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What Doesn't Kill you Makes you Weaker: Prenatal Pollution Exposure and Educational Outcomes

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Abstract

I examine the impact of prenatal suspended particulate pollution on educational outcomes, using ambient total suspended particulates (TSPs) as a measure of particulate exposure and standardized test scores of exposed individuals as a measure of educational achievement. I focus on individuals born between 1979 and 1985 to exploit the shock of the industrial recession of the early 1980s. This variation helps separate the causal effects of pollution reduction from general time trends. Considering the 7-year time period as a whole yields statistically insignificant results, but focusing on the 3-year period around the recession (1981-1983) yields negative and statistically significant results, suggesting that the relationship is subtle enough to require large-scale changes to be detectable. My findings suggest a standard deviation decrease in the mean pollution level in a student's year of birth is associated with 1.87% of a standard deviation increase in test scores in high school. I also employ an instrumental variables strategy, using changes in relative manufacturing employment driven by the recession as an instrument for TSP levels. Instrumental variables results are approximately 3.7 times the size of the OLS results, suggesting the potential presence of measurement error in ambient pollution. Results are robust to the inclusion of school fixed effects, year of birth and year of test fixed effects, and various demographic and economic covariates. I also investigate the potential bias sources of migration and selection into motherhood, and show these are unlikely to explain my results.

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1 Introduction

Early-life pollution exposure may have negative impacts beyond those measured by standard observable physical indicators of health. The concept of "fetal origins", recently discussed in TIME magazine, suggests that the "kind and quality of nutrition [we] received in the womb; the pollutants, drugs and infections [we] were exposed to during gestation [...] shape our susceptibility to disease, our appetite and metabolism, our intelligence and temperament."[1] If the effects of pollution exposure effects extend to cognitive development, they could carry long-term consequences such as decreased performance in school, lower educational attainment, and reduced earnings and lifespan. It is important that we understand the lasting cognitive impacts of prenatal pollution exposure, as policy decisions made solely on the basis of avoiding physically observable damages may underestimate costs of ambient pollution. There is growing evidence on the contemporaneous negative impacts of pollution on infant health (e.g., Chay and Greenstone (2003a), Chay and Greenstone (2003b), Currie and Neidell (2005), Currie, Neidell, and Schmieder (2009), Currie and Walker (2011), Currie and Schmieder (2009), Knittel, Miller, and Sanders (2009)), but little is known about whether impacts extend further in the life cycle. I speak to these potential consequences by considering how prenatal pollution exposure impacts high school test performance. I do so by combining several data sets containing economic, demographic, weather, pollution, and test information from the state of Texas. I exploit a period of industrial recession in Texas from 1981-1983, and its dramatic impact on manufacturing production, as a source of variation in ambient pollution in the form of total suspended particulate matter (TSPs).

The economy of Texas underwent a sectoral shift as a result of the recession in the early 1980s. The manufacturing sector saw decreases in both employment and capacity utilization, and employment shifted to sectors such as retail and services (Pia M. Orrenius and Caputo

[1] "How the First Nine Months Shape the Rest of Your Life", TIME, 22 September 2010 (available online at http://www.time.com/time/health/article/0,8599,2020815,00.html, adapted from Paul (2010)).

2005). This led to a sharp drop in statewide TSPs in a short period of time. Average TSP levels exhibited the greatest changes between 1981-1983, as shown in Figure 1, when state average TSP levels fell by almost 10 micrograms per cubic meter (μg/m^3), a change of approximately 14%. This is the largest decrease in Texas in such a short period since the early 1970s.[2] The magnitudes of these TSP changes varied by county, where counties with greater shares of their pre-recession economy in manufacturing saw greater relative decreases in pollution. I use this source of plausibly exogenous variation to better identify the causal impacts of prenatal pollution on high school test performance. I further account for issues such as measurement error in pollution by using this variation and instrumenting for ambient pollution levels, using the relative share of county-level manufacturing employment as an instrument for pollution. In alternate specifications, I use a "shift-share" instrument where statewide changes in relative manufacturing are allocated to counties based on their pre-recessionary levels of relative manufacturing employment. This instrument is weaker in the first stage, but second stage estimates remain statistically similar. To account for the strong correlation between the recession, TSPs and changes in income, I also instrument for per capita income using changes in national oil prices.

Ordinary least squares (OLS) results suggest that, during the recessionary period, a within-county standard-deviation decrease in the mean pollution level in a child's year of birth is associated with 1.9% of a within-county standard deviation increase in high school test performance. Instrumental variables (IV) results are larger, suggesting an identical change is associated with approximately 7% of a within-county standard deviation increase in test performance. Based on the ambient pollution reductions seen in Texas over the period of interest, the IV results suggest that around 10% of the score gain seen over the

[2]From 1977 to 1978, the annual geometric mean dropped by approximately 8 μg/m^3, which is likely attributable to the sizable temporary spike in pollution levels seen in 1977. This may have been caused by dust storms that took place in February and March of that year. Unfortunately, test data are not available back far enough to use the storms as an additional source of exogenous variation in this analysis.

1979-1985 birth cohorts in my sample could be attributed to the rapid reduction in ambient TSPs in their respective years of birth, and that prenatal pollution exposure can have an impact on outcomes beyond those measured by standard health indicators.[3] These results are statistically detectable only in the years of greatest pollution variation, suggesting that the effect may be too subtle to identify out using only mild changes in ambient pollution caused by time variation or making across-county cross-sectional comparisons.

My results are robust to the inclusion of covariates for weather and income, population density, income in the year of the test, school-level measures of school quality and overall demographic makeup, and individual level student demographics, as well as the inclusion of school fixed effects and year of birth by year of test effects, which allow each year of birth/year of test cohort to have their own baseline. This additional flexibility controls for annual statewide testing variations driven by factors such as test difficulty as well as statewide year of birth specific shocks. Though my results are found using cohorts born in the late 1970s and early 1980s, the suggested policy implications remain relevant today. Particulate matter is a common pollutant still monitored by the Environmental Protection Agency (EPA), and it remains a frequent atmospheric problem.[4]

The rest of this paper is organized as follows. Section 2 provides the background motivation of the analysis. Section 3 describes the data. Section 4 describes the empirical methods used. Section 5 presents OLS results. Section 6 presents IV results. Section 7 considers potential confounders to identifying the effects of pollution, including selective migration and selection into motherhood. Section 8 provides some discussion of my findings. Section 9 concludes.

[3] Test score increases use only students included in the main analysis.

[4] Information on the current nationwide state of particulate matter pollution can be found at http://www.epa.gov/oar/particlepollution.

2 Pollution, health, and educational outcomes

Recently, economists have given substantial attention to the health effects of three EPA monitored criteria pollutants: carbon monoxide (CO), ozone (O3), and particulate matter (PM).[5] All three have been tied to negative physical health impacts on children. CO appears to increase infant mortality rates, negative birth outcomes, and school absences and asthma rates in children, O3 has been associated with increased asthma rates and respiratory conditions, and PM has been shown to increase infant mortality rates.[6]

Recent findings suggest that pollution can have longer-run psychological and cognitive impacts as well. For example, higher lead levels have been associated with lower IQ scores and increased deviant behavior (Reyes 2007), and elevated prenatal radiation exposure has been linked to lower test scores (Almond, Edlund, and Palme 2009). A recent medical study followed a sample of nonsmoking black and Dominican-American women in New York who wore personal air monitoring systems during pregnancy and found that higher prenatal pollution exposure was associated with lower IQ scores at age 5 (Perera et al. 2009). I further the research on prenatal effects by considering the impacts of particulate matter on long run outcomes, specifically educational achievement in high school.

I focus on airborne TSPs, the measure of airborne particulate pollution used by the EPA in the earlier years of the Clean Air Act, as my pollutant of interest.[7] The term TSPs refers to all suspended, airborne liquid or solid particles smaller than 100 micrometers in size.[8]

[5]The term criteria pollutants refers to six commonly found air pollutants that are regulated by developing health-based and/or environmentally-based criteria for allowable levels. The current criteria pollutants are: particular matter, ground-level ozone, carbon monoxide, sulfur oxides, nitrogen oxides and lead.

[6]See for example Wang et al. (1997), Ritz and Yu (1999), Friedman et al. (2001), Maisonet et al. (2001), Chay and Greenstone (2003a), Chay and Greenstone (2003b), Neidell (2004), Currie and Neidell (2005), Ponce et al. (2005), Lleras-Muney (2010), Neidell (2009), Currie et al. (2009), Currie, Neidell, and Schmieder (2009), Currie and Walker (2011), Knittel, Miller, and Sanders (2009), Moretti and Neidell (2011), and Currie and Walker (2011).

[7]The full text of the original Clean Air Act and all following amendments can be found at http://www.epa.gov/air/caa. For a discussion of the impacts of the Clean Air Act and ambient TSP levels, see Chay, Dobkin, and Greenstone (2003).

[8]As monitoring technology has advanced, regulatory attention has shifted to finer sizes of particulate

Suspended particulates can be both naturally occurring (e.g., dust, dirt, and pollen) and a by-product of common economic activities such as fuel combustion (e.g., coal, gasoline and diesel), fires, and industrial activity. Particulates are the cause of a number of environmental problems, including decreased visibility, increased acidity of both water and soil, and plant death. Inhaled particulates have been associated with a number of health problems including difficulty breathing, decreased lung function, aggravated asthma, and cardiac difficulties. Smaller particulates can be transferred from the lungs into the bloodstream, causing further internal damage.[9]

Exposure to particulate matter may impact fetal development in a number of ways. The mother's health may be compromised via any of the above listed problems, which in and of itself could hinder or alter fetal development. In addition, particulate matter could alter fetal development independent of mother health conditions. Associations have been found between polycyclic aromatic hydrocarbons (PAHs), a byproduct of fuel burning and one type of particulate matter, and a number of pre- and early post-natal developmental problems including damage to the immune system, hindered neurological development, reduced birth weight and smaller head circumference, and impairment of neuron behavior associated with long-term memory formation.[10] Due to the number of potential pathways through which particulate matter might cause harm, I am unable to tease out the specific physiological mechanism that impacts the individuals in my sample. Regardless of the mechanism, however, exposure to particulate matter presents a danger to both mother and fetus alike.

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matter, with much of the attention now on two size classifications: particulate matter smaller than 10 micrometers (PM10) and particulate matter smaller than 2.5 micrometers (PM2.5). Both of these size classifications are contained with the older TSP measure.

[9]For greater discussion of particulate matter and health, see World Health Organization 1979, available at http://www.inchem.org/documents/ehc/ehc/ehc008.htm.

[10]For a brief review of findings on the potential consequences of PAH exposure, see Perera et al. (2009).

3 Data

I combine several data sets on pollution, weather, school quality, economic conditions, demographics, test scores, and data on racial population makeup and motherhood characteristics. In this section I describe each data source. Due to availability of data, weather, economic covariates, mother characteristics, demographics, and ambient TSPs are all calculated at the county level, and in my main results I collapse all outcomes and student covariates to the demographic group by year of birth by school by year of test level and weight by the number of students in each cell.

The EPA maintains an online database of historical air quality data.[11] The system includes readings from all EPA monitors for a variety of pollutants. I use data on mean TSP values, which are measured in micrograms per cubic meter. The EPA reports annual geometric means, the total number of valid measurements made, and the location of the pollution monitor by latitude and longitude.[12] Monitors sometimes turn on and off, and in order to avoid interpreting such activation or deactivation as a change in pollution levels, I use a balanced panel of monitors by keeping only those that were active during the entire period of analysis and two years prior to the beginning of my sample to allow for the inclusion of lags in Section 5.1. In Section 8, I relax this constraint to include all monitors active during the period of greatest pollution variation (1981-83).[13]

I employ a strategy similar to that of Neidell (2004), Currie and Neidell (2005), and Knittel, Miller, and Sanders (2009) in forming county-level pollution measures. First, I calculate the distance between each county centric and each pollution monitor. I keep all pollution monitors within 20 miles of a centroid and weight each monitor's value by the

[11] http://www.epa.gov/aqspubl1/.

[12] The EPA uses the geometric mean in determining county-level Clean Air Act attainment. As such, I use the geometric mean in this analysis as well. All results are similar when using the arithmetic mean.

[13] TSP monitors take a varied number of samples per year. I currently keep sensors that take at least an average of one reading every two weeks (26 readings per year) to avoid means be influenced by singular extreme events.

inverse of the distance from the centroid.[14] I use the population centroid, as reported by the Census, rather than the geographic centroid. I do this for two primary reasons: exposure to the areas of greater population is the factor of interest, and this increases the total number of counties available for analysis. Twenty-nine counties have population centroids within 20 miles of at least one balanced panel pollution monitor. In Section 7, I repeat my analysis using distances of 10 and 30 miles — results are largely similar across mileage choice.

My preferred specifications exclude Harris County (county FIPS 48201). According to recent census estimates, Harris is the most populous county in Texas, and the third most populous county in the United States. It also appears to have had the largest migration changes, presenting a potential confounder to identifying the true effects of prenatal pollution exposure. In addition, its substantial population meant that overall (student weighted) results would be driven largely by results within one county. I relax this restriction in Section 7. The remaining 28 counties in my analysis include approximately 49% of the 1979 population of the state.

