect global balance, up to the level of "coarsening" or bin size, and an L1 value of 1 indicates complete separation. Prior to matching, we calculate the multidimensional imbalance measure on the sample of students with a BLL $\leq$ 5 µg/dL (1,747,688 student-year observations) as L1 = 0.25. After CEM, we retain 520,795 student-year observations and have an imbalance measure of L1=0.02. This is a reduction in the multidimensional imbalance of 92%. (The univariate imbalance parameters also show improved balance for each variable, except gender, where the imbalance measure goes from 0.018 to 0.024.)

The matching procedure shifts the distribution of BLL in the final matched sample such that a greater proportion of retained observations range from 1 to 3 µg/dL than in the unmatched sample. This results in a decline in mean BLL from 2.9 µg/dL in the full $\leq$ 5 µg/dL sample to 2.5 µg/dL in the matched $\leq$ 5 µg/dL sample. We also observe a reduction in both the fraction of non-Hispanic Black and economically disadvantaged children in the matched sample. This is not unexpected as children in these categories are more likely to exhibit higher BLL values.

Results

Our estimates for equation (1) are summarized in Table 2. The dependent variable for the first three models is the student's percentile score in math. The dependent variable for the second three models is the percentile score in reading. We estimate cluster-robust standard errors for each model, where the cluster is at the school level to allow errors to be correlated within, but not between schools. Models 1 and 4 in Table 2 are based on the full sample of students who had their BLL tested in early childhood and had a maximum BLL $\leq$ 10 µg/dL. In the subsequent models in Table 2, we examine the robustness of the results when focusing on students with a maximum BLL $\leq$ 5 µg/dL (models 2 and 5 in Table 2), a range that is more consistent with the current population of children. To examine the robustness of our results, we use coarsened exact matching to obtain a more balanced sample across the control and treated groups within the BLL $\leq$ 5 µg/dL sample in terms of key covariates that may be correlated with both percentile rank and BLL (models 3 and 6 in Table 2).

Blood Lead Level

The coefficients corresponding to the ***BLL*** vector capture the effect of a student's early childhood lead exposure on test performance. The estimates in models 1 and 4 in Table 2 are negative for both math and reading, and are generally increasing in magnitude as BLL increases. Focusing on the effects of BLL on math percentile in model 1, we find that students with a BLL of 2 µg/dL have a percentile rank 0.34 ($p < 0.001$) points lower than students in the control group with BLL ≤ 1 µg/dL. This negative effect increases at higher lead levels, suggesting up to a 3.80 percentile decrement ($p < 0.001$) among students with an early childhood lead exposure level of 10 µg/dL. These trends, also depicted in Figure 2, are similar when examining reading score percentiles. While these effects are statistically significant, they are substantially smaller in magnitude than the unadjusted associations between BLL and percentile rank shown in Figure 1, which confirms the importance of controlling for student and school characteristics in our regressions.

Focusing attention on the full and matched samples of children with BLL ≤ 5 µg/dL, we see that the results are extremely similar.[6] This suggests that the estimates based on the full sample with BLL ≤ 10 µg/dL are not driven by unobserved heterogeneity across students with different BLLs, and lends greater support to a causal interpretation of the effects of early childhood lead exposure on later math and reading test performance.

Child and Mother Characteristics

Our models include control variables that are known to be important determinants of test scores and educational achievement (see for example, Jaffee et al. 2001; Sirin 2005). These variables describe the student at the time of birth or when in grade *g*, and the mother at the time of the student's birth. The corresponding coefficient estimates are shown in Table 2. In general, we find that percentile rankings in math are higher for males than for females, but the reverse is true for reading. Non-Hispanic Black students (*Black*) tend to score lower while non-Hispanic White students (*White*) tend to score higher relative to all other racial groups. Children who are older in grade 3 (*Age in 3rd Grade*) also do less well, possibly reflecting selection bias driven by parent choice on when to enter a child into school. Students who are economically disadvantaged (*EconDisadv*) and enrolled in *Medicaid* also score lower than students who are economically better off.

We find that children born to unmarried mothers and mothers who smoked while pregnant have significantly lower percentile ranks on reading and math tests. The mother's self-reported reported alcohol consumption during pregnancy (*Alcohol Use*) is positively associated with percentile rank, though this result is not statistically significant in all models. Mother's age at the time of the child's birth is also a significant predictor of percentile rank, with older mothers having higher-performing children than women who have children prior to age 21.

Putting our core results in context, we find that having a BLL of 5 µg/dL (relative to ≤ 1 µg/dL), for example, leads to a similar percentile decline as having a mother who is unmarried at the time

[6] We also used our CEM algorithm to generate a matched set of "control" and "treatment" observations in the BLL ≤ 10 µg/dL sample and, again, our results remain robust. These results are available from the authors upon request.

of the student's birth (1.45 to 2.13 points). On the other hand, this same elevated BLL has a less negative effect than that associated with being Black, being economically disadvantaged or enrolled in Medicaid, or having a mother who smoked while pregnant (each of which are associated with losses of 3-10 percentiles).

Persistence of the Effects of Lead Across Grades

Equation (2) allows us to investigate whether the effects of early childhood lead exposure change as children progress through grade school and into adolescence. This is done by including interaction terms between ***BLL*** and a scalar variable, *grade*. All other control variables included in the model (except birth month) also are interacted with *grade* to allow the effects of the covariates on test score percentiles to vary by grade. Table 3 presents the coefficients of primary interest, but the full set of coefficient estimators are available in the Supplemental Material, Table S1.

The series of coefficient estimates corresponding to ***BLL*** in Table 3 captures the average effect of early childhood BLL on third grade test score percentiles. The set of coefficients on the ***BLL***×*grade* interaction terms capture the average incremental change in test score percentile for each successive year in school from fourth through eighth grade at each BLL. For example, based on model 1 in Table 3, we find a 1.50 decrement ($p < 0.001$) in math percentile among students in third grade with a BLL of 5 µg/dL, relative to students with a BLL ≤ 1 µg/dL. The estimate corresponding to *BLL 5 × grade*, while negative, is small relative to the direct effect of *BLL 5* and is not significantly different from zero. Summing the coefficient on *BLL 5* with the coefficient on *BLL 5 × grade* multiplied by five gives the percentile deficit for eighth graders. We find a 2.07 decrement ($p < 0.001$) in math percentile for eighth graders with a BLL of 5 µg/dL, relative to students with a BLL ≤ 1 µg/dL. Effects on reading test scores are similar: model 4 in Table 3 shows a 1.94 decrement ($p < 0.001$) in percentile scores for third graders and a 2.43 decrement ($p < 0.001$) in percentile scores for eighth graders with a BLL of 5 µg/dL, relative to students with a BLL ≤ 1 µg/dL. Our results indicate that the negative effect of early childhood lead exposure on test performance not only persists through subsequent grades, but it also does not attenuate as students reach higher grades. This suggests that children are not able to counteract the negative effects of early childhood lead exposure on their educational performance, at least not without medical intervention. We find similar results at different BLL levels and across both math and reading test performance. This result is robust to models considering more homogenous samples (models 2, 3, 5, and 6 in Table 3), and while not shown here, it is robust to using raw test scores in lieu of percentiles. Joint significance tests confirm the *grade* x *BLL* effects are jointly not significantly different from zero in all models ($p = 0.31$-0.99).

Figure 3 illustrates the results from models 1 and 4. The left panel shows the math percentile decrement with respect to BLL, and the right panel shows the same for reading. The dashed lines show this relationship among students in third grade and demonstrates the downward trend previously noted. Percentile ranks continue to decrease as BLL increases, reaching a nearly 4 percentile decrement among students with an early childhood exposure level of 10 µg/dL. The solid black line depicts the same relationship among eighth grade students. The slope of the BLL-percentile rank relationship is slightly steeper for eighth graders than for third graders, suggesting that, if anything, the effects are even more pronounced. The two lines are quite close together, however, and the 95% confidence intervals overlap. Our results show that the negative effect of early childhood lead exposure on percentile rank persists as a child progresses through eighth grade.