Weather is a potential confounder in the regression of student test outcomes on prenatal pollution exposure levels as weather factors have been associated with health outcomes such as birth weight and mortality.[15] Recent work also suggests extreme weather conditions may have long run mental development consequences (Stoecker 2010). Weather effects are also a concern in my first stage regression of ambient TSPs on manufacturing employment changes. Rainfall has been found to impact ambient pollution levels by clearing the air, and particulate matter pollution levels are often higher in colder temperatures.[16] Therefore, I include mean annual temperature and the number of days with rainfall.[17] Weather data come from the

[14]When calculating county annual means, prior to collapsing to county-level readings I expand each monitor mean observation by the total number of readings taken during the year so as to provide greater weight to monitors that were active more frequently.

[15]See Deschênes and Greenstone (2007), Bantje and Niemeyer (2008), Barreca (2008), Shukla et al. (2008), and Deschênes, Greenstone, and Guryan (2009).

[16]In prior drafts, I have included average yearly humidity, days with snow, days with fog, and average yearly windspeed,. Results were similar and are available in Table A-1.

[17]Annual values are calculated by collapsing daily measurements to the yearly monitor level. I keep only

National Climatic Data Center Global Surface Summary of the Day, a collection of data from weather stations throughout the world. I create county-level annual weather measures using a method similar to my calculations for pollution. Due to the limited number of weather stations active during this period, I expand the distance cutoff to include all counties within 50 miles of at least one weather station.

To control for changes in school quality I include school by year pupil-to-teacher ratios using data from the Common Core of Data (CCD).[18] To help control for peer effects, I also include the fraction of the school population who are black, the fraction who are Hispanic, and the fraction that receive free or discounted lunch, also from the CCD.

To account for the potential relationship between income, birth outcomes and test scores, I include county-level per capita income from the Bureau of Economic Analysis Regional Economic Information System (REIS) in both the year of birth and the year of the test. [19] All values are inflated to 2009 dollars using the Consumer Price Index from the Bureau of Labor Statistics. Industry level employment estimates are also from the REIS. To account for differences in both pollution and test outcomes related to urban development, I use population estimates from the REIS and land area estimates from the Census to calculate population density in both the year of birth and the year of the test.

The industrial recession undoubtedly had effects on the population beyond those identified by changes in pollution and economic conditions. Of particular concern are systematic changes to population makeup, which would then impact the composition of the student population. In addition, Lleras-Muney and Dehejia (2004) show that economic conditions can impact the composition of mothers, which could also confound the attempt to identify the

monitors with readings for at least 95% of days for both weather factors. Average daily temperature is the minimum and maximum daily values divided by two, as in Deschênes, Greenstone, and Guryan (2009).

[18] I drop schools with pupil-teacher ratios that are likely "coding errors", where I call any given year a coding error if that year's pupil-teacher ratio is at least 3 times the size of the average of all other years at that school.

[19] Per capita income values include wages as well as income from all other sources including all forms of government transfers.

true effects of pollution on test scores. In Section 7, I consider how the recession potentially changed both the overall racial makeup of counties and the makeup of mothers. Here, population estimates are from the National Cancer Institute (due to richer racial information), as derived using intercensus population estimates provided by the Census Bureau. Mother characteristics are taken from the natality data files provided by the National Bureau of Economic Research.

Table 1 compares counties included and excluded from the analysis for the years 1980 and 1985 as points of comparison before and after the recession (I do not use the 1979 base year because population and natality data are missing for many counties). On average, included counties had higher income per capita and larger shares of their employment in manufacturing. Mothers are older and more likely to be black in the included counties, the population is more likely to be black overall, and average density is substantially higher. Finally, note that the counties do not sum to the total (254) due to omitting counties with missing demographic data from the summary.

Test score data come from Texas Education Agency (TEA) monitored Texas Assessment of Academic Skills (TAAS) high school exit exams. TAAS standardized exams began in Texas in 1990 and were replaced by the Texas Assessment of Knowledge and Skills (TAKS) in the 2002/2003 school year. From 1994 to 2002, tenth graders were required to exhibit competency on both a TAAS math exam and reading exam before being allowed to graduate high school. Competency is a score of 70 or higher on the Texas Learning Index (TLI), an annually adjusted score intended to equate difficulty of passing across test years.[20,21]

A number of factors make the TAAS data well-suited for this analysis. First, while the test is rewritten each year with different questions, the basic structure of the exit exam has

[20] See Martorell (2004) for a more detailed discussion of the TAAS exit exams, and Haney 2000 for discussion of difficulty of the exam across test years.

[21] See http://ritter.tea.state.tx.us/student.assessment/resources/techdigest/2008/chapter_18.pdf for further discussion of the TLI calculation mechanisms.

remained consistent throughout its administration, making comparison across years more valid.[22] Second, the TAAS data have a wealth of information on each student, including race, ethnicity, gender, free lunch status, and special education status, which I use as student controls. Assuming that the student population somewhat reflects the overall population, these controls also stand in for the population makeup of the counties and partially control for differences in outcomes spanning from variation in overall racial and ethnic makeup across regions.

I observe the absolute number of questions correct and the TLI-adjusted scores for both the math and reading exams (the two tests are scored independently), school of attendance at the time of each exam, the year and month in which the exams were taken, and whether the student has taken either exam multiple times. In this analysis, I focus solely on the math portion of the exam as an outcome variable, as math scores are often considered more informative of learning when discussing standardized exams and used more frequently in the education literature. Most importantly, the TAAS tenth grade exit exam cohorts have years of birth that span the industrial recession period of 1981-1983, which I use as a source of exogenous variation in pollution. Specifically, the majority of students taking exit exams between 1994 and 2002 have years of birth between 1979 and 1985, allowing me to view birth cohorts in a period before the recession (1979-1981), during the recession (1981-1983), and very briefly after the recession during a period of recovery (1983-1985).

I begin with 1,755,857 tenth grade students with valid student identification numbers taking at least one of the exit exams between 1994-2002. I then drop all students with a year of birth outside of the range of the analysis (522,444), those with missing test scores, exempt testing status, or nonstandard test administration (430,274), students who have

[22] The TLI score is calculated using the number of correct responses on each test. The reading test has 50 questions. The math test has 60 questions. It appears test difficulty has remained largely constant — as noted in Klein et al. (2000), “the format and content of the questions in one year are very similar to those used the next year.”

taken the exam more than once or have duplicate observations (14,291), and those with missing covariates (30,118).[23] I also drop students listed as limited English proficient, English language learners, or migrant students, as these are most likely subject to migration bias, and students who have a year of birth that indicates they are unusually young or unusually old when they take the exam, as they are likely coding errors (73,746).[24] Finally, I drop students with TLI scores under 20 as they are unlikely to represent a true student effort (728). After merging with CCD data, a total of 1,120,115 observations remain.

After matching students to counties for which I have economic, pollution, and weather covariates, and creating a balanced panel in both pollution and schools, the remaining sample consists of 572,438 students in 28 counties (omitting Harris county as discussed above). Figure 2 shows the distribution of the student test scores used in the primary analysis, with an indicator line for the passing score of 70. It appears the TAAS has a very high passage rate. In Section 5 I consider not just the overall score but also the passage rate as an outcome.

To conduct my analysis, I match individuals to prenatal pollution exposure. The TAAS data do not contain information on the student's region of birth. In order to assign pollution, I first match schools to counties using information from the CCD. I then assume that the county in which I observe a student taking the exam is the county in which they were born (similar to Ludwig and Miller 2007). If individuals migrate between birth and taking the exam, there will be measurement error in the assignment of pollution. An advantage of

[23]Though I focus on math scores, I omit students with missing reading scores as well. If schools "selected" individuals to miss the exam as a strategic way to increase passage rates, this could bias my results. There are two factors that make this less of a concern: (1) students have to pass this exam in order to graduate, and as such they are going to be less likely to be willing to skip the exam (and administrators are probably less likely to encourage them to do so), and (2) selection into missing the exam is unlikely to be correlated with prior TSP levels.

[24]Due to student confidentiality concerns, publicly available TAAS data do not have specific date of birth, only year of birth. In order to remove students whose year of birth (or test) is likely a coding error, I calculate a student's "age at test taking" by subtracting their year of birth from the year of the exam. Beginning in 1994, all first-time exams were administered in the spring of the tenth grade year. The majority of students have "ages" of 16 and 17 — I keep all students with calculated ages between 15 and 18. Texas has an enrollment birthday cutoff of September 1st, meaning students could begin 1st grade if they were age 6 by September 1st of the enrollment year.

using high school test scores as a measured outcome is that assignment of pollution based on region of school attendance is less subject to such measurement error or bias than measures taken later in the life cycle (e.g., total educational attainment).[25] If the measurement error is classical in that it is unrelated to the error term, results will be biased toward zero. Section 7.1 addresses the concern of potential non-random error in pollution assignment.

Table 2 shows means and standard deviations for student data across all included years. Included schools have a higher relative population of black and Hispanic students, and students receiving free or reduced price lunch or classified as special education. Average TLI scores and math test passage rates slightly lower in the included counties. All of these factors are likely attributable to the included counties being, on average, more urban than excluded counties (see Table 1).

4 Identification strategy and instrument construction

Similar to Chay and Greenstone (2003b), I exploit variation in TSP levels caused by the industrial recession of the early 1980s as a source of exogenous identification. Figure 3 shows the progression of TLI scores over time for the 28 counties by tercile, where counties are grouped by relative change in TSPs. The "Low" group contains 10 counties with an average increase of 1% in TSPs over the 1981-1983 period. The "Middle" group contains 9 counties, with an average ambient TSP decrease of 11%. The "High" group contains the remaining 9 counties, which saw an average TSP decrease of 16% across the recessionary period. Only the Middle and High groups appear to have experienced a deviation from prior growth in test scores.

The use of the industrial recession as a quasi-experimental strategy, combined with the

[25] Longer lifetime outcomes are of interest, but the further into the life cycle, the more likely it becomes that individuals have migrated, and the greater the probability that migration is not random. For example, students who go on to college are probably more likely to end up living in regions different than those in which they were born. Any tie between outcomes and mobility will cause error in pollution assignment that may be systematic in such a way as to bias the results.

region- and time-specific fixed effects allowable in panel data, help to alleviate the identification concerns associated with basic time series or cross-sectional analysis. Even after controlling for a number of covariates and regional and time effects, basic OLS results could still suffer from econometric difficulties. County pollution levels are likely measured with error due to factors such as variation in proximity to sensors, number of sensors in an area, and geographic surroundings. TSPs are measured infrequently, and individual measurements might be influenced by ambient conditions or unusual, unobservable circumstances (e.g., measurements taken on a particularly windy day). In addition, the method of pollution assignment means that the variation in between-county annual pollution levels may not appear as great as it truly is. For example, two different counties, each within 20 miles of the same pollution monitor, will be assigned the same ambient levels despite potential differences in true levels. To address such issues, I employ an instrumental variables strategy.

My preferred instrument is built using the relative share of manufacturing employment present in a county in any given year. Given that ambient pollution variation is correlated with manufacturing production, using a county-specific manufacturing-based instrument allows for a greater level of between-county variation in ambient TSPs — each county now has a unique source of variation. As a further consideration, I also employ a shift-share instrument in manufacturing employment, which, while weaker, yields similar second-stage results.

4.1 The model

The basic OLS estimation model is:

$$y_{s,b,t} = \beta TSP_{c,b} + \alpha_s + \theta_{b,t} + \delta X_{s,t} + \omega B_{c,b} + \psi T_{c,t} + \gamma W_{c,b} + \epsilon_{s,b,t}, \tag{1}$$

where s, b, and t refer to school, year of birth, and year of the test, respectively. The parameter β is the estimated achievement impact of an additional unit of TSP exposure in the child's year of birth, α_s is a vector of school fixed effects, $\theta_{b,t}$ is a vector of year of birth by year of test fixed effects, $X_{s,t}$ is a vector of (collapsed individual) school-level student and school covariates, $B_{c,b}$ is a vector of economic and demographic covariates in the year of birth, $T_{c,t}$ is a vector of economic and demographic covariates in the year of the test, $W_{c,b}$ is a vector of county-level weather covariates in the year of birth, and ϵ is an error term.[26] As noted in Section 3, weather and economic covariates and pollution are measured at the county level to allow me to use the REIS county-level data for controls and to build my instrument. When collapsing data, student characteristics, school quality measures, and student outcomes are all measured at the school level to limit potential omitted variables bias caused by higher levels of aggregation (see Hanushek, Rivkin, and Taylor 1996).

A good instrument will be correlated with county-level pollution but be appropriately excludable from the second stage in that it does not impact test outcomes independent of its effect on pollution. Manufacturing was responsible for a large portion of ambient TSPs during the period of interest. Almost 50% of all national particulate emissions in 1976 came from industrial production (EPA 1985). Also important for my instrumental variables identification strategy, the decrease in TSPs seen nationwide during the industrial recession correlated strongly with a decrease in industrial and manufacturing production, and by 1985 industry's contribution to total national particulates was down to approximately 37% (EPA 1985, Chay and Greenstone 2003b).

I model TSPs as a function of all workers in a county employed in the manufacturing industry (SIC code 400) over total county employment levels in a given year. Given a linear relationship where Π is defined as the marginal impact of changes in relative manufacturing

[26] As the source of pollution and instrument variation is the county/year level, I cannot include county-by-year fixed effects.

employment, this can be written as:

$$TSP_{c,t} = \Pi * \frac{manufacturing_{c,t}}{all_{c,t}} * 100, \tag{2}$$

where both $TSP_{c,t}$ and the instrument are what remains after partialling out fixed effects and other relevant covariates of interest, and the result is multiplied by 100 to make Π interpretable as percentage changes.

One potential concern is that the instrument in (2) may be correlated with the second-stage errors. For example, changes in the sectoral makeup of a county may be associated with migratory factors, which drive later test results. I address this issue to some degree in Section 8 by demonstrating that the instrument is not related in a statistically significant fashion to the demographic makeup of the student population. I also show that, even after controlling for manufacturing employment levels and total employment levels, the effects remain approximately the same, suggesting that individual level changes in either factor are not driving my results.

As an alternative I also explore the use of a shift-share instrument. Shift-share instruments first appeared in immigration literature, where a macro-scale influx of immigrants is dispersed to regions based on earlier shares of each particular immigrant group (for example, see Card (2001), Ottaviano and Peri (2006), and Saiz (2007)). I assign the statewide relative manufacturing employment rate to each individual county weighted by the county pre-recession relative manufacturing ratios, using the average of 1976-1978 as the "pre-recession" period. This helps alleviate the concern of county-specific annual migration factors, as changes are now driven by macro-level variation. Let county-level and state-level relative manufacturing rates be $county\_ratio_{c,t} = manufacturing_{c,t}/all_{c,t}$ and $state\_ratio_t = manufacturing_t/all_t$, respectively. The basis for the instrument (again after partialling out other relevant covariates) is

$$TSP_{c,t} = \Omega * \frac{county\_ratio_{c,pre-recession}}{state\_ratio_{pre-recession}} * state\_ratio_t * 100 \tag{3}$$

As income is likely to be strongly correlated with both pollution levels and the recession, I treat it as endogenous and instrument for per capita income as well. To do so I exploit the drastic changes in national oil prices over the period and the substantial link between national oil prices and local income, particularly in Texas. In the mid 1970s, oil prices were relatively stable. But in 1979, revolution in Iran led to drops in oil supply and a rapid growth in price. Rising oil prices helped Texas partially avoid the earlier stages of the industrial recession, but by 1981, oil-producing countries both inside and outside of the Organization of the Petroleum Exporting Countries increased oil supply substantially, leading to an equally rapid decrease in the real price of oil (see Figure 4). I use this variation, combined with the assumption that counties with larger oil extraction sectors would have their per capita incomes change more drastically with oil price, to instrument for per capita income. Due to the limited availability of specific oil extraction employment, I use the more general mining employment (SIC code 200), which contains within it petroleum extraction, drilling, and other similar oil-mining employment sources. My final income instrument is the annual inflation-adjusted price of oil weighted by the fraction of county employment in the mining and extraction industry prior to the recession (again using a weighted average of 1976-1978)[27]:

$$income_{c,t} = \Gamma * \frac{mining_{c,baseline}}{all_{c,baseline}} * oilprice_t.$$

In Section 6 I repeat my regressions treating income as exogenous and using only the single

[27] For a similar design using coal reserves and variations in annual coal prices as an instrument for county wages bills see Black, Daniel, and Sanders (2002).

manufacturing instrument for TSPs — results are largely unchanged.

5 OLS Results: TSPs and educational achievement

As noted in Section 3, my measure of educational performance is the TLI difficulty-adjusted standardized test score for the math portion of the Texas high school exit exams.[28] My primary analysis is done at the demographic group by year of birth by school by year of test level.[29] I weight all regressions by the number of students in each cell. I also perform this analysis at the individual level and unweighted at the collapsed level (Tables A-2 and A-3 in the Appendix) to verify that results are not driven by weighting or oversampling of one particular county — results are similar in both cases. All standard errors are clustered on county to allow for county-specific correlated errors over time. In the remaining discussion, the term "standard deviation" refers to a within-county standard deviation.

As noted above, my sample consists of individuals born between 1979 and 1985. Considering the average effect over time appears to mask the true relationship between test scores and ambient pollution levels in the year of birth. Column 1 of Table 3 shows the estimated impact of TSPs are not statistically different from zero. This identification difficulty may be due to the subtle relationship between pollution and ambient TSPs. Specifically, the relationship may be undetectable when analyzing mild variations in TSPs, or gradual changes driven by long-run trends. For this reason, I focus on the period of the largest, most drastic variation, the recession period of 1981-1983. This is similar to Chay and Greenstone (2003b), who exploit a similar methodology to identify the effects of pollution exposure on infant mortality, though they use a first-differences approach.[30] Columns 2, 3, and 4 show

[28]Earlier versions of this paper used the absolute number of questions answered correctly as an outcome, as well as scores normalized by test year. Not surprisingly, these results are very similar to those for TLI scores and omitted for simplicity.

[29]For example, one cell would be non-special education white students on free lunch at campus c born in year b taking the exam in year t.

[30]Chay and Greenstone (2003b) focus on the 1980-1982 period, which is the timeframe of the greatest variation on a nationwide level. Texas, however, had the recession hit slightly later due to the oil price

OLS results for a sample restricted to those born in the periods spanning 1979-1981, 1981-1983, and 1983-1985, respectively (note this causes some overlap in students across samples). The results are statistically insignificant for 1979-1981 and 1983-1985. However, for 1981-1983 the coefficient is statistically significant and has the anticipated negative sign. The OLS coefficient suggests that a standard deviation decrease in average pollution levels in the year of birth is associated with 1.87% of a standard deviation increase in test scores.

Table 4 shows that the 1981-1983 result is robust to various specifications. Starting with simple OLS with only school and year of birth by year of test fixed effects, the following columns add economic and demographic covariates (column 2), weather effects (column 3), student covariates (column 4), and school level covariates (column 5). The estimated effects of a standard deviation drop in pollution range from 1.45% to 2.06% of a standard deviation increase in test scores.

The mean effects of pollution exposure and total test scores provide some insight into the potential link between ambient conditions and long run outcomes. Of particular policy interest, however, is the impact on the fraction of students passing the standardized exit exams and being granted the ability to graduate.[31] I consider the impact of prenatal pollution exposure on the probability of obtaining a passing math score (a TLI score greater than 70) on the first try. The outcome variable is now a 0-1 binary variable on the student level, and becomes the fraction of the student cohort passing once data are collapsed.

Table 5 shows the results from regressing cohort passage rates on ambient pollution in the year of birth for the entire period and the three birth periods discussed above. Again, results are significant for only the 1981-1983 birth cohorts, and now suggest that a standard deviation decrease in ambient pollution in the year of birth is associated with an approximate

changes discussed in Section 4.1.

[31]While some students that fail the test on the first attempt undoubtedly take the exam over and pass at a later date, failing the exit exams on the first attempt may drive changes in future student behavior, though prior research suggest such effects are not present for the Texas exams taken in tenth grade (Martorell 2004).

1 percentage point increase in the cohort passage rate on the first attempt (approximately 1.8% of a standard deviation).

5.1 Causal effects vs. general trends?

When considering time related variation, the researcher must watch for the presence of secular background trends. For example, over time pollution is decreasing (though not steadily, as was shown in Figure 1) as test scores are increasing, and the two need not be causally related. While the shock of the recession and its varied effect on pollution levels across counties somewhat addresses this concern, other issues such as migration remain. Perhaps the recession led to a particular type of parent moving their child out of certain counties and into others, or longer-run effects caused a certain type of parent to move in to Texas. Here I address the issue of general background time correlations. Potential migration effects are discussed in Section 7.

The varied effect across periods helps to assuage trend concerns. If results were driven by long-run background trends, we would expect to see similarly signed (and similarly significant) effects across all time periods. Table 3 shows statistically significant effects are only present during the 1981-1983 period. As a further check into the presence of background trends, I run regressions similar to those in Table 3, but including one and two year lags and leads of TSPs. Table 6 shows the results for the three individual time periods. For simplicity I report only the coefficients on TSPs in all periods. Column 1 covers the 1979-1981 period, column 2 the 1981-1983 period, and column 3 the 1983-1985 period. Note that data constraints prevent the use of TSP values beyond 1985, and as such including the lead values is not possible in the 1983-1985 period.

In the 1979-1981 period, the addition of lags and leads has a substantial impact on both the size and significance of the impacts of current pollution. All lags and leads are economically and statistically significant as well. The coefficients exhibit a clear pattern, with lags being negative and leads being positive. This suggests the presence of background effects that may be correlated with both pollution and future test scores, which makes identification of the impacts of pollution problematic.

During the period of the most drastic pollution change, however, the results appear to be robust to the inclusion of both lags and leads. Though the one-year lagged value is statistically significant, this is not in itself problematic. The TAAS data only allow me to identify year of birth, and for some individuals the pollution exposure in the prior year is actually the most relevant. For example, a student born on January 1st of year t was more exposed to the pollution in year $t-1$. All other lags and leads are insignificant, suggesting that the sharp break in pollution caused by the recession was sufficiently drastic so as to deviate from background factors that may confound the estimates of pollution on test scores in the full sample. Chay and Greenstone (2003b) note a similar time variation across pre, during, and post-recession periods. Though they focus on 1980-1982 (when the recession had its largest impacts nationwide), they note that the recession period is most useful as "there appears to be greater potential for confounding in cross-sectional analyses and analysis of changes in the surrounding nonrecession years." It appears the quasi-experimental nature of the recession provides an identification strategy for this relationship beyond general trends.

6 Instrumental variables results

The shock of the recession, however, is unable to overcome the potential complication of measurement error. Such error, if classical, will bias OLS estimates toward zero. This problem can be addressed to some extent by using an instrumental variables strategy. There are three main types of measurement error that may be present in this analysis. First, pollution is measured with error at the monitor location — monitors are in different ambient surroundings, and unusual readings can bias the mean in the presence of few annual readings. Second, pollution information from air monitors is assigned by using the weighted distance formula as described in Section 3. If two counties are similarly located from the same monitors, those two counties will receive similar, if not identical, assignment of pollution levels, thus reducing the variation in county pollution levels beyond its true value. Finally, I assign pollution levels to students by assuming the county in which they take the exam is the county in which they were born, which may not be the case for some students. My instrument can help with the first and second error sources, but unfortunately cannot impact the third.

As a demonstration of the first stage, I first present the relationship between the relative manufacturing instrument shown in equation (2) and ambient TSP levels. I then show IV results for test scores on the mathematics TAAS exam. Instrumental variables results are in the same direction as OLS, and are approximately 4 times larger, suggesting the presence of measurement error or potential omitted variables bias.

Counties with higher levels of relative manufacturing employment experienced different changes in TSPs both due to their economies being driven by dirtier industries and by facing a greater manufacturing employment shock induced by the recession. This effect is shown in Figure 5, which splits counties into terciles based on the (absolute) change in relative manufacturing employment counties experienced during the recessionary period. The groups with the greatest decrease in relative manufacturing (the "High" group in Figure 5) ended up with greater proportional drops in their ambient TSP levels by the end of the recession. As further support of the relationship between the changes in the manufacturing sector and ambient pollution, Figure 6 plots the mean TSP level and the mean instrument value for all counties in the analysis across birth cohort years. Visually, the instrument is correlated with pollution, particularly so during and after the recessionary period.

To further illustrate this relationship, I regress mean annual county TSP levels on my primary instrument discussed in Section 4. Coefficients and robust standard errors, clustered on county, are shown in Table 7. Column 1 includes only the primary instrument. I then add county fixed effects, year fixed effects, weather controls, and demographic covariates in Columns 2, 3, 4, and 5, respectively. After adding fixed effects, the instrument shows a positive and statistically significant relationship at the 1% level in all specifications. Column 5 is similar to my preferred first stage specification, minus year-of-test effects, second stage covariates and per capita income, for which I will instrument in the IV specifications. Using values from column 5, a predicted 1 percentage point change in county-level manufacturing share of employment is associated with a mean annual ambient TSP level increase of 0.85 $\mu g/m^3$, or approximately 12% of a within-county standard deviation.

Table 8 compares OLS and IV results for the full sample and for 1981-1983.[32] I use limited information maximum likelihood in all estimations due to its greater robustness to weak instruments. In order to assess the strength of the first stage, I report a variety of test statistics. Standard errors are clustered on county, and basic Cragg-Donald Wald tests assume that errors are i.i.d. Baum, Schaffer, and Stillman (2007) suggest the Kleibergen-Paap F-statistic (Kleibergen and Paap 2006) as a cluster-robust test, which I include in my primary tables. Angrist and Pischke (2009) suggest that, in a model with multiple endogenous regressors and multiple instruments, the overall equation test statistic is not as useful.[33] I report the "Angrist-Pischke" multivariate F-test as described in Angrist and Pischke (2009) and as reported by the user-written xtivreg2 (Shaffer 2010). Finally, I report the p-value for the Stock-Wright S-statistic as described in Stock and Wright (2000), which tests for joint significance of endogenous regressors in the case of weak-instrument robust inference.