Persistence of Lead Impacts Across Grades for Different Racial and Socioeconomic Groups

There is some question about whether the effects of lead on health and cognitive outcomes vary by race or socioeconomic status (Bellinger 2008; Hicken et al. 2013; Ferrie et al. 2015). The evidence on this issue is mixed for achievement test scores. For example, Magzamen et al. (2015) did not find statistically significant racial or socioeconomic heterogeneity in the effect of lead on test scores, but Evens et al. (2015) did find significant interactions, with a larger adverse effect of lead found in non-Hispanic White children than non-Hispanic Black or Hispanic children. We expand on this literature by examining whether there is heterogeneity in the impacts of early childhood lead exposure by grade across racial and socioeconomic groups.

We estimate equation (3), which includes interaction terms between the vector ***BLL*** with dummy variables identifying students who are Black (*Black*), economically disadvantaged (*EconDisadv*), and enrolled in Medicaid (*Medicaid*). The BLL and grade interaction terms are also interacted with these racial and socioeconomic group variables.

Figure 4 illustrates the results of interest, estimated using the full sample of students with BLL ≤ 10 µg/dL.[7] The top panel in Figure 4 displays the test score percentile decrement with respect to BLL for math (left) and reading (right) for the reference group, which includes students identified as a race other than Black, not listed as economically disadvantaged, and not enrolled in Medicaid. Lower panels display the results for each of the respective racial and socioeconomic groups. Compared to the previous model results, the confidence intervals are wider due to the additional parameter estimates through the added interaction terms, and there are some non-monotonicities introduced at higher BLLs. These results may occur due to the smaller number of observations in the higher BLL range when examining individual groups separately. Nonetheless, among all racial and socioeconomic groups, we see a similar downward trend showing that increases in BLL lead to a larger decrement in percentile rank. The one possible exception is among students enrolled in Medicaid. Here the trend is relatively flat, and not statistically different from zero at some BLL levels, however the confidence intervals are relatively wide among this group.

[7] Results are available upon request.

Across all groups depicted in Figure 4 we see that the relationship between the test score percentile decrement and BLL is similar among third and eighth grade students. In other words, even when examining these racial and socio-economic groups separately, we still find a persistent negative effect of early childhood lead exposure on percentile rank as a student progresses into adolescence.

Discussion

While a substantial body of literature suggests that early childhood lead exposure has adverse effects on cognitive development, much of the evidence is based on tests taken by students in early grade school or is based on relatively high BLLs that are no longer representative of the current population of children in the US. To develop effective policies to protect the health and welfare of children, it is of fundamental importance to build knowledge on how low-level lead exposure affects a child's long-term well-being.

This study is the first to examine how the effect of BLL on achievement test performance varies as a child progresses from early grade school into secondary school. We find strong evidence that even low-level lead exposure during early childhood has a negative effect on children's school performance, and this effect is persistent from third through eighth grade. These findings are robust across different models and samples. Our findings are also consistent when restricting the BLL≤ 10 μg/dL and BLL≤ 5 μg/dL samples to a balanced panel that only includes students whose test scores are available for every year from third to eighth grade. In addition, our results are robust to alternative outcome variables, including a continuous variable measuring the raw test score and a dichotomous variable representing whether the student's score met the cutoff for "proficient" set by the North Carolina Department of Public Instruction, Division of Accountability. These results are not presented here but are available from the authors upon request.

Our study has some limitations. First, the sample of children screened for lead in North Carolina does not represent a random draw from the child population, which could lead to selection bias. Even though we have a relatively large cohort of students in North Carolina, this cohort may not be representative of the general population of the state (or the United States). The children captured in the North Carolina Lead Prevention Surveillance Program are more likely to be economically disadvantaged or otherwise "at risk" for lead exposure. Although such selection bias may affect any inference to the broader population of children, it does not affect our within-sample estimates of how early childhood lead exposure impacts educational performance.

Second, most blood lead testing occurs when children are age 1 to 2 years, and there are very few observations in the lead surveillance data beyond five years. Although we examine the educational deficit from early childhood BLL, it is possible that continued low-level lead exposure into early adolescence partly explains our results. This is an important caveat to keep in mind when interpreting our findings. Given the paucity of data on BLL in older children and the positive association between past lead exposure and later BLL, disentangling the effects of early-childhood from later-childhood lead exposure is beyond the scope of our study.[8]

Third, we do not have reliable information on parent education, parent occupation, or household income, which are known to be important determinants of a child's school performance and may well be correlated with a child's BLL. If so, this may introduce bias into our results, despite the inclusion of numerous observed covariates, including dummy variables denoting each grade at a particular school and in a specific year. The robustness of our results to exact covariate matching, where the control and treatment groups are balanced in terms of observed covariates (and presumably unobserved covariates as well) lends to the credibility of our findings.

Despite these limitations, our study advances the understanding of how low-level lead exposure in early childhood affects a child's school performance across grades by making several advancements. First, by following the same children from third to eighth grade, we are able to show that the negative effects of BLL on test performance in early grades persist in later grades. Second, by adopting a coarsened exact matching algorithm, we create balanced distributions between the "treated" (BLL > 1 μg/dL) and "control" (BLL ≤ 1 μg/dL) groups on a set of observables that may affect percentile rank non-parametrically, thereby reducing omitted variable bias and aiding our ability to interpret the results as a causal association. The robustness of our results across the matched sample and the full samples (BLL ≤ 10 μg/dL and ≤ 5 μg/dL) strengthens our argument that we have captured a causal relationship between early childhood lead exposure and educational deficits that persists across grades. Finally, by focusing on samples of children with low-level lead exposure (BLL ≤ 10 μg/dL and ≤ 5 μg/dL), our work provides information on some of the likely benefits of reducing early childhood lead exposure among the current population of children.

Conclusions

This is the first paper to examine how the effect of low-level early childhood lead exposure on educational performance varies as a child progresses from early grade school into secondary school. Our analysis demonstrates that even low BLLs have a measurable and persistent effect on a child's educational performance in math and reading across grades. Furthermore, we find that the magnitude of the educational deficit is stable between grades 3-8. This indicates that physical maturation and additional schooling are not sufficient to offset the damage caused by early childhood exposure. Our results highlight the benefits to children's educational performance from preventing early childhood exposure to lead.

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[8] The half-life of lead in blood is roughly 30 days. Lead is also stored in bone, however, and can be released from bone to blood over much longer time spans (U.S. EPA 2013).

References

Aizer, A., Currie, J., Simon, P., & Vivier, P. (2018). "Do Low Levels of Blood Lead Reduce Children's Future Test Scores?" *American Economic Journal: Applied Economics* 10(1), 307-341. doi:10.1257/app.20160404.

Billings, S.B. and Schnepel, K.T. (2018). "Life after Lead: Effects of Early Interventions for Children Exposed to Lead." *American Economic Journal* 10(3), 315-344. doi:10.1257/app.20160056.

Bellinger, D.C. (2008). "Lead Neurotoxicity and Socioeconomic Status: Conceptual and Analytical Issues." *Neurotoxicology* 29(5), 828-832. doi: 10.1016/j.neuro.2008.04.005.

Bellinger, D.C., Stiles, K.M., & Needleman, H.L. (1992). "Low-Level Lead Exposure, Intelligence and Academic Achievement: A Long-term Follow-up Study." *Pediatrics* 90(6), 855-851. PMID: 1437425.