[32] In the 1979-1981 and 1983-1985 periods, the first stage is substantially weaker, and thus results are not shown here. This suggests that, similar to the subtlety of the effects of pollution on test scores, the relationship between manufacturing production and pollution is harder to discern in the presence of mild levels of variation.

[33] Consider the case where one instrument very strongly predicts both endogenous regressors, while the other instrument is weak and provides little explanatory power. Using the overall F-statistic can cause the econometrician to assume the first stage is well identified when, in fact, one instrument is carrying the weight of both endogenous regressors.

Columns 1-4 use the TLI score as the outcome of interest. In the full sample, the IV (column 2), like the OLS (column 1), is statistically insignificant, but is now negative and of economically significant magnitude. For the 1981-1983 sample, the IV result (column 4) is statistically significant and approximately 3.7 times the size of the OLS result (column 3), suggesting a standard deviation decrease in pollution is associated with 7% of a standard deviation increase in test scores. Columns 5-8 use TLI passage rates as the outcome variable, as in Table 5. Similar to TLI scores, the full sample remains statistically insignificant for both OLS and IV, but both are significant in the 1981-1983 period. IV results suggest that a standard deviation decrease in pollution is associated with a 2.5 percentage point increase in countywide passage rates, or 6.6% of a standard deviation.

In both time periods, the Angrist-Pischke F-values for both endogenous regressors are close to the classic, single endogenous variables $F = 10$ region for TSPs, and are substantially larger for income. In the 1981-1983 period, the Stock-Wright S statistic rejects at the 1% level. Finally, a comparison of the Kleibergen-Paap F statistic to the Stock-Yogo weak identification critical values as reported in Stock and Yogo (2002) indicates that the instruments clear the 10% maximal size threshold when using LIML estimation in the 1981-1983 period.[34] All tests suggest that income and TSPs are well defined and significant in the second stage results for the period of greatest variation.

I next explore the robustness of the IV results. First, I rerun my regressions treating only pollution as endogenous to test if treating multiple variables as endogenous is driving my results. I then repeat the original IV specifications, but include the additional controls of manufacturing employment levels and total county employment levels. This helps to address the concern that effects of manufacturing of total employment beyond those related to TSPs drive my IV results. Finally, I use the alternate shift-share instrument based on equation 3.

[34]The maximal critical values provided in Stock and Yogo (2002) are used to bound asymptotic bias and true rejection rates in the presence of potentially weak instruments. See Baum, Schaffer, and Stillman (2007) for a discussion of LIML weak identification values and the use of the Kleibergen-Paap F statistic.

Table 9 compares the original OLS and IV results for the 1981-1983 period with the results from the alternative specifications discussed above. I focus on TLI scores as the outcome of interest (results for passage rates are quantitatively similar). Column 1 reports the standard instrument as used in Table 8 for comparison. Column 2 treats income as exogenous and instruments for only TSPs, using only the manufacturing instrument. This lowers the strength of the first stage, as income is highly correlated with pollution. However, the coefficient on TSPs remains significant at the 10% level, and similar in magnitude. Column 3 is similar to column 1, but adds county-level manufacturing as a control. Column 4 adds total county employment as well, where all first-stage exogenous variation now comes from the relationship between manufacturing and total employment after controlling for individual levels — results are unchanged. Finally, column 5 shows results similar to column 1 but using the shift-share instrument specified in equation 3. As with column 2, the first stage is not as well identified, but the coefficient is again of similar magnitude and remains statistically significant at the 10% level. In summary, the impacts of TSPs appear robust across specifications, being of similar magnitude and significant for at least the 10% level in all models discussed.

7 Further considerations

Both the OLS and IV results find negative, statistically significant impacts of prenatal pollution exposure on high school test performance. In this section, I expand on these results by considering how migration and selection into motherhood may impact my findings. I also expand the number of counties used and vary the cutoff distance for calculating pollution levels by county. My results do not appear to be driven by migration or selection, and are robust to all variations considered.

7.1 Migration and motherhood

Variation in pollution used in my analysis is driven by recessionary changes in the makeup of the Texas economy, and other factors correlated with both recessions and student outcomes are of concern. As noted by Lleras-Muney and Dehejia (2004), babies born in periods of high unemployment are more likely to have better birth outcomes. This could be attributable to behavior modification during recessions or a selection into motherhood effect. I do not have the necessary means to address the issue of behavior modification. However, using the natality birth records from Texas during the period of my analysis, I can consider how the composition of mothers may have changed. This selection into motherhood effect might change the makeup of students I see in my sample in a way that is related to the recession or my instrument, but not through TSPs, thus causing me to erroneously assign motherhood effects to pollution. Note, however, that there are two factors that help indicate that selection into motherhood is not driving my results. First, the majority of the jobs lost as a result of the recession were in the manufacturing sector, an employment source that was largely male dominated, and as such it is unlikely that many women saw a decrease in the cost of childbearing as a result. This is particularly true given that the findings of Lleras-Muney and Dehejia (2004) suggest that positive effects are present largely for black women of higher education. Second, any choice to engage in childbearing behavior must come with a lag. Even if a mother were to become pregnant the instant the recession began (around 1981-1982), there would still be a lag between that period and birth, and the compositional change in students should appear in the post-recession period.

Maternal education level would be a good indicator of selection factors. Unfortunately, during the period around the recession Texas did not record the education level of either the mother or father in the natality data. Instead I consider other factors that are commonly related to socioeconomic status and child outcomes — maternal age and race, and when prenatal care began.[35] I also consider the total number of births. Figure 7 shows the movement of these factors over time by county groups, with separation into High, Middle, and Low relative 1981-1983 TSP changes as in Figure 3. Only the month in which prenatal care began and the total number of births appear to have substantial differences across groups, with the variation coming largely in how the middle group deviates from trend in 1982.

As a more analytical check, I regress mother characteristics on TSPs, year fixed effects, county fixed effects, and per capita income to see if changes in pollution are systematically correlated with any of the mother characteristics described above. All regressions are done at the county by year level and weighted by the total number of births. I also repeat this process using my instrument in lieu of TSPs to see if changes in employment makeup are strongly correlated with changes in the population of birthing mothers. Results are displayed in columns 1-3 of Table 10. Panels A through D show results for the full period using TSPs, the full period using my preferred instrument, the 1981-1983 period using TSPs, and the 1981-1983 period using my preferred instrument, respectively. Neither ambient TSP levels nor the instrument appear to be statistically significant predictors of mother characteristics in either period. In column 4, I also consider total births (note this regression is not weighted). Neither TSPs nor the instrument are statistically significant predictors of the number of births.

The recession may also be correlated with migration. Changes in job composition may have altered the makeup of families at the time of birth (families of poorer performing children move out, or families of higher performing children move in). Similarly, counties hit by the recession in different ways may have seen different migration patterns later, perhaps bringing in students from other locations in ways that are systematically related to prior

[35] In prior drafts I considered the proportion of mothers who are married and the number of prenatal visits as well. Data from 1979 for both variables had a large number of missing values and/or errors, making analysis difficult, and thus both are omitted here. No differences in trends were visible.

TSP levels, and these population changes may be correlated with changes in the student composition in ways that bias my results. If those who have worse performing children either (a) moved out of counties that saw greater pollution changes as a result of the recession, or (b) were less likely to move in to greater pollution counties after the recession in systematic ways, my results would be biased upward. Similarly, my results would be biased downward if the opposite were true. The finding of zero effect in either the 1979-1981 or the 1983-1985 periods partially suggests this effect is *not* present. If systematic migration were a confounding issue, we would expect to see effects in all periods both during and after the recession, as some of those that migrated would have not yet had children but then done so in the following years. Similarly, if there were something systematically different about the type of child that was brought *in* through migration after the recession, that effect should be present in the other, non-recession periods.

Using inter-census estimates of population from the National Cancer Institute (discussed in Section 3), I consider changes in the racial makeup of counties during the recession and during the years of testing. Figure 8 shows the changes in the population described as white, black, and "other", respectively. Counties are again grouped into High, Middle, and Low by TSP change, and the graphs show the population levels relative to 1970. The unusual jumps in the late 1980s and 1990s are likely due to errors in the intercensus estimation. Prior to the 1990 census, data on Hispanic populations was not recorded in the Census, and such individuals are likely contained within the "white" category. There is substantial variation across the groups, but there do not appear to be noteworthy breaks during the recessionary period.

I further examine this issue in columns 5 and 6 of Table 10, where I regress the percentage of the population in the year of birth that are black and white, respectively, on TSPs (Panels A and C) and my preferred instrument (Panels B and D). Like total births, these regressions are unweighted. There is a marginally significant relationship with TSPs in both the full sample and the 1981-1983 period, where a standard deviation decrease in TSPs is associated with approximately 3% of a standard deviation decrease in the share of the population who are black and a 4% of a standard deviation increase in the share that are white. However, there is no statistically significant relationship with the instrument in either period.

As a final check for how the recession might have changed the composition of students, I consider changes in the student covariates. Similar to Table 10, in Table 11 I run regressions with each of my demographic covariates as an outcome variable, controlling now for school and year of birth fixed effects, per capita income, and TSPs (Panels A and C) or my instrument (Panels B and D). In the full sample, both the instrument and TSPs appear correlated with the fraction of students who are male. There also appears to be a statistically strong correlation between TSPs in year of birth and a later Hispanic student presence, and the instrument appears correlated with the fraction of students at a given campus who are classified as special education. However, when considering the period of interest, only the fraction of the school population that is black remains correlated with TSPs, and no covariates are statistically correlated with the instrument. Once again, the shock of the recession appears to have sufficiently separated pollution effects from general trends.

7.2 Balanced panels from 1981-1983 and the addition of Harris County

I now restrict my analysis to the 1981-1983 period, the time of greatest variation in pollution levels. In doing so, I can expand the total number of counties in the analysis to cover a larger portion of the student population by using all pollution sensors that were present and active from 1981-1983 rather than 1977-1985. This increases the total number of usable counties to 41, though it introduces few additional students, as the original sample contained the more populous counties in Texas. Table 12 repeats the preferred OLS and IV specifications for TLI scores (columns 1 and 2) and math passage rates (columns 3 and 4) using this expanded sample of counties (note that this sample still lacks Harris county). Though the results are similar, there are changes in the new sample. Both findings are now significant at the 1% level, and have increased in size. The IV results in particular are substantially larger, approximately 1.5 times the results in Table 8.

Why do IV results increase by approximately 50% over the original 28 counties? It may be that counties close to sensors that were active only for a shorter time frame around the recession may have had more sensitive populations. However, there is little change in the OLS results. This may again be attributable to the error in the assignment of pollution. Adding 13 additional counties creates 13 independent sources of variation in the IV, but not so in the OLS due to commonly shared pollution readings among counties. Regardless, these results should not be interpreted as "more accurate" than the results found in the longer, balanced sample. Rather, they illustrate that the original effects found are likely not a byproduct of the particular counties within the more balanced panel.

Table 13 repeats column 1 of Table 3 and column 3 of Table 8 but now includes Harris County. OLS results, while of similar magnitude, are now only marginally significant. The IV result, however, remains significant at the 5% level and is larger than prior results, though the first stage, particularly for TSPs, is substantially weaker. The Kleibergen-Paap statistic is now 3.04, below the cutoff for the 25% maximal bias size calculated by Stock and Yogo (2002). It appears that the relationship between manufacturing production and pollution is substantially weaker in Harris County, which is not surprising given that it is the third most populous county in the United States and no doubt has a larger amount of other ambient factors impacting pollution (e.g., automobile traffic).

7.3 Varying the pollution calculation distance

Throughout this analysis, I have defined county pollution using all pollution censors within a 20-mile distance of a county population centroid. In order to verify that my results are not driven by distance choice, I repeat the analysis using cutoffs of 10 miles (13 counties) and

30 miles (47 counties). I include the TLI results from Tables 3 and 8 for comparison. At a distance of 10 miles, the OLS results are larger and much closer to the IV findings. At a distance of 30 miles, the OLS results have decreased and are no longer statistically significant, though they remain negatively signed. If the probability of incorrectly assigning pollution to counties increases with distance from the pollution sensors, these findings support the earlier hypothesis that OLS results are subject to attenuation toward zero caused by measurement error.

In all three cases, the IV results remain statistically significant and negative. The results for the 20-mile cutoff are within one standard error of both the 10 and 30-mile results, suggesting stability in the coefficient, though in the 30-mile case the coefficient is approximately a third again as large. Similar to the 1981-1983 sample findings above, this may be due to a difference between counties located close to and further away from regularly running pollution monitors.