Borghans, L., Golsteyn, B.H., Heckman, J.J., & Humphries, J.E. (2016). "What Grades and Achievement Tests Measure." PNAS, 113(47), 13354-13359. doi/10.1073/pnas.1601135113.

Caldwell, K., P-Y. Cheng, J. Jarrett, et al. (2017). "Measurement Challenges at Low Blood Lead Levels." *Pediatrics* 140(2). doi: 10.1542/peds.*2017*-0272.

Canfield, R.L., Henderson, C.R., Cory-Slechta, D.A., Cox, C., Jusko, T.A., & Lanphear, B.P. (2003). "Intellectual Impairments in Children with Blood Lead Concentrations below 10 µg per Deciliter." *New England Journal of Medicine* 348(16), 1517-1526. PMID: 12700371.

Centers for Disease Control and Prevention & National Center for Health Statistics, (2016). *National Health and Nutrition Examination Survey Data.* Hyattsville, MD: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention.

Dewalt, G.F., Cox, D.C., O'Haver, R., Salatino, B., Holmes, D., Ashley, P.J., … & Fraser, A. (2015) "Prevalence of Lead Hazards and Soil Arsenic in U.S. Housing." *Journal of Environmental Health,* 78(5), 22-29. https://www.hud.gov/sites/documents/LEADHAZARDS_SOILARSENIC.PDF.

Dickman, J. & Safer Chemicals, Healthy Families. (2017) "Children at Risk: Gaps in State Lead Screening Policies." https://saferchemicals.org/sc/wpcontent/uploads/2017/01/saferchemicals.org_children-at-risk-report.pdf

Dietrich, K.N., Berger, O.G., Succop, P.A., Hammond, P.B., Bornschein R.L. (1993). “The Developmental Consequences of Low to Moderate Prenatal and Postnatal Lead Exposure: Intellectual Attainment in the Cincinnati Lead Study Cohort Following School Entry.” *Neurotoxicology Teratology* 23, 511-518. https://doi.org/10.1016/0892-0362(93)90043-N

Dietrich, K.N., Ware, J.H., Salganik, M., Radcliffe, J., Rogan, W.J., Rhoads, G.G.,…, & Jones, R.L. (2004). “Effect of chelation therapy on the neuropsychological and behavioral development of lead-exposed children after school entry.” *Pediatrics* 114(1), 19-26. PMID 15231903.

Elliott, M.R., N. Zhang, and D. Small. (2015). “Application of Propensity Scores to a Continuous Exposure: Effect of Lead Exposure in Early Childhood on Reading and Mathematics Scores.” *Observational Studies* 1: 30-55.

Evens, A., Hryhorczuk, D., Lanphear, B.P., Rankin, R.M., Lewis, D.A., Forst, L., & Rosenberg, D. (2015). “The Impact of Low-Level Lead Toxicity on School Performance Among Children in the Chicago Public Schools: A Population Based Retrospective Cohort Study.” *Environmental Health* 14(21). https://doi.org/10.1186/s12940-015-0008-9.

Ferrie, J.P, Rolf, K, & Troesken, W. (2015). “Lead Exposure and the Perpetuation of Low Socioeconomic Status.” Working Paper. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.681.982&rep=rep1&type=pdf

Hernberg, S. (2000). “Lead Poisoning in a Historical Perspective.” American Journal of Industrial Medicine 38:244-254. PMID 10940962.

Hicken, M.T., Gee, G.C., Connell, C., Snow, R.C., Morenoff, J., & Hu, H. (2013) “Black-white blood pressure disparities: depressive symptoms and differential vulnerability to blood lead.” *Environmental Health Perspectives.* 2013 Feb;121(2):205-9. doi: 10.1289/ehp.1104517.

Iacus, S.M., King, G. & Porro, G., (2012). “Matching for Causal Inference Without Balance Checking: Coarsened Exact Matching.” Political Analysis 20(1), 1-24. doi:10.1093/pan/mpr013.

Jaffee, S., Caspi, A., Moffitt, T., Belsky, J., & Silva, P. (2001). Why are children born to teen mothers at risk for adverse outcomes in young adulthood? Results from a 20-year longitudinal study. *Development and Psychopathology, 13*(2), 377-397. PMID: 11393652

Lanphear, B.P., Hornung, R., Khoury, J., Yolton, K., Baghurst, P., Bellinger, D., …, Roberts, R. (2005). “Low-Level Environmental Lead Exposure and Children’s Intellectual Function: An

International Pooled Analysis." Environmental Health Perspectives 113(7) 894-899. July. doi:10.1289/ehp.7688.

Magzamen S., Imm P., Amato, M.S., Havlena, J.A., Anderson, H.A., Moore, C.F., & Kanarek, M.S. (2013). "Moderate Lead Exposure and Elementary School End-of-Grade Examination Performance." Annals of Epidemiology 23(11), 700-707. PMID 24095655.

Magzamen, S., Amato, M.S., Imm, P., Havlena, J.A., Coons, M.J., Anderson, H.A., Kanarek, M.S., & Moore, C.F. (2015). "Quantile Regression in Environmental Health: Early Life Lead Exposure and End-of-Grade Exams." *Environmental Research* 137(108), 108-119. PMID: 25531815.

Mazumdar, M., Bellinger, D., Gregas, M., Abinalla, K., Bacic, J., & Needleman, H. (2011). "Low-Level Environmental Lead Exposure in Childhood and Adult Intellectual Function: A Follow-Up Study." *Environmental Health* 10:24. http://www.ehjournal.net/content/10/1/24.

McLaine, P., Navas-Acien, A., Lee, R., Simon, P., Diner-West, M., & Agnew, J. (2013). "Elevated Blood Lead Levels and Reading Readiness at the Start of Kindergarten." Pediatrics 131(6), 1081-1089. doi:10.1542/peds.2012-2277.

Miranda, M.L., Kim, D., Overstreet, M.A., Paul, C.J., Hull, A.P., & Morgan, S.P. (2007). "The Relationship between Early Childhood Blood Lead Levels and Performance on End-of-Grade Tests." *Environmental Health Perspectives* 115(8), 1242-1247. doi:10.1289/ehp.9994.

Miranda, M.L., Kim, D., Reiter, J., Overstreet, M.A., & Maxon, P. (2009). "Environmental Contributors to the Achievement Gap." *Neurotoxicology* 30(6), 1019-1024. doi:10.1016/j.neuro.2009.07.012.

National Toxicology Program (2012), "NTP Monograph on Health Effects of Low Level Lead" U.S. Department of Health and Human Services. https://ntp.niehs.nih.gov/ntp/ohat/lead/final/monographhealtheffectslowlevellead_newissn_508.pdf.

Needleman, H.L. (1989). "Childhood Lead Poisoning: The Promise and Abandonment of Primary Prevention." *American Journal of Public Health*, 88(12), 1871-1877. doi/10.2105/AJPH.88.12.1871.

Needleman, H.L., Schell, A., Bellinger, D., Leviton, A., & Allred, E. N. (1990). "The Long-Term Effects of Exposure to Low Doses of Lead in Childhood – An 11-Year Follow-up Report." *New England Journal of Medicine*, 322(2), 83-88. doi: 10.1056/NEJM199001113220203.

North Carolina Childhood Lead Poisoning Prevention Program, (2004). *North Carolina Childhood Lead Screening Data*. Raleigh, NC: Children's Environmental Health Branch, North Carolina Department of Environment and Natural Resources.

Pocock, S. J., Smith, M., & Baghurst, P. (1994). “Environmental Lead and Children’s Intelligence: A Systematic Review of the Epidemiological Evidence.” *British Medical Journal* 309(6963), 1189-1195. doi:10.1136/bmj.309.6963.1189.