8 Discussion

There remain additional considerations when determining how to interpret my results. Since the exit exams were first administered, math exam passage rates increased from 57% in 1994 to 83% in 2002.[36] This increase may be due to improved schooling, decreases in ambient pollution levels, or other, less socially productive changes such as "teaching to the test," where class time is spent specifically preparing students for the standardized tests rather than working on general education.[37] In order for such effects to bias my results, such practices must vary across counties over time in a manner that is correlated with TSPs as well as my instrument, and present only during the 1981-1983 birth cohorts. The test is written and graded on a state level, which removes the concern of different regions facing

[36] Average passage rates are calculated using all first time test-takers.

[37] For example, see Giroux and Schmidt (2004) and Haney (2000) for a summary of the controversy over the TAAS scores and Klein et al. (2000) for a comparison of the gains in TAAS scoring vs. the National Assessment of Educational Progress.

more difficult grading, and by including year of test fixed effects I control for any such factors that are constant across regions by year. Jacob (2007) notes that, particularly for eighth graders, differences in performance gains across the National Assessment of Educational Progress (NAEP) and the TAAS cannot be explained by skill or format differences, further raising concerns about factors such as student effort, cheating, or test exclusion. While I cannot categorically exclude any of these possible effects, the plausibly exogenous nature of the earlier recession shock provides some safeguard against such confounders, and a RAND report on gains seen on the NAEP tests found that Texas saw NAEP test score improvements during this period as well, which further suggests general improved performance and that at least some of the TAAS score gains were from productive factors (Grissmer et al. 2000).

There were two important testing policy changes during the period of analysis. First, school accountability rankings were instituted starting in the first year of the TAAS tenth grade exit exams. This could explain my findings only if a school's ranking causes it to respond by increasing effort to raise test scores is such a way that is correlated with changes in pollution that occurred in years prior, and that only appeared in the 1981-1983 period. Second, Texas changed how special education students were treated in the 2000 test year. Prior to 2000, special education students did not have their test scores used in the calculation of school-wide passage rates, which were then used to grade schools and determine sanctions. After the 1999-2000 school year, special education scores were included. This could have caused schools/districts to change which population of students were classified as special education, and the relevant policy change occurs during the testing timeframe associated with birth cohorts during the recessionary period.[38] Richardson (2010) notes that the policy change may have more generally influenced how teachers allocated their time, and caused them to focus on lower achieving students they may have ignored before due to exempt status.

[38]This policy change means that considering the probability of a student being special education as an additional outcome is infeasible.

In my specifications I include indicators for special education students to help control for any changes this may have had in the school's performance, but this forces the effect to be constant across time. In prior drafts I allowed the special education effect to vary by year of test, and results were unchanged. There remains the issue of peer effects noted by Richardson (2010), though again the quasi-experimental nature of the research design helps to negate such problems.

TAAS data lack specific birth date. My approximation of prenatal pollution exposure is to assign students the average TSP level for their current county of residence in the year of their birth. There is potential misuse of the term "prenatal" to describe the pollution exposure seen by these students, which I have used throughout for simplicity. As noted above, a student born in January of year t is not exposed to year t pollution prenatally, but rather year $t-1$. Perhaps a more general term would be "perinatal" exposure, which covers later stages of pregnancy and the early weeks of life. Mental development may continue early after birth, so such exposure is still of concern. A better interpretation of my results may be that early life pollution exposure, spanning both the pre- and early postnatal periods, has lasting cognitive effects.

Finally, a likely administrative data error means the number of students on free or reduced price lunch increases substantially in 1999 and then returns to trend after one year. This can be problematic in that the effect of the free lunch covariate might vary over time. Similar to the special education situation, in prior drafts I allowed the effect of free lunch to vary by year of test and results were unchanged.

8.1 Pinning down the mechanism

Prior work has found that increased TSP levels are associated with a higher probability of being of low birth weight (Wang et al. 1997; Chay and Greenstone 2003b; Currie and Walker 2011). Other work suggests a link between low birth weight and long run outcomes such as education (Behrman, Rosenzweig, and Taubman 1994; Behrman and Rosenzweig 2004; Almond, Chay, and Lee 2005; Currie and Moretti 2007). This means prenatal pollution might impact educational outcomes through at least two channels: (1) pollution may cause lower birth weight, which in itself somehow causes students to perform worse, and (2) pollution might have a direct and separate impact beyond birth weight. I am unable to separate these effects from one another, as birth weight is not an available variable in my data set. Regardless of the mechanism, the lifelong negative impacts remain a concern.

Prenatal TSP levels also have an impact on fetal and infant death, which is shifting the distribution of surviving infants that take the exam. That is, lower TSP levels result in a higher number of marginal infants surviving who then go on to take the exam. For instance, Chay and Greenstone (2003b) found that 2,500 fewer infants died nationwide as a result of the TSP reductions in the early 1980s. The number of additional survivors is unlikely to be sufficient to drive my results. In addition, it seems unlikely that newfound survivors would be more heavily from the upper tail of the testing distribution, which would be the only manner in which this would bias my estimates in the direction of negative impacts. More believable is that the marginal students that survive fall more heavily in the lower portion of the distribution which, if anything, biases my results toward zero and suggests that my estimates are a lower bound of the true mean impact.

9 Conclusion

I find a statistically significant relationship between prenatal pollution exposure and educational outcomes, specifically performance on standardized high school exit exams. These effects are present even after controlling for student characteristics, county economic and demographic variables, weather variables, and school, and year of birth by year of test fixed effects. Results are statistically significant only in the periods of the most drastic pollution variation, suggesting a subtle relationship that may be difficult to separate from background trends using minor differences in pollution across counties or gradual changes driven by time. Ordinary least squares results suggest a negative link between educational performance and prenatal pollution exposure, where a within-county standard deviation decrease in the average annual ambient TSP level during the year of birth is associated with an increase of 1.87% of a within-county standard deviation in test scores, and just under 1 percentage point increase in countywide test passage rates. Instrumental variables results suggest the same drop in TSPs is associated with 6.95% of a within-county standard deviation increase in test performance and an increase in county passage rates of over 2 percentage points. As an additional frame of reference, consider the recent finding in Rockoff (2004) — moving one standard deviation up in the distribution of teacher quality raises same-year test scores by approximately 10% of a standard deviation. Though the one-time impact of this finding makes it less directly comparable to the long-run effects found with pollution reduction, the magnitudes are nevertheless an interesting comparison. These results do not appear to be driven by selection into motherhood, selective migration, or factors unique to the 28 counties used in the main analysis.

My findings introduce an additional consideration for designing environmental policy beyond those found in the previous literature. Infants that survive in higher pollution environments may not escape the consequences of exposure simply because they avoid becoming mortality statistics. Instead, they continue to suffer the effects years later in the form of reduced educational performance. Given that such performance may impact their total educational attainment, lifetime earnings, health, and longevity, there are substantial policy implications. For example, if we believe that socially marginalized groups are more likely to grow up in polluted environments, pollution exposure may help to partially explain differences in test scores seen across races and socioeconomic groups, and environmental improvement may help to close such gaps. As noted by Reyes (2007), environmental policy and social policy may sometimes be one and the same.

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Table 1
Means of Excluded vs. Included Counties in 1979 and 1985

	Excluded Counties	Included Counties
	1980	
Per Capita Income	21,145	25,311
	(3,723)	(5,397)
% Mothers Black	9.89	10.35
	(10.53)	(9.56)
% Mothers White	89.55	88.64
	(10.60)	(9.97)
Avg. Mother Age	2403.33	2463.53
	(65.11)	(72.22)
Month Prenatal Began	3.11	2.92
	(0.32)	(0.30)
% Population Black	8.58	8.64
	(8.83)	(7.23)
% Population White	90.82	90.37
	(8.81)	(7.47)
Population Density	37.44	284.67
	(108.56)	(373.81)
Manufacturing Ratio	10.29	15.08
	(8.39)	(7.23)
Share of Texas Population	0.51	0.48
Total Counties	202	28
	1985	
Per Capita Income	23,291	27,564
	(3,904)	(5,988)
% Mothers Black	8.67	9.72
	(9.79)	(8.93)
% Mothers White	90.72	88.99
	(9.91)	(9.53)
Avg. Mother Age	2447.77	2523.07
	(70.01)	(74.53)
% Population Black	7.76	8.63
	(8.33)	(7.45)
% Population White	91.53	89.94
	(8.36)	(7.96)
Population Density	39.83	328.03
	(119.01)	(424.58)
Manufacturing Ratio	8.75	12.10
	(7.74)	(5.48)
Share of Texas Population	0.50	0.49
Total Counties	208	28

Note: Standard deviations shown in parenthesis. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. All results shown are for a balanced panel of counties from 1979-1985. Population shares do not sum to 1 due to counties without data.

Table 2
Means of Excluded vs. Included Student Population (All Years)

	Excluded Counties	Included Counties
Male	48.24	48.31
	(49.97)	(49.97)
Black	11.57	13.64
	(31.99)	(34.33)
Hispanic	26.22	28.00
	(43.98)	(44.90)
Special Ed	3.02	3.81
	(17.10)	(19.14)
Free/Reduced Lunch	23.43	23.02
	(42.36)	(42.09)
Pupil/Teacher Ratio	15.04	16.03
	(2.39)	(2.10)
% School Black	12.72	13.82
	(15.56)	(18.57)
% School Hispanic	29.87	30.69
	(27.40)	(28.33)
% School Free Lunch	25.17	22.16
	(17.42)	(19.00)
TLI Math	79.17	78.59
	(11.32)	(11.85)
Math Passage Rate	82.66	81.04
	(37.86)	(39.20)
Students	550,611	572,438

Note: Standard deviations shown in parenthesis. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. All results shown are for a balanced panel of counties from 1979-1985.

Table 3
Estimated Impact of Prenatal Pollution Exposure on Standardized Test Performance: TLI Scores

	(1) 1979-1985	(2) 1979-1981	(3) 1981-1983	(4) 1983-1985
TSP	0.0058	0.0181	−0.0297**	0.0032
	(0.0081)	(0.0122)	(0.0119)	(0.0126)
Income (YOB)	0.2650	2.2627	0.3255	−1.1600
	(0.6668)	(2.1129)	(0.7640)	(0.8756)
Income (YOT)	−2.3760***	−6.0868***	−1.7849***	−1.1694***
	(0.4080)	(1.3612)	(0.4950)	(0.3087)
Male	1.8079***	2.3791***	1.8231***	1.1885***
	(0.0730)	(0.0859)	(0.0803)	(0.0594)
Black	−8.2951***	−10.1865***	−8.0857***	−6.3416***
	(0.1941)	(0.2518)	(0.2205)	(0.2304)
Hispanic	−4.2938***	−5.5098***	−4.0730***	−3.1068***
	(0.1728)	(0.2262)	(0.1818)	(0.1389)
Asian	2.0853***	2.9931***	1.9241***	1.4905***
	(0.1697)	(0.2388)	(0.1769)	(0.2206)
Special Ed	−13.7079***	−16.6712***	−13.6415***	−10.7161***
	(0.3868)	(0.3700)	(0.4408)	(0.4641)
Free/Reduced Lunch	−1.8519***	−2.4270***	−1.8638***	−1.3302***
	(0.2074)	(0.2645)	(0.1892)	(0.1814)
Pupil/Teacher Ratio	−0.0432	0.0042	−0.0455	−0.0426
	(0.0638)	(0.0513)	(0.0669)	(0.0439)
% School Black	−4.8721	−3.3184	−0.7736	−2.1388
	(2.8715)	(6.2430)	(4.0771)	(3.5846)
% School Hispanic	−2.1213	−2.7380	2.9755	−3.7574
	(4.4319)	(7.2358)	(4.4696)	(2.5781)
% School Free Lunch	0.0297	1.4948	−1.1013	0.5673
	(1.1118)	(2.2078)	(1.0878)	(1.1079)
Days with Rain	−0.0072	−0.0012	−0.0080*	−0.0042
	(0.0045)	(0.0047)	(0.0044)	(0.0066)
Avg. Yearly Temp.	0.0452	−0.1407	−0.1656	0.0856
	(0.0906)	(0.1097)	(0.1545)	(0.0755)
Pop. Density (YOB)	1.7190***	1.5492**	0.6173	0.2576
	(0.2972)	(0.6101)	(0.3770)	(0.1985)
Pop. Density (YOT)	−1.9584***	−1.6560*	−0.8288**	0.1036
	(0.3077)	(0.9265)	(0.3495)	(0.3154)
Result of 1 SD Change	0.36	1.14	-1.87	0.20
Observations	56,816	24,455	26,692	23,116
Total Students	572,438	245,408	252,366	240,751

Notes: Data are collapsed on school, year of birth, year of test, and student demographic cells and weighted accordingly (see Section 5). All regressions control for school and year of birth by year of test fixed effects. Covariates are described in Section 3. Estimated standard errors, clustered on county, are displayed in parentheses. Results are for a balanced panel of schools corresponding to birth cohorts 1979-1985 and test years 1994-2002. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. Total number of counties is 28. YOB and YOT indicate "year of birth" and "year of test", respectively. Per capita income is in tens of thousands of dollars, and density is in hundreds of people per square mile. The line "Result of 1 SD change" refers to the percentage of a within-county standard deviation change in TLI scores associated with a one within-county standard deviation increase in TSPs.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4
Robustness of 1981-1983 TLI effects across model specifications