Reuben A., Caspi A., Belsky D.W., et al. (2017). “Association of Childhood Blood Lead Levels with Cognitive Function and Socioeconomic Status at Age 38 Years and With IQ Change and Socioeconomic Mobility between Childhood and Adulthood.” *Journal of the American Medical Association* 317(12):1244–1251. doi:10.1001/jama.2017.1712.

Reyes, J.W. (2015). “Lead Policy and Academic Performance: Insights from Massachusetts.” *Harvard Educational Review.* 85(1), 75-107. doi:10.17763/haer.85.1.bj34u74714022730.

Reyes, J.W. (2015). “Lead Exposure and Behavior: Effects on Antisocial and Risky Behavior Among Children and Adolescents.” *Economic Inquiry* 53(3), 1580-1605. doi:10.1111/ecin.12202.

Roberts, E.M., Madrigal, D., Valle, J., King, G., & Kite, L. (2017). “Assessing Child Lead Poisoning Case Ascertainment in the US, 1999-2010.” Pediatrics, 139(5). doi: 10.1542/peds.2016-426.

Sirin, S. R**.** (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75*(3), 417-453. https://doi.org/10.3102/00346543075003417

Strayhorn, J.C. & Strayhorn Jr., J.M. (2012). “Lead Exposure and the 2010 Achievement Test Scores of Children in New York Counties.” *Child and Adolescent Psychiatry and Mental Health*. 6(1):4. doi: 10.1186/1753-2000-6-4.

Tong, S. (2015). “Environmental Lead Exposure and Childhood Development: The Port Pirie Cohort.” In Butler C., Dixon J., & Capon A. (Eds.), *Health of People, Places and Planet: Reflections based on Tony McMichael’s four decades of contribution to epidemiological understanding* (pp. 137-144). ANU Press. Retrieved from http://www.jstor.org/stable/j.ctt1729vxt.22.

U.S. EPA. Integrated Science Assessment (ISA) for Lead (Final Report, Jul 2013). U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-10/075F, 2013.

Wheeler, W. (2013). “Blood Lead Levels in Children Aged 1-5 Years – United States, 1999-2010.” *Morbidity and Mortality Weekly Report* 62(13), 245-247.

Zahran, S., Mielke, H., Weiler, S., Berry, K.J,. & Gonzales, C. (2009). “Children's Blood Lead and Standardized Test Performance Response as Indicators of Neurotoxicity in Metropolitan New Orleans Elementary Schools.” *Neurotoxicology* 30, 888-97. doi:10.1016/j.neuro.2009.07.017.

Zhang, N, Baker, H.W., Tufts, M., Raymond, R.E., Salihu, H., & Elliot, M.R. (2013). “Early Childhood Lead Exposure and Academic Achievement: Evidence from Detroit Public Schools, 2008-2010.” *American Journal of Public Health* 103(3), e72-e77. doi/10.2105/AJPH.2012.301164.

Table 1. Summary Statistics

	Full (≤ 10 µg/dL)		Full (≤ 5 µg/dL)		CEM (≤ 5 µg/dL)	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
BLL[a] (µg/dL)	3.6805	1.9045	2.904	1.180	2.507	1.244
Math Score	45.6648	28.0095	47.4457	28.0885	55.3841	28.3592
Reading Score	45.6833	28.0572	47.5124	28.1111	55.1277	28.3777
Male	0.4967	0.4500	0.4912	0.4500	0.4932	0.5000
White	0.5115	0.4999	0.5524	0.4972	0.7687	0.4217
Black	0.3625	0.4807	0.3169	0.4653	0.1667	0.3727
Age in 3rd Grade	8.4239	0.5677	8.4004	0.5523	8.3607	0.5204
EconDisadv	0.5867	0.4924	0.5495	0.4975	0.3257	0.4686
Medicaid	0.4389	0.4963	0.4251	0.4944	0.2438	0.4294
Mother Not Married	0.4317	0.4953	0.3974	0.4894	0.2111	0.4081
Mother Used Alcohol	0.0121	0.1093	0.0105	0.1017	0.0077	0.0876
Mother Smoked	0.1815	0.3854	0.1751	0.3801	0.1315	0.3379
Mother 21-29 years	0.4990	0.5000	0.5031	0.5000	0.5526	0.4972
Mother 30+ years	0.2411	0.4277	0.2574	0.4373	0.3294	0.4700
No. of Observations	2,294,074		1,747,688		520,795	
No. of Students	538,493		419,272		179,313	

[a] Each child's BLL is measured as the geometric mean of their BLL measurements taken during 0 – 5 years of age.

Table 2. Effects of BLL on Test Score: Base Regression Results

	Math Percentile			Reading Percentile		
	Full sample BLL ≤ 10	Full sample BLL ≤ 5	CEM sample BLL ≤ 5	Full sample BLL ≤ 10	Full sample BLL ≤ 5	CEM sample BLL ≤ 5
	(1)	(2)	(3)	(4)	(5)	(6)
BLL 2	-0.34***	-0.29**	-0.54***	-0.40***	-0.39***	-0.77***
	(0.10)	(0.10)	(0.16)	(0.09)	(0.09)	(0.15)
BLL 3	-0.74***	-0.64***	-0.89***	-0.98***	-0.95***	-1.39***
	(0.09)	(0.09)	(0.16)	(0.09)	(0.09)	(0.16)
BLL 4	-1.23***	-1.22***	-1.62***	-1.56***	-1.60***	-1.98***
	(0.10)	(0.10)	(0.19)	(0.10)	(0.10)	(0.19)
BLL 5	-1.72***	-1.65***	-1.45***	-2.13***	-2.10***	-2.00***
	(0.11)	(0.12)	(0.22)	(0.11)	(0.12)	(0.23)
BLL 6	-2.11***			-2.70***		
	(0.12)			(0.12)		
BLL 7	-2.13***			-2.80***		
	(0.14)			(0.15)		
BLL 8	-2.75***			-3.39***		
	(0.17)			(0.17)		
BLL 9	-2.98***			-3.98***		
	(0.20)			(0.20)		
BLL 10	-3.80***			-4.55***		
	(0.32)			(0.33)		
Male	0.63***	0.73***	0.87***	-2.93***	-2.87***	-2.71***
	(0.06)	(0.07)	(0.12)	(0.05)	(0.06)	(0.12)
White	4.26***	4.16***	3.80***	7.56***	7.65***	6.22***
	(0.13)	(0.14)	(0.30)	(0.14)	(0.15)	(0.31)
Black	-8.83***	-8.93***	-9.64***	-5.39***	-5.27***	-7.37***
	(0.14)	(0.15)	(0.43)	(0.14)	(0.15)	(0.42)

EconDisadv	-8.58***	-8.63***	-10.38***	-9.30***	-9.33***	-10.66***
	(0.09)	(0.09)	(0.22)	(0.09)	(0.09)	(0.22)
Medicaid	-3.27***	-3.38***	-3.39***	-3.04***	-3.12***	-3.49***
	(0.07)	(0.08)	(0.24)	(0.07)	(0.08)	(0.25)
Mother Not Married	-2.49***	-2.58***	-2.11***	-1.86***	-1.90***	-1.74***
	(0.07)	(0.08)	(0.26)	(0.07)	(0.08)	(0.27)
Mother Used Alcohol	0.47*	0.24	1.05	0.64**	0.33	1.57**
	(0.21)	(0.27)	(0.61)	(0.22)	(0.27)	(0.60)
Mother Smoked	-4.03***	-4.17***	-5.70***	-3.26***	-3.33***	-4.78***
	(0.08)	(0.09)	(0.19)	(0.08)	(0.09)	(0.19)
Age in 3rd Grade	-8.19***	-7.90***	-6.46***	-7.61***	-7.25***	-5.71***
	(0.07)	(0.07)	(0.15)	(0.07)	(0.07)	(0.15)
Mother 21-29 years	1.04***	1.12***	0.56*	0.81***	0.85***	0.41
	(0.07)	(0.08)	(0.26)	(0.07)	(0.08)	(0.25)
Mother 30+ years	4.08***	4.31***	4.69***	4.49***	4.65***	4.71***
	(0.10)	(0.11)	(0.30)	(0.10)	(0.11)	(0.30)
N	2,294,074	1,747,688	520,795	2,294,074	1,747,688	520,795
R2	0.302	0.303	0.368	0.280	0.279	0.346

Note: The omitted categories for the categorical explanatory variables correspond to BLL = 1, female, all other races/ethnicities, not economically disadvantaged, not on Medicaid, mother married at the time of birth, mother did not use alcohol during pregnancy, mother did not smoke during pregnancy, and mother less than 21 years old at the time of birth. All estimates are from regression models that include school-grade-year dummy variables, and dummy variables denoting the month of birth. Robust standard errors clustered at the school level are presented in parentheses. *** indicates the corresponding coefficient is significantly different from zero at the 0.1% level; ** indicates the corresponding coefficient is significantly different from zero at the 1% level; and * indicates the corresponding coefficient is significantly different from zero at the 5% level.

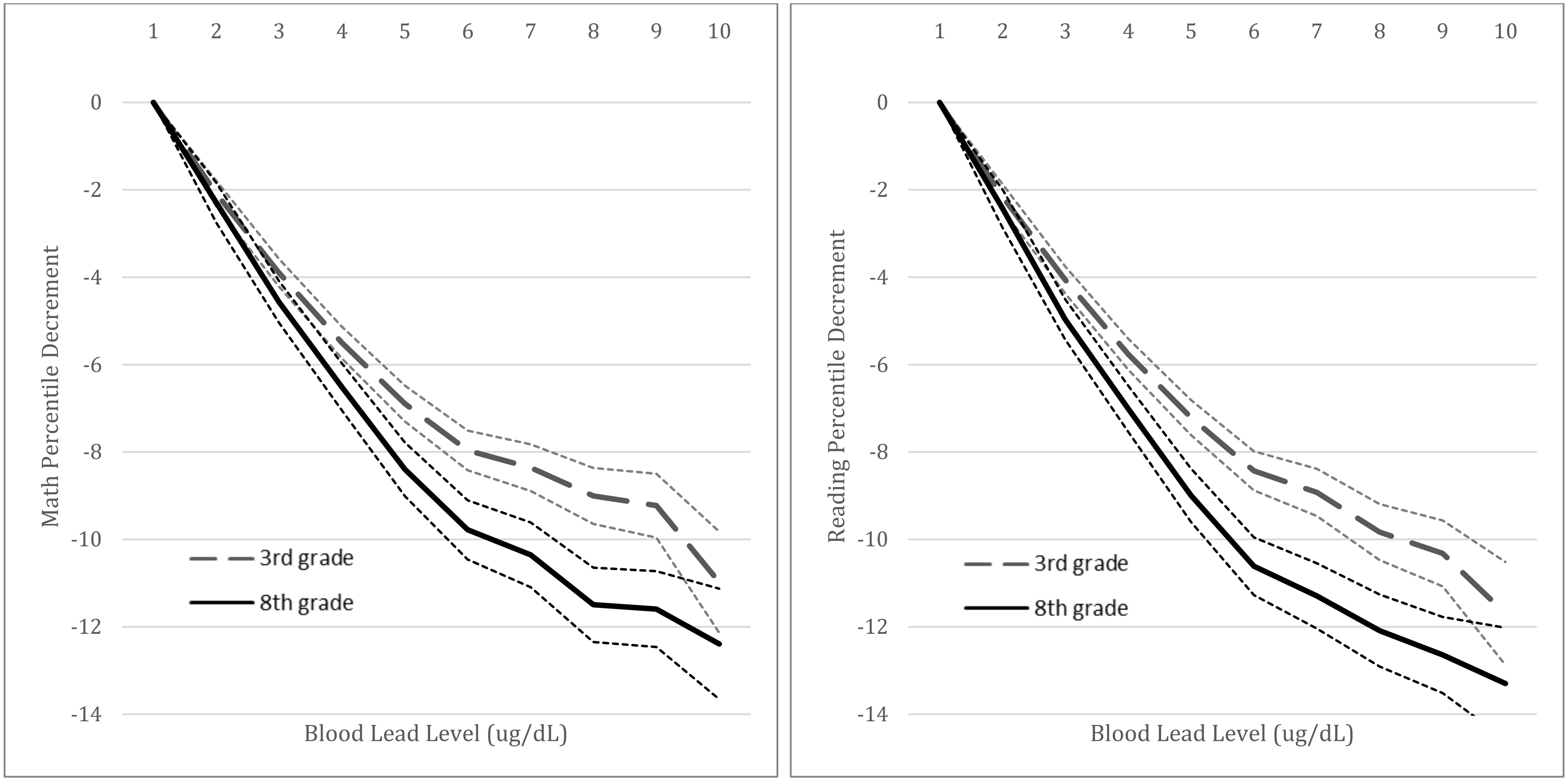
Table 3. Changes in BLL Effects on Test Score Percentiles by Grade: Regression Results for Key Coefficients

	Math Percentile			Reading Percentile		
	Full sample BLL ≤ 10	Full sample BLL ≤ 5	CEM sample BLL ≤ 5	Full sample BLL ≤ 10	Full sample BLL ≤ 5	CEM sample BLL ≤ 5
	(1)	(2)	(3)	(4)	(5)	(6)
BLL 2	-0.26*	-0.22	-0.54*	-0.33*	-0.34**	-0.74***
	(0.13)	(0.13)	(0.23)	(0.13)	(0.13)	(0.22)
BLL 2 × grade	-0.04	-0.04	-0.00	-0.04	-0.03	-0.01
	(0.05)	(0.05)	(0.08)	(0.05)	(0.05)	(0.08)
BLL 3	-0.59***	-0.50***	-0.82***	-0.82***	-0.80***	-1.29***
	(0.13)	(0.13)	(0.24)	(0.13)	(0.13)	(0.24)
BLL 3 × grade	-0.08	-0.08	-0.04	-0.09	-0.08	-0.04
	(0.05)	(0.05)	(0.08)	(0.05)	(0.05)	(0.09)
BLL 4	-1.11***	-1.09***	-1.63***	-1.46***	-1.50***	-1.90***
	(0.15)	(0.15)	(0.27)	(0.14)	(0.15)	(0.28)
BLL 4 × grade	-0.07	-0.07	0.00	-0.06	-0.05	-0.03
	(0.05)	(0.06)	(0.10)	(0.05)	(0.05)	(0.10)
BLL 5	-1.50***	-1.41***	-1.43***	-1.94***	-1.89***	-2.03***
	(0.16)	(0.18)	(0.36)	(0.16)	(0.18)	(0.37)
BLL 5 × grade	-0.11	-0.11	-0.01	-0.10	-0.10	0.01
	(0.06)	(0.06)	(0.11)	(0.06)	(0.06)	(0.12)
BLL 6	-1.82***			-2.38***		
	(0.18)			(0.18)		
BLL 6 × grade	-0.14*			-0.15*		
	(0.06)			(0.06)		
BLL 7	-1.86***			-2.52***		
	(0.21)			(0.22)		
BLL 7 × grade	-0.13			-0.13		
	(0.07)			(0.08)		
BLL 8	-2.38***			-3.28***		
	(0.26)			(0.27)		

BLL 8 × grade	-0.17			-0.05		
	(0.09)			(0.09)		
BLL 9	-2.57***			-3.75***		
	(0.32)			(0.33)		
BLL 9 × grade	-0.18			-0.11		
	(0.10)			(0.10)		
BLL 10	-3.81***			-4.59***		
	(0.51)			(0.52)		
BLL 10 × grade	-0.01			0.01		
	(0.16)			(0.17)		
Joint significance of grade x BLL variables (p-value)	0.31	0.40	0.99	0.45	0.41	0.98
N	2,294,074	1,747,688	520,795	2,294,074	1,747,688	520,795
R2	0.303	0.303	0.369	0.280	0.280	0.346