	(1)	(2)	(3)	(4)	(5)
TSP	−0.0230	−0.0260	−0.0328**	−0.0303**	−0.0297**
	(0.0162)	(0.0161)	(0.0152)	(0.0122)	(0.0119)
Income (YOB)	−0.0173	0.3012	0.0964	0.3427	0.3255
	(0.9407)	(0.9673)	(0.8674)	(0.7620)	(0.7640)
Income (YOT)	−2.6409***	−2.2592***	−2.4881***	−1.8147***	−1.7849***
	(0.6156)	(0.5977)	(0.5410)	(0.5337)	(0.4950)
Pop. Density (YOB)		0.0946	0.0584	0.6277	0.6173
		(0.5630)	(0.4700)	(0.3767)	(0.3770)
Pop. Density (YOT)		−0.5700	−0.3721	−0.8216**	−0.8288**
		(0.5052)	(0.4274)	(0.3646)	(0.3495)
Days with Rain			−0.0099*	−0.0085*	−0.0080*
			(0.0057)	(0.0044)	(0.0044)
Avg. Yearly Temp.			−0.1880	−0.1552	−0.1656
			(0.1733)	(0.1578)	(0.1545)
Male				1.8232***	1.8231***
				(0.0802)	(0.0803)
Black				−8.0858***	−8.0857***
				(0.2187)	(0.2205)
Hispanic				−4.0703***	−4.0730***
				(0.1814)	(0.1818)
Asian				1.9245***	1.9241***
				(0.1774)	(0.1769)
Special Ed				−13.6419***	−13.6415***
				(0.4407)	(0.4408)
Free/Reduced Lunch				−1.8686***	−1.8638***
				(0.1869)	(0.1892)
Pupil/Teacher Ratio				−0.0473	−0.0455
				(0.0659)	(0.0669)
% School Black					−0.7736
					(4.0771)
% School Hispanic					2.9755
					(4.4696)
% School Free Lunch					−1.1013
					(1.0878)

Notes: See Table 3. Total number of observations is 26,692, representing 252,366 students.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5
Estimated Impact of Prenatal Pollution Exposure on Standardized Test Performance: Passage Rates

	(1) 1979-1985	(2) 1979-1981	(3) 1981-1983	(4) 1983-1985
TSP	0.0002	0.0006	−0.0010**	0.0003
	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Income (YOB)	−0.0001	0.0449	0.0094	−0.0283
	(0.0198)	(0.0534)	(0.0267)	(0.0272)
Income (YOT)	−0.0631***	−0.1788***	−0.0596***	−0.0198**
	(0.0136)	(0.0357)	(0.0190)	(0.0092)
Male	0.0458***	0.0698***	0.0477***	0.0202***
	(0.0027)	(0.0030)	(0.0030)	(0.0021)
Black	−0.2182***	−0.2912***	−0.2182***	−0.1410***
	(0.0057)	(0.0073)	(0.0065)	(0.0067)
Hispanic	−0.1056***	−0.1577***	−0.1008***	−0.0554***
	(0.0045)	(0.0060)	(0.0054)	(0.0033)
Asian	0.0271***	0.0552***	0.0232***	0.0112**
	(0.0037)	(0.0056)	(0.0052)	(0.0048)
Special Ed	−0.3620***	−0.4388***	−0.3650***	−0.2813***
	(0.0114)	(0.0081)	(0.0131)	(0.0175)
Free/Reduced Lunch	−0.0453***	−0.0656***	−0.0463***	−0.0276***
	(0.0056)	(0.0080)	(0.0048)	(0.0048)
Pupil/Teacher Ratio	−0.0012	−0.0001	−0.0012	−0.0006
	(0.0022)	(0.0016)	(0.0023)	(0.0016)
% School Black	−0.1513	−0.1042	−0.0203	0.0054
	(0.0956)	(0.1654)	(0.1307)	(0.1110)
% School Hispanic	0.1199	0.0673	0.2232*	0.0119
	(0.1594)	(0.2147)	(0.1273)	(0.0936)
% School Free Lunch	0.0094	0.0777	−0.0445*	0.0395
	(0.0354)	(0.0712)	(0.0233)	(0.0389)
Days with Rain	−0.0001	0.0002	−0.0002	−0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Avg. Yearly Temp.	−0.0014	−0.0068*	−0.0042	0.0008
	(0.0036)	(0.0035)	(0.0053)	(0.0028)
Pop. Density (YOB)	0.0653***	0.0381*	0.0172	0.0218**
	(0.0115)	(0.0194)	(0.0123)	(0.0082)
Pop. Density (YOT)	−0.0725***	−0.0432*	−0.0266**	−0.0147
	(0.0107)	(0.0251)	(0.0103)	(0.0108)
Result of 1 SD Change	0.34	1.14	–1.82	0.55
Observations	56,814	24,455	26,692	23,116
Total Students	572,438	245,408	252,366	240,796

Notes: See Table 3. Passage rate is for first time taking the exam only.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6
Estimated Impact of Prenatal Pollution Exposure on Standardized Test Performance: TLI Score with Lags and Leads in Pollution

	(1) 1979-1981	(2) 1981-1983	(3) 1983-1985
Two-Year Lagged TSP	−0.0179*	−0.0057	0.0125
	(0.0093)	(0.0127)	(0.0094)
One-Year Lagged TSP	−0.0331**	−0.0305**	0.0012
	(0.0127)	(0.0117)	(0.0099)
Current TSP	0.0314***	−0.0488**	0.0069
	(0.0104)	(0.0184)	(0.0125)
One-Year Lead TSP	0.0207*	−0.0060	
	(0.0109)	(0.0173)	
Two-Year Lead TSP	0.0652***	−0.0121	
	(0.0179)	(0.0157)	

See Table 3. Regressions include all variables in Table 3 as well as lags and leads in pollution. Leads are not available for birth years where the lead value extends beyond 1985 due to pollution data limitations.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7
The Relationship Between Ambient TSPs and Relative Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)
Manufacturing Ratio	0.1161	1.5618***	0.8952***	0.8266***	0.8236***
	(0.1381)	(0.2909)	(0.2259)	(0.2192)	(0.2252)
Days with Rain				−0.1308**	−0.1297**
				(0.0575)	(0.0578)
Avg. Yearly Temp.				0.3633	0.3385
				(0.3904)	(0.4144)
Population Density					3.9232**
					(1.4856)
County Effects		X	X	X	X
Year Effects			X	X	X
F-stat	0.71	28.83	15.70	14.22	13.38
Observations	196	196	196	196	196

Notes: Estimated standard errors, clustered on county, are displayed in parentheses. Results are for a balanced panel of counties from 1979-1985. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. Population density is in hundreds of people per square mile.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8
Estimated Impact of Prenatal Pollution Exposure on Standardized Test Performance: IV Results

	(1) OLS 79-85	(2) IV 79-85	(3) OLS 81-83	(4) IV 81-83	(5) OLS 79-85	(6) IV 79-85	(7) OLS 81-83	(8) IV 81-83
TSP	0.0058	−0.0477	−0.0297**	−0.1104**	0.0002	−0.0008	−0.0010**	−0.0035**
	(0.0081)	(0.0718)	(0.0119)	(0.0418)	(0.0003)	(0.0019)	(0.0004)	(0.0015)
Income (YOB)	0.2650	0.2602	0.3255	1.2820	−0.0001	0.0043	0.0094	0.0403
	(0.6668)	(1.1461)	(0.7640)	(0.8724)	(0.0198)	(0.0297)	(0.0267)	(0.0314)
Income (YOT)	−2.3760***	−2.3237***	−1.7849***	−1.7217***	−0.0631***	−0.0619***	−0.0596***	−0.0577***
	(0.4080)	(0.3755)	(0.4950)	(0.4459)	(0.0136)	(0.0131)	(0.0190)	(0.0178)
Male	1.8079***	1.8074***	1.8231***	1.8233***	0.0458***	0.0458***	0.0477***	0.0477***
	(0.0730)	(0.0728)	(0.0803)	(0.0803)	(0.0027)	(0.0027)	(0.0030)	(0.0030)
Black	−8.2951***	−8.2949***	−8.0857***	−8.0838***	−0.2182***	−0.2182***	−0.2182***	−0.2182***
	(0.1941)	(0.1942)	(0.2205)	(0.2208)	(0.0057)	(0.0057)	(0.0065)	(0.0065)
Hispanic	−4.2938***	−4.2932***	−4.0730***	−4.0716***	−0.1056***	−0.1056***	−0.1008***	−0.1007***
	(0.1728)	(0.1722)	(0.1818)	(0.1822)	(0.0045)	(0.0045)	(0.0054)	(0.0054)
Asian	2.0853***	2.0849***	1.9241***	1.9250***	0.0271***	0.0271***	0.0232***	0.0232***
	(0.1697)	(0.1703)	(0.1769)	(0.1778)	(0.0037)	(0.0037)	(0.0052)	(0.0052)
Special Ed	−13.7079***	−13.7100***	−13.6415***	−13.6416***	−0.3620***	−0.3620***	−0.3650***	−0.3650***
	(0.3868)	(0.3876)	(0.4408)	(0.4406)	(0.0114)	(0.0114)	(0.0131)	(0.0130)
Free/Reduced Lunch	−1.8519***	−1.8495***	−1.8638***	−1.8644***	−0.0453***	−0.0452***	−0.0463***	−0.0463***
	(0.2074)	(0.2066)	(0.1892)	(0.1895)	(0.0056)	(0.0055)	(0.0048)	(0.0048)
Pupil/Teacher Ratio	−0.0432	−0.0452	−0.0455	−0.0616	−0.0012	−0.0012	−0.0012	−0.0017
	(0.0638)	(0.0668)	(0.0669)	(0.0695)	(0.0022)	(0.0022)	(0.0023)	(0.0024)
% School Black	−4.8721	−4.6598	−0.7736	−0.0676	−0.1513	−0.1484	−0.0203	0.0016
	(2.8715)	(2.7715)	(4.0771)	(3.8928)	(0.0956)	(0.0936)	(0.1307)	(0.1251)
% School Hispanic	−2.1213	−1.7502	2.9755	2.7598	0.1199	0.1246	0.2232*	0.2162
	(4.4319)	(4.4569)	(4.4696)	(4.6256)	(0.1594)	(0.1611)	(0.1273)	(0.1368)
% School Free Lunch	0.0297	0.0211	−1.1013	−0.9446	0.0094	0.0096	−0.0445*	−0.0395
	(1.1118)	(1.0807)	(1.0878)	(1.0620)	(0.0354)	(0.0348)	(0.0233)	(0.0235)
Days with Rain	−0.0072	−0.0143*	−0.0080*	−0.0120**	−0.0001	−0.0003	−0.0002	−0.0003*
	(0.0045)	(0.0074)	(0.0044)	(0.0051)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Avg. Yearly Temp.	0.0452	0.0699	−0.1656	−0.1862	−0.0014	−0.0010	−0.0042	−0.0047
	(0.0906)	(0.1074)	(0.1545)	(0.1595)	(0.0036)	(0.0040)	(0.0053)	(0.0053)
Pop. Density (YOB)	1.7190***	1.6676***	0.6173	0.2598	0.0653***	0.0649***	0.0172	0.0059
	(0.2972)	(0.2707)	(0.3770)	(0.4621)	(0.0115)	(0.0109)	(0.0123)	(0.0183)
Pop. Density (YOT)	−1.9584***	−1.7485***	−0.8288**	−0.7948**	−0.0725***	−0.0701***	−0.0266**	−0.0256**
	(0.3077)	(0.3401)	(0.3495)	(0.3498)	(0.0107)	(0.0107)	(0.0103)	(0.0101)
Result of 1 SD Change	0.36	-3.01	-1.87	-6.95	0.34	-1.42	-1.82	-6.61
Angrist-Pischke F for TSPs		8.36		18.60		8.36		18.60
Angrist-Pischke F for Income		52.29		186.00		52.29		186.00
Kleibergen-Paap F		3.81		9.63		3.81		9.63
Stock-Wright p-value		0.8092		0.0024		0.9237		0.0068

Notes: See Table 3. Angrist-Pischke, Kleibergen-Paap, and Stock-Wright statistics discussed in Section 6.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9
Robustness of IV results with respect to model choice: 1981-1983