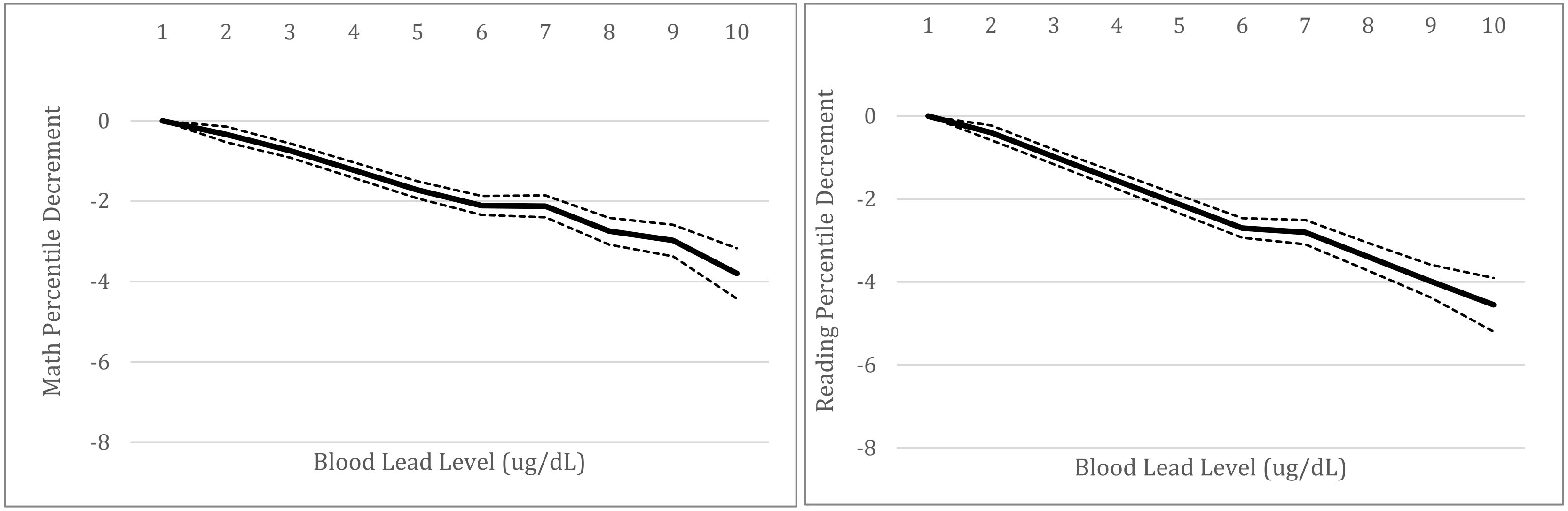
Note: The omitted categories for the categorical explanatory variables correspond to BLL = 1, female, all other races/ethnicities, not economically disadvantaged, not on Medicaid, mother married at the time of birth, mother did not use alcohol during pregnancy, mother did not smoke during pregnancy, and mother less than 21 years old at the time of birth. All estimates are from regression models that include school-grade-year dummy variables, dummy variables denoting the month of birth, all covariates listed in Table 2 are included, both as a main effect and as an interaction term with grade. Only estimates corresponding to BLL are presented here. Robust standard errors clustered at the school level are presented in parentheses. *** indicates the corresponding coefficient is significantly different from zero at the 0.1% level; ** indicates the corresponding coefficient is significantly different from zero at the 1% level; and * indicates the corresponding coefficient is significantly different from zero at the 5% level.

Figure 1. Association between BLL and Math and Reading Test Score Percentiles at 3rd and 8th grade (without controlling for confounders)



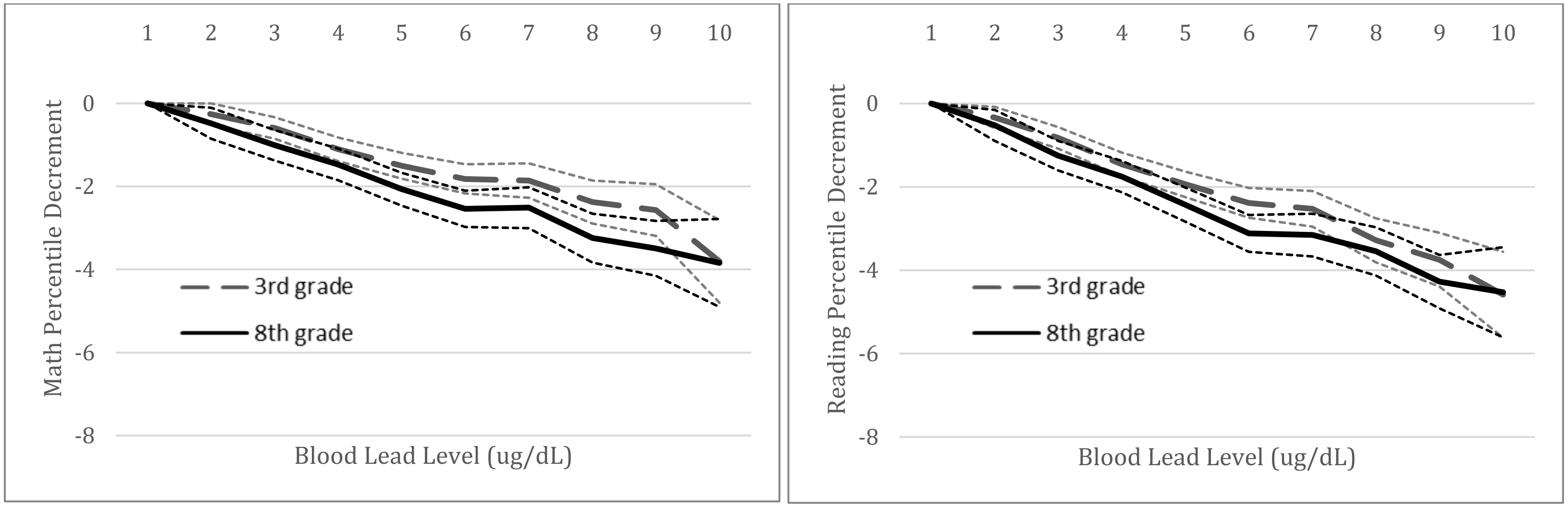
Note: Dotted lines denote 95% confidence intervals.

Figure 2. Effect of BLL on Math and Reading Test Score Percentiles (Average Across All Grades)



Note: Dotted lines denote 95% confidence interval. Left panel displays impact of BLL on end-of-grade math test score percentiles (from column 1 in Table 2). Right panel displays impact of BLL on end-of-grade reading test score percentiles (from column 4 in Table 2).

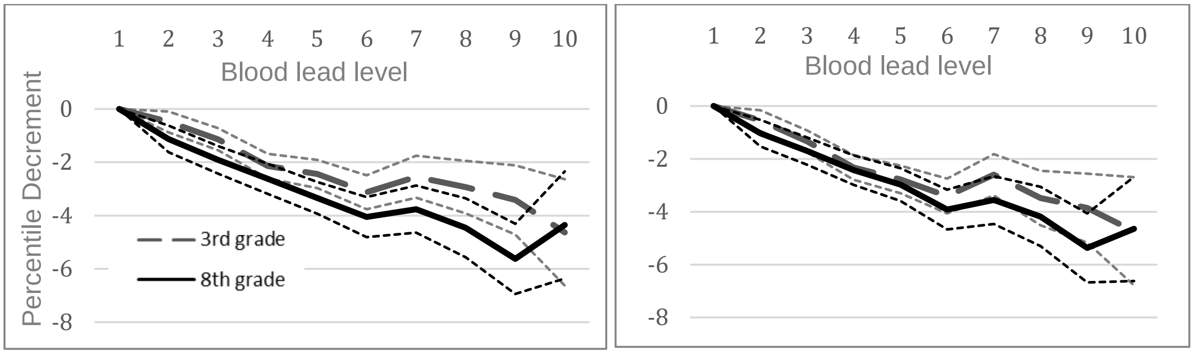
Figure 3. Effect of BLL on Math and Reading Test Score Percentiles at 3rd and 8th grade



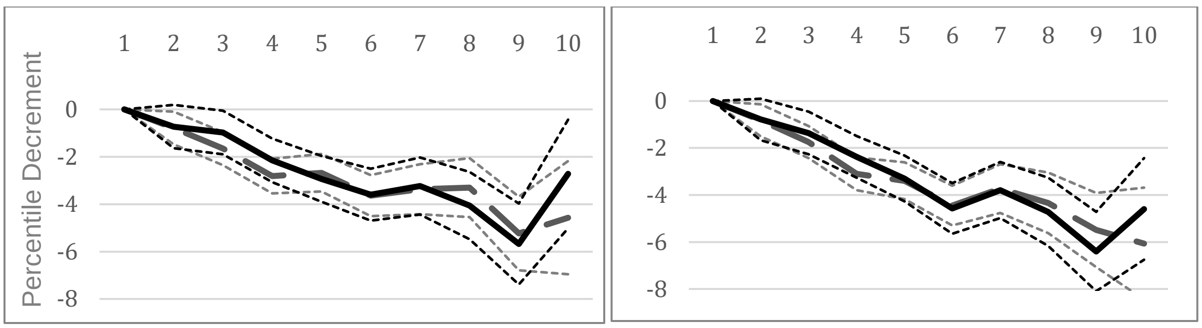
Note: Dotted lines denote 95% confidence interval. Left panel displays impact of BLL on end-of-grade math test score percentiles (from column 1 in Table 3). Right panel displays impact of BLL on end-of-grade reading test score percentiles (from column 4 in Table 3).

Figure 4. Effect of BLL on Math and Reading Test Score Percentiles at 3rd and 8th Grade across Race and Socioeconomic Groups

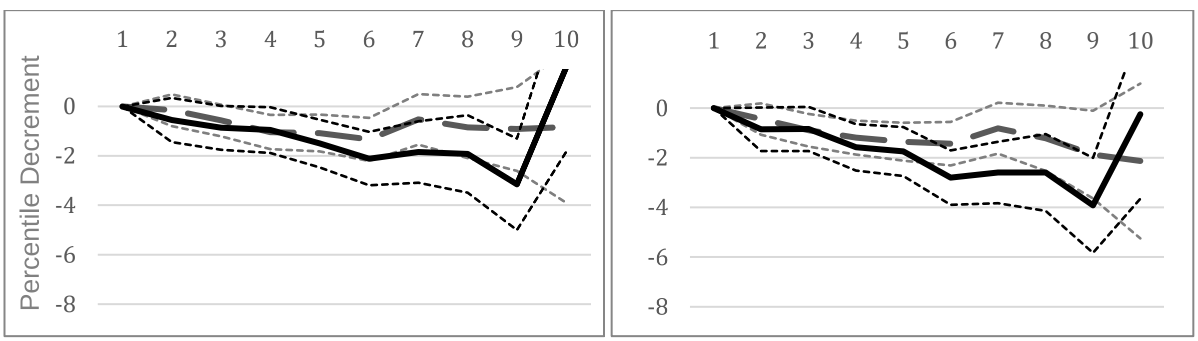
Math Scores | Reading Scores



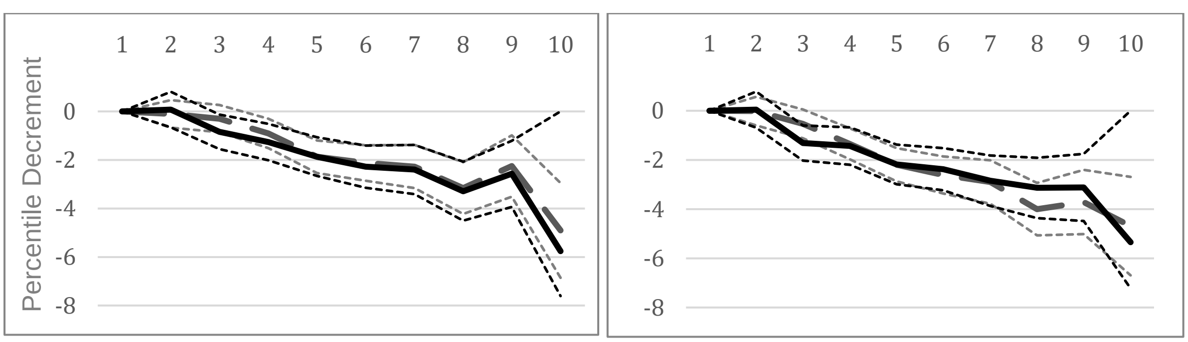
Reference group (not Black, not Medicaid, not economically disadvantaged)



Black (not Medicaid, not economically disadvantaged)



Medicaid (not Black, not economically disadvantaged)



Economically disadvantaged (not Black, not on Medicaid)

Appendix

Table S1. Changes in BLL Effects on Test Scores by Grade: Full Regression Results (corresponding to Table 3 in main text)

	Math Full sample BLL ≤ 10 (1)	Full sample BLL ≤ 5 (2)	CEM sample BLL ≤ 5 (3)	Reading Full sample BLL ≤ 10 (4)	Full sample BLL ≤ 5 (5)	CEM sample BLL ≤ 5 (6)
BLL 2	-0.26*	-0.22	-0.54*	-0.33*	-0.34**	-0.74***
	(0.13)	(0.13)	(0.23)	(0.13)	(0.13)	(0.22)
BLL 2 × grade	-0.04	-0.04	-0.00	-0.04	-0.03	-0.01
	(0.05)	(0.05)	(0.08)	(0.05)	(0.05)	(0.08)
BLL 3	-0.59***	-0.50***	-0.82***	-0.82***	-0.80***	-1.29***
	(0.13)	(0.13)	(0.24)	(0.13)	(0.13)	(0.24)
BLL 3 × grade	-0.08	-0.08	-0.04	-0.09	-0.08	-0.04
	(0.05)	(0.05)	(0.08)	(0.05)	(0.05)	(0.09)
BLL 4	-1.11***	-1.09***	-1.63***	-1.46***	-1.50***	-1.90***
	(0.15)	(0.15)	(0.27)	(0.14)	(0.15)	(0.28)
BLL 4 × grade	-0.07	-0.07	0.00	-0.06	-0.05	-0.03
	(0.05)	(0.06)	(0.10)	(0.05)	(0.05)	(0.10)
BLL 5	-1.50***	-1.41***	-1.43***	-1.94***	-1.89***	-2.03***
	(0.16)	(0.18)	(0.36)	(0.16)	(0.18)	(0.37)
BLL 5 × grade	-0.11	-0.11	-0.01	-0.10	-0.10	0.01
	(0.06)	(0.06)	(0.11)	(0.06)	(0.06)	(0.12)
BLL 6	-1.82***			-2.38***		
	(0.18)			(0.18)		
BLL 6 × grade	-0.14*			-0.15*		
	(0.06)			(0.06)		
BLL 7	-1.86***			-2.52***		
	(0.21)			(0.22)		
BLL 7 × grade	-0.13			-0.13		