	(1) Base IV	(2) Only TSP IV	(3) Add Man. IV	(4) Add Emp. IV	(5) Shift Share
TSP	−0.1104**	−0.1058*	−0.0857**	−0.1068**	−0.0851*
	(0.0418)	(0.0601)	(0.0382)	(0.0512)	(0.0477)
Income (YOB)	1.2820	1.1886	1.5606	1.4037	1.5783
	(0.8724)	(0.9789)	(0.9598)	(0.9741)	(0.9636)
Income (YOT)	−1.7217***	−1.7184***	−1.3963***	−1.4889***	−1.8444***
	(0.4459)	(0.4507)	(0.4873)	(0.5044)	(0.4906)
Male	1.8233***	1.8232***	1.8236***	1.8234***	1.8234***
	(0.0803)	(0.0804)	(0.0803)	(0.0804)	(0.0804)
Black	−8.0838***	−8.0839***	−8.0843***	−8.0845***	−8.0849***
	(0.2208)	(0.2208)	(0.2211)	(0.2211)	(0.2204)
Hispanic	−4.0716***	−4.0716***	−4.0711***	−4.0711***	−4.0723***
	(0.1822)	(0.1824)	(0.1825)	(0.1825)	(0.1822)
Asian	1.9250***	1.9249***	1.9266***	1.9279***	1.9250***
	(0.1778)	(0.1778)	(0.1776)	(0.1781)	(0.1772)
Special Ed	−13.6416***	−13.6416***	−13.6410***	−13.6404***	−13.6411***
	(0.4406)	(0.4406)	(0.4405)	(0.4404)	(0.4406)
Free/Reduced Lunch	−1.8644***	−1.8643***	−1.8650***	−1.8648***	−1.8648***
	(0.1895)	(0.1894)	(0.1893)	(0.1896)	(0.1893)
Pupil/Teacher Ratio	−0.0616	−0.0606	−0.0601	−0.0585	−0.0578
	(0.0695)	(0.0695)	(0.0689)	(0.0680)	(0.0697)
% School Black	−0.0676	−0.0898	−0.1807	−0.4142	−0.5496
	(3.8928)	(3.9565)	(3.9684)	(4.0824)	(4.2054)
% School Hispanic	2.7598	2.7806	2.6309	1.6618	2.6978
	(4.6256)	(4.5137)	(4.5965)	(4.5641)	(4.6490)
% School Free Lunch	−0.9446	−0.9553	−0.9329	−0.9247	−0.9648
	(1.0620)	(1.0662)	(1.0274)	(1.0534)	(1.0464)
Days with Rain	−0.0120**	−0.0117**	−0.0167***	−0.0162**	−0.0117***
	(0.0051)	(0.0056)	(0.0053)	(0.0068)	(0.0040)
Avg. Yearly Temp.	−0.1862	−0.1892	−0.1219	−0.1489	−0.1186
	(0.1595)	(0.1590)	(0.1477)	(0.1509)	(0.1721)
Pop. Density (YOB)	0.2598	0.2812	−0.7283	−2.2021*	0.3519
	(0.4621)	(0.5044)	(0.6971)	(1.2547)	(0.4361)
Pop. Density (YOT)	−0.7948**	−0.7923**	−0.7872**	−0.6834**	−0.8719**
	(0.3498)	(0.3449)	(0.3410)	(0.3221)	(0.3891)
Manufacturing Emp.			−0.0001*	−0.0001*	
			(0.0000)	(0.0000)	
Total County Emp.				0.0000	
				(0.0000)	
Observations	26,692	26,692	26,692	26,692	26,692
Angrist-Pischke F for TSPs	18.60	4.95	18.08	12.65	5.34
Angrist-Pischke F for Income	186.00	.	153.39	113.87	16.90
Kleibergen-Paap F	9.63	4.95	9.43	6.33	2.18
Stock-Wright p-value	0.0024	0.0270	0.0029	0.0039	0.0217

Notes: See Table 3. Angrist-Pischke, Kleibergen-Paap, and Stock-Wright statistics discussed in Section 6. Instruments are described in Section 6.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10

The Relationship Between TSPs, the Instrument, and Mother and Population Characteristics

	(1) Mother Age	(2) Prenatal Visit	(3) % Mother Black	(4) Total Births	(5) % Pop. Black	(6) % Pop. Other
Panel A: 1979-1985 (N = 196)						
TSP	−0.0029	−0.0003	−0.0010	2.6022	−0.0001*	0.0001*
	(0.0034)	(0.0002)	(0.0029)	(8.2912)	(0.0000)	(0.0001)
Result of 1 SD Change	−0.35	−0.57	−0.33	2.21	−2.91	3.79
Panel B: 1981-1983 (N = 196)						
Manf. Ratio	−0.0529	0.0013	−0.0540	−67.7166	−0.0009	0.0019
	(0.0414)	(0.0019)	(0.0325)	(166.0327)	(0.0016)	(0.0024)
Result of 1 SD Change	−0.01	0.00	−0.01	−11.20	−5.77	11.71
Panel C: 1979-1985 (N = 84)						
TSP	0.0012	−0.0003	0.0005	−8.3603	−0.0001*	0.0001*
	(0.0038)	(0.0002)	(0.0050)	(7.9452)	(0.0000)	(0.0001)
Result of 1 SD Change	0.15	−0.49	0.19	−7.11	−3.08	4.46
Panel D: 1981-1983 (N = 84)						
Manf. Ratio	0.0172	−0.0009	−0.0156	38.0779	−0.0006	0.0011
	(0.0345)	(0.0021)	(0.0264)	(86.7077)	(0.0009)	(0.0013)
Result of 1 SD Change	0.40	−0.33	−1.05	6.30	−3.63	6.50

Notes: Regressions include per capita income and year and county fixed effects as controls. Outcome variable is as noted in each column header. Regressions are weighted by total births in columns 1-3. Estimated standard errors, clustered on county, are displayed in parentheses. Natality and population data are as described in Section 3. Manufacturing ratio is as described in Section 4.1. The line "Result of 1 SD change" refers to the percentage of a within-county standard deviation change in TLI scores associated with a one within-county standard deviation increase in TSPs.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11

The Relationship Between TSPs, the Instrument, and Student Characteristics

	(1) Male	(2) % Black	(3) % Hispanic	(4) % Asian	(5) % Special Ed.	(6) % Free Lunch
Panel A: 1979-1985 (N = 7,522)						
TSP	0.0012	0.0001	0.0008	0.0000	−0.0002	0.0006
	(0.0006)*	(0.0004)	(0.0004)*	(0.0002)	(0.0002)	(0.0005)
Result of 1 SD Change	1.48	0.18	1.37	0.11	−0.57	0.92
Panel B: 1981-1983 (N = 7,522)						
Manf. Ratio	−0.2729	−0.1129	0.0438	−0.0523	−0.2645	−0.0571
	(0.1326)**	(0.0793)	(0.1598)	(0.0393)	(0.1039)**	(0.2614)
Result of 1 SD Change	−1.09	−0.69	0.23	−0.64	−2.77	−0.29
Panel C: 1979-1985 (N = 3,363)						
TSP	−0.0007	0.0015	−0.0005	−0.0004	−0.0004	−0.0004
	(0.0008)	(0.0006)**	(0.0009)	(0.0003)	(0.0004)	(0.0011)
Result of 1 SD Change	−0.86	2.90	−0.90	−1.41	−1.20	−0.70
Panel D: 1981-1983 (N = 3,363)						
Manf. Ratio	−0.2001	0.1365	−0.2068	0.1160	−0.1078	−0.0764
	(0.4323)	(0.2034)	(0.2748)	(0.1291)	(0.2601)	(0.2810)
Result of 1 SD Change	−0.80	0.83	−1.09	1.42	−1.13	−0.39

Regressions include per capita income and school and year of birth fixed effects as controls and are performed at the school/year of birth/year of test level and weighted by the number of students in each cell. Outcome variable is as noted in each column header. Estimated standard errors, clustered on county, are displayed in parentheses. Student data are as described in Section 3. Manufacturing ratio is as described in Section 4.1. The line "Result of 1 SD change" refers to the percentage of a within-county standard deviation change in TLI scores associated with a one within-county standard deviation increase in TSPs.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 12
Results for Balanced Panel of Pollution Sensors in 1981-1983 Period Only

	(1) TLI OLS	(2) TLI IV	(3) Passrate OLS	(4) Passrate IV
TSP	−0.0314***	−0.1670***	−0.0011***	−0.0057***
	(0.0103)	(0.0433)	(0.0003)	(0.0017)
Income (YOB)	2.9689	6.4838***	0.0995	0.2197**
	(2.3174)	(2.2051)	(0.0801)	(0.0856)
Income (YOT)	−9.2032***	−12.4488***	−0.3013***	−0.4117***
	(1.9133)	(2.5963)	(0.0649)	(0.0917)
Male	1.7686***	1.7703***	0.0454***	0.0455***
	(0.0763)	(0.0764)	(0.0028)	(0.0028)
Black	−8.0595***	−8.0549***	−0.2172***	−0.2170***
	(0.2151)	(0.2156)	(0.0065)	(0.0065)
Hispanic	−4.1125***	−4.1058***	−0.1015***	−0.1013***
	(0.1784)	(0.1786)	(0.0053)	(0.0053)
Asian	1.8744***	1.8739***	0.0216***	0.0216***
	(0.1703)	(0.1714)	(0.0050)	(0.0051)
Special Ed	−13.9656***	−13.9573***	−0.3740***	−0.3737***
	(0.4169)	(0.4166)	(0.0121)	(0.0120)
Free/Reduced Lunch	−1.9755***	−1.9771***	−0.0500***	−0.0500***
	(0.1868)	(0.1869)	(0.0048)	(0.0049)
Pupil/Teacher Ratio	−0.0386	−0.0576	−0.0009	−0.0015
	(0.0591)	(0.0593)	(0.0020)	(0.0020)
% School Black	−1.5013	−0.3884	−0.0252	0.0126
	(4.3274)	(4.2002)	(0.1341)	(0.1308)
% School Hispanic	−1.3232	−1.4023	0.0863	0.0836
	(4.3994)	(4.6086)	(0.1270)	(0.1381)
% School Free Lunch	−0.3861	0.0915	−0.0256	−0.0093
	(0.8918)	(0.8405)	(0.0247)	(0.0298)
Days with Rain	−0.0088*	−0.0194**	−0.0002	−0.0006**
	(0.0051)	(0.0074)	(0.0002)	(0.0003)
Avg. Yearly Temp.	−0.1395	−0.3866***	−0.0036	−0.0120**
	(0.1253)	(0.1406)	(0.0046)	(0.0053)
Pop. Density (YOB)	1.6821***	1.4447***	0.0505***	0.0424**
	(0.3173)	(0.4080)	(0.0112)	(0.0181)
Pop. Density (YOT)	−2.0608***	−1.8013***	−0.0633***	−0.0545***
	(0.2666)	(0.2383)	(0.0085)	(0.0076)
Observations	30,583	30,583	30,583	30,583
Total Students	283,803	283,803	283,803	283,803
Angrist-Pischke F for TSPs		14.56		14.56
Angrist-Pischke F for Income		90.45		90.45
Kleibergen-Paap F		6.97		6.97
Stock-Wright p-value		0.0015		0.0009

Data are collapsed on school, year of birth, year of test, and student demographic cells and weighted accordingly (see Section 5). All regressions control for school and year of birth by year of test fixed effects. Covariates are described in Section 3. Estimated standard errors, clustered on county, are displayed in parentheses. Results are for a balanced panel of schools corresponding to birth cohorts 1981-1983 and test years 1996-2001. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. Total number of counties is 28. YOB and YOT indicate "year of birth" and "year of test", respectively. Per capita income is in tens of thousands of dollars, and density is in hundreds of people per square mile.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 13
Results Including Harris County

	(1) TLI OLS	(2) TLI IV	(3) Passrate OLS	(4) Passrate IV
TSP	−0.0194*	−0.1507*	−0.0006*	−0.0048*
	(0.0100)	(0.0740)	(0.0003)	(0.0024)
Income (YOB)	−0.0000	0.0001	−0.0000	0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Income (YOT)	−0.0002***	−0.0002**	−0.0000***	−0.0000**
	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Male	1.8224***	1.8225***	0.0474***	0.0474***
	(0.0614)	(0.0616)	(0.0023)	(0.0023)
Black	−7.9248***	−7.9222***	−0.2102***	−0.2101***
	(0.2118)	(0.2117)	(0.0079)	(0.0079)
Hispanic	−3.9916***	−3.9913***	−0.0989***	−0.0989***
	(0.1516)	(0.1514)	(0.0043)	(0.0043)
Asian	2.0159***	2.0190***	0.0237***	0.0238***
	(0.1419)	(0.1445)	(0.0034)	(0.0035)
Special Ed	−13.5538***	−13.5507***	−0.3618***	−0.3617***
	(0.3499)	(0.3503)	(0.0105)	(0.0105)
Free/Reduced Lunch	−1.5562***	−1.5542***	−0.0379***	−0.0378***
	(0.2648)	(0.2661)	(0.0072)	(0.0073)
Pupil/Teacher Ratio	−0.0298	−0.0390	−0.0005	−0.0008
	(0.0530)	(0.0541)	(0.0018)	(0.0019)
% School Black	−2.4734	−0.9828	−0.0664	−0.0195
	(3.7524)	(3.7197)	(0.1143)	(0.1167)
% School Hispanic	8.3926*	8.5699*	0.3748***	0.3803**
	(4.6902)	(4.8333)	(0.1295)	(0.1380)
% School Free Lunch	−0.5510	−0.4868	−0.0226	−0.0205
	(1.0806)	(1.0575)	(0.0297)	(0.0290)
Days with Rain	−0.0069	−0.0111	−0.0001	−0.0003
	(0.0056)	(0.0073)	(0.0002)	(0.0002)
Avg. Yearly Temp.	−0.1742	−0.3291	−0.0047	−0.0096
	(0.1545)	(0.2521)	(0.0052)	(0.0081)
Pop. Density (YOB)	0.0011	−0.0109	0.0000	−0.0004
	(0.0024)	(0.0104)	(0.0001)	(0.0003)
Pop. Density (YOT)	−0.0049	0.0006	−0.0002*	0.0000
	(0.0029)	(0.0071)	(0.0001)	(0.0002)
Angrist-Pischke F for TSPs		7.62		7.62
Angrist-Pischke F for Income		29.58		29.58
Kleibergen-Paap F		3.51		3.51
Stock-Wright p-value		0.0064		0.0098

Notes: Data are collapsed on school, year of birth, year of test, and student demographic cells and weighted accordingly (see Section 5). All regressions control for school and year of birth by year of test fixed effects. Covariates are described in Section 3. Estimated standard errors, clustered on county, are displayed in parentheses. Results are for a balanced panel of schools corresponding to birth cohorts 1979-1985 and test years 1994-2002. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates. Total number of counties is 29. YOB and YOT indicate "year of birth" and "year of test", respectively. Per capita income is in tens of thousands of dollars, and density is in hundreds of people per square mile.