	(0.07)			(0.08)		
BLL 8	-2.38***			-3.28***		
	(0.26)			(0.27)		
BLL 8 × grade	-0.17			-0.05		
	(0.09)			(0.09)		
BLL 9	-2.57***			-3.75***		
	(0.32)			(0.33)		
BLL 9 × grade	-0.18			-0.11		
	(0.10)			(0.10)		
BLL 10	-3.81***			-4.59***		
	(0.51)			(0.52)		
BLL 10 × grade	-0.01			0.01		
	(0.16)			(0.17)		
Male	1.84***	1.90***	2.11***	-3.17***	-3.14***	-2.87***
	(0.08)	(0.09)	(0.18)	(0.08)	(0.09)	(0.18)
Male x grade	-0.56***	-0.55***	-0.51***	0.11***	0.12***	0.07
	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)	(0.06)
White	5.76***	5.65***	5.17***	8.92***	8.98***	7.89***
	(0.18)	(0.19)	(0.44)	(0.19)	(0.20)	(0.44)
White x grade	-0.73***	-0.73***	-0.60***	-0.69***	-0.69***	-0.78***
	(0.07)	(0.07)	(0.16)	(0.07)	(0.08)	(0.16)
Black	-8.61***	-8.69***	-8.44***	-3.56***	-3.50***	-4.28***
	(0.18)	(0.20)	(0.50)	(0.19)	(0.21)	(0.53)
Black x grade	-0.15*	-0.16*	-0.55*	-0.90***	-0.89***	-1.33***
	(0.07)	(0.08)	(0.22)	(0.07)	(0.08)	(0.22)
EconDisadv	-8.43***	-8.45***	-9.69***	-9.40***	-9.38***	-10.65***
	(0.13)	(0.14)	(0.37)	(0.13)	(0.14)	(0.37)
EconDisadv x grade	-0.06	-0.07	-0.22	0.06	0.04	0.03
	(0.04)	(0.05)	(0.12)	(0.04)	(0.05)	(0.12)
Medicaid	-3.66***	-3.78***	-4.01***	-3.46***	-3.57***	-4.26***
	(0.10)	(0.12)	(0.38)	(0.11)	(0.12)	(0.40)

Medicaid x grade	0.17***	0.18***	0.21	0.18***	0.20***	0.27*
	(0.03)	(0.04)	(0.13)	(0.04)	(0.04)	(0.13)
Mother Not Married	-2.08***	-2.20***	-2.25***	-1.41***	-1.52***	-1.48***
	(0.10)	(0.12)	(0.39)	(0.10)	(0.12)	(0.41)
Mother Not Married	-0.19***	-0.18***	0.05	-0.20***	-0.18***	-0.10
x grade	(0.04)	(0.04)	(0.14)	(0.04)	(0.04)	(0.14)
Mother Used Alcohol	0.36	0.36	1.28	0.67*	0.54	1.96
	(0.33)	(0.41)	(1.05)	(0.33)	(0.41)	(1.02)
Mother Used Alcohol	0.06	-0.04	-0.09	-0.01	-0.08	-0.15
x grade	(0.11)	(0.15)	(0.32)	(0.11)	(0.15)	(0.32)
Mother Smoked	-3.14***	-3.26***	-4.32***	-2.91***	-2.95***	-4.30***
	(0.11)	(0.13)	(0.28)	(0.12)	(0.13)	(0.30)
Mother Smoked	-0.41***	-0.42***	-0.55***	-0.17***	-0.18***	-0.20*
x grade	(0.04)	(0.05)	(0.10)	(0.04)	(0.05)	(0.10)
Age in 3rd grade	-7.31***	-7.07***	-5.32***	-7.17***	-6.82***	-4.87***
	(0.09)	(0.10)	(0.21)	(0.09)	(0.11)	(0.22)
Age in 3rd grade	-0.41***	-0.39***	-0.47***	-0.21***	-0.20***	-0.34***
x grade	(0.03)	(0.04)	(0.07)	(0.03)	(0.04)	(0.07)
Mother 21-29 Years	0.84***	0.85***	-0.09	0.40***	0.43***	-0.32
	(0.09)	(0.11)	(0.38)	(0.09)	(0.11)	(0.39)
Mother 21-29 Years	0.09**	0.12**	0.24	0.19***	0.20***	0.27*
x grade	(0.03)	(0.04)	(0.14)	(0.03)	(0.04)	(0.13)
Mother 30+ Years	3.33***	3.44***	3.27***	3.61***	3.70***	3.18***
	(0.14)	(0.15)	(0.45)	(0.13)	(0.15)	(0.46)
Mother 30+ Years	0.35***	0.41***	0.54***	0.40***	0.44***	0.57***
x grade	(0.05)	(0.06)	(0.15)	(0.05)	(0.05)	(0.16)
February Birthdate	-1.65***	-1.63***	-1.46***	-1.43***	-1.48***	-0.94**
	(0.12)	(0.15)	(0.30)	(0.12)	(0.15)	(0.30)
March Birthdate	-1.96***	-1.99***	-1.76***	-1.94***	-1.99***	-1.98***
	(0.13)	(0.15)	(0.29)	(0.13)	(0.15)	(0.29)
April Birthdate	-2.23***	-2.23***	-2.03***	-2.20***	-2.22***	-2.06***

	(0.13)	(0.15)	(0.31)	(0.12)	(0.14)	(0.30)
May Birthdate	-2.23***	-2.42***	-2.47***	-2.15***	-2.28***	-2.21***
	(0.13)	(0.14)	(0.28)	(0.12)	(0.14)	(0.27)
June Birthdate	-2.38***	-2.52***	-2.30***	-2.53***	-2.62***	-2.40***
	(0.13)	(0.15)	(0.30)	(0.13)	(0.14)	(0.29)
July Birthdate	-2.79***	-2.96***	-2.51***	-2.80***	-2.92***	-2.49***
	(0.12)	(0.14)	(0.30)	(0.12)	(0.14)	(0.29)
August Birthdate	-2.69***	-2.83***	-2.80***	-2.70***	-2.89***	-2.82***
	(0.12)	(0.14)	(0.28)	(0.12)	(0.14)	(0.28)
September Birthdate	-2.69***	-2.83***	-2.37***	-2.93***	-3.09***	-2.75***
	(0.13)	(0.15)	(0.30)	(0.12)	(0.14)	(0.29)
October Birthdate	-1.23***	-1.32***	-1.15***	-1.35***	-1.42***	-1.16***
	(0.13)	(0.15)	(0.29)	(0.12)	(0.15)	(0.29)
November Birthdate	1.81***	1.81***	1.90***	1.83***	1.80***	1.84***
	(0.13)	(0.15)	(0.30)	(0.13)	(0.15)	(0.29)
December Birthdate	2.67***	2.58***	2.39***	2.76***	2.62***	2.19***
	(0.14)	(0.16)	(0.32)	(0.14)	(0.16)	(0.31)
Constant	124.76***	122.59***	113.56***	119.03***	116.08***	107.01***
	(0.56)	(0.64)	(1.33)	(0.57)	(0.65)	(1.35)
N	2,294,074	1,747,688	520,795	2,294,074	1,747,688	520,795
R-sq	0.303	0.303	0.369	0.280	0.280	0.346

The omitted categories for the categorical explanatory variables correspond to BLL = 1, female, all other races/ethnicities, not economically disadvantaged, not on Medicaid, mother married at the time of birth, mother did not use alcohol during pregnancy, mother did not smoke during pregnancy, and mother less than 21 years old at the time of birth. All estimates are from regression models that include school-grade-year dummy variables and dummy variables denoting the month of birth. Robust standard errors clustered at the school level are presented in parentheses. *** indicates the corresponding coefficient is significantly different from zero at the 0.1% level; ** indicates the corresponding coefficient is significantly different from zero at the 1% level; and * indicates the corresponding coefficient is significantly different from zero at the 5% level.