* significant at 10%; ** significant at 5%; *** significant at 1%

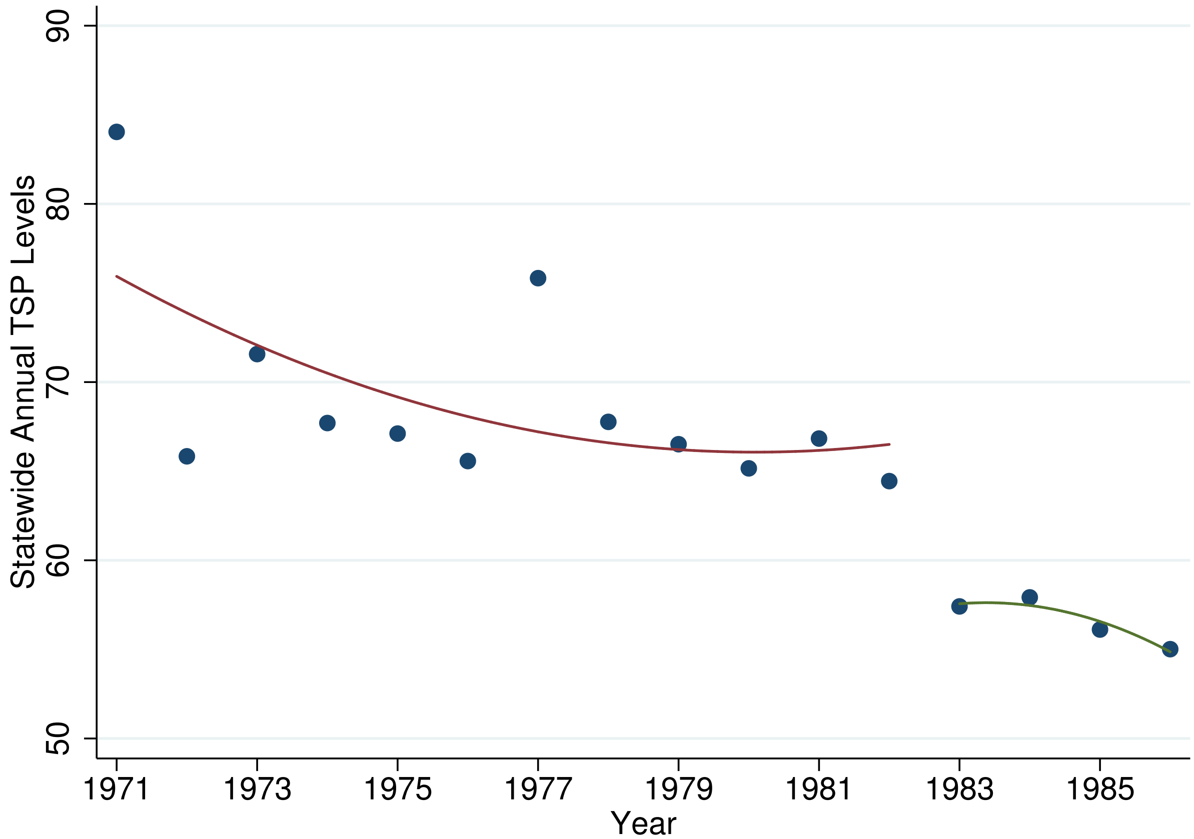
Table 14
Robustness of 1981-1983 findings to distance cutoff choice

	(1) OLS 10 miles	(2) IV 10 miles	(3) OLS 20 miles	(4) IV 20 miles	(5) OLS 30 miles	(6) IV 30 miles
TSP	−0.0455***	−0.0913**	−0.0297**	−0.1104**	−0.0138	−0.1442**
	(0.0093)	(0.0361)	(0.0119)	(0.0418)	(0.0105)	(0.0647)
Income (YOB)	2.9523***	5.6969***	0.3255	1.2820	0.6502	1.9789*
	(0.7866)	(1.4968)	(0.7640)	(0.8724)	(0.7356)	(1.1192)
Income (YOT)	−2.4266**	−2.9878**	−1.7849***	−1.7217***	−1.6525***	−1.9991***
	(0.9183)	(1.0064)	(0.4950)	(0.4459)	(0.5144)	(0.6551)
Male	1.8797***	1.8808***	1.8231***	1.8233***	1.7940***	1.7940***
	(0.1017)	(0.1017)	(0.0803)	(0.0803)	(0.0712)	(0.0714)
Black	−8.1580***	−8.1555***	−8.0857***	−8.0838***	−7.9977***	−7.9971***
	(0.2659)	(0.2659)	(0.2205)	(0.2208)	(0.2209)	(0.2211)
Hispanic	−4.0442***	−4.0420***	−4.0730***	−4.0716***	−4.0566***	−4.0578***
	(0.2204)	(0.2205)	(0.1818)	(0.1822)	(0.1738)	(0.1737)
Asian	1.8770***	1.8793***	1.9241***	1.9250***	1.8849***	1.8853***
	(0.2035)	(0.2053)	(0.1769)	(0.1778)	(0.1647)	(0.1656)
Special Ed	−13.9950***	−13.9934***	−13.6415***	−13.6416***	−13.7106***	−13.7118***
	(0.6054)	(0.6046)	(0.4408)	(0.4406)	(0.3801)	(0.3805)
Free/Reduced Lunch	−1.8608***	−1.8636***	−1.8638***	−1.8644***	−1.8276***	−1.8280***
	(0.2195)	(0.2202)	(0.1892)	(0.1895)	(0.1607)	(0.1609)
Pupil/Teacher Ratio	−0.0724	−0.0937	−0.0455	−0.0616	−0.0564	−0.0594
	(0.0799)	(0.0783)	(0.0669)	(0.0695)	(0.0594)	(0.0612)
% School Black	2.0622	2.8797	−0.7736	−0.0676	−1.9277	−0.9195
	(3.7821)	(3.6728)	(4.0771)	(3.8928)	(4.1352)	(3.8147)
% School Hispanic	8.3588*	8.1291*	2.9755	2.7598	3.6323	3.0550
	(3.9827)	(4.1054)	(4.4696)	(4.6256)	(4.1646)	(4.3411)
% School Free Lunch	−0.8179	−0.7171	−1.1013	−0.9446	−1.3127	−1.4893
	(1.0788)	(1.0796)	(1.0878)	(1.0620)	(1.0170)	(1.1235)
Days with Rain	−0.0085*	−0.0108**	−0.0080*	−0.0120**	−0.0075	−0.0156*
	(0.0040)	(0.0038)	(0.0044)	(0.0051)	(0.0051)	(0.0081)
Avg. Yearly Temp.	−0.0029	0.1172	−0.1656	−0.1862	−0.0271	0.0606
	(0.1521)	(0.1829)	(0.1545)	(0.1595)	(0.1440)	(0.2282)
Pop. Density (YOB)	−0.4234	−0.8779**	0.6173	0.2598	0.9287**	0.5741
	(0.3922)	(0.3555)	(0.3770)	(0.4621)	(0.4091)	(0.4603)
Pop. Density (YOT)	−0.4544	−0.5248	−0.8288**	−0.7948**	−1.0666***	−0.8371**
	(0.3852)	(0.3762)	(0.3495)	(0.3498)	(0.3282)	(0.3966)
Angrist-Pischke F for TSPs		5.79		18.60		11.17
Angrist-Pischke F for Income		9.07		186.00		79.35
Kleibergen-Paap F		2.82		9.63		5.85
Stock-Wright p-value		0.0986		0.0024		0.0053
Counties	13	13	28	28	47	47
Observations	20,165	20,165	26,692	26,692	32,637	32,637
Total Students	187,271	187,271	252,366	252,366	303,715	303,715

Notes: Data are collapsed on school, year of birth, year of test, and student demographic cells and weighted accordingly (see Section 5). All regressions control for school and year of birth by year of test fixed effects. Covariates are described in Section 3. Estimated standard errors, clustered on county, are displayed in parentheses. Results are for a balanced panel of schools corresponding to birth cohorts 1979-1985 and test years 1994-2002. Included counties are those with a population centroid within 10, 20, or 30 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. YOB and YOT indicate "year of birth" and "year of test", respectively. Per capita income is in tens of thousands of dollars, and density is in hundreds of people per square mile. Angrist-Pischke, Kleibergen-Paap, and Stock-Wright statistics discussed in Section 6.

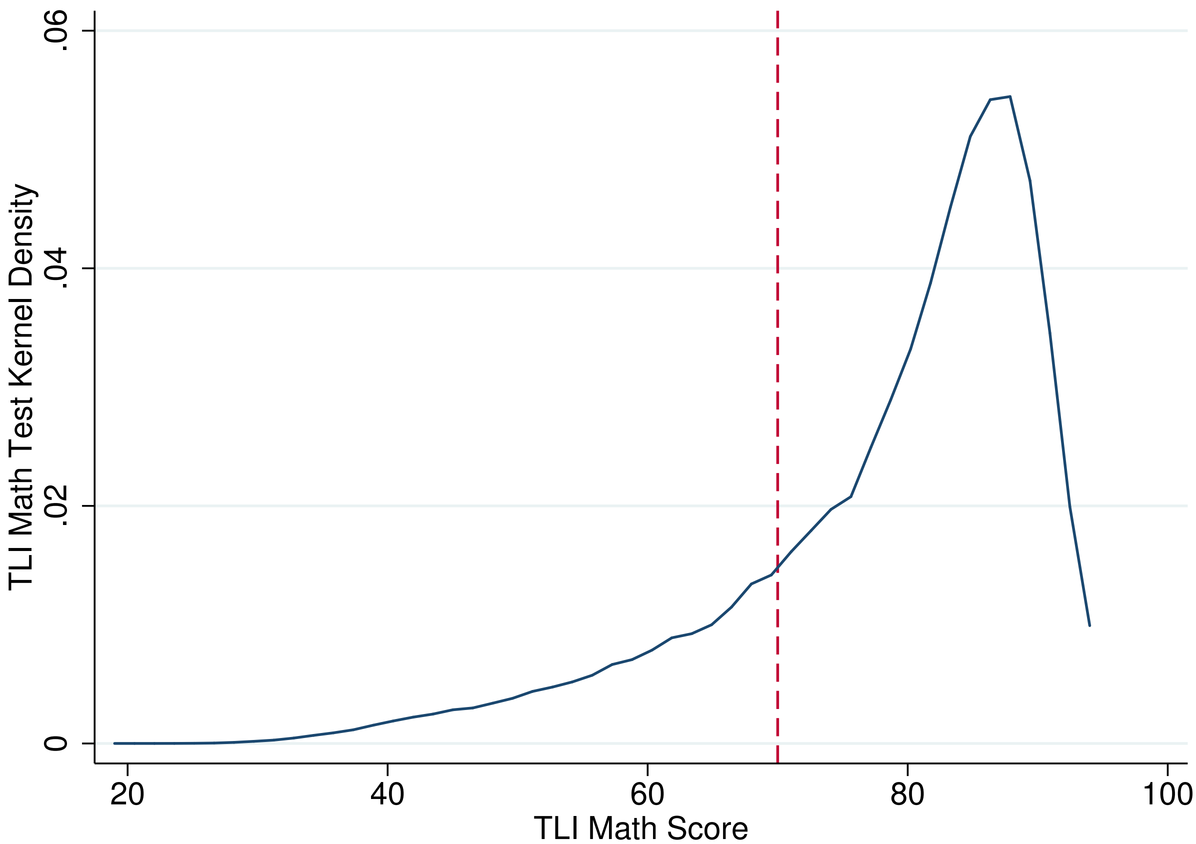
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1
Average Texas Total Suspended Particulates Levels Over Time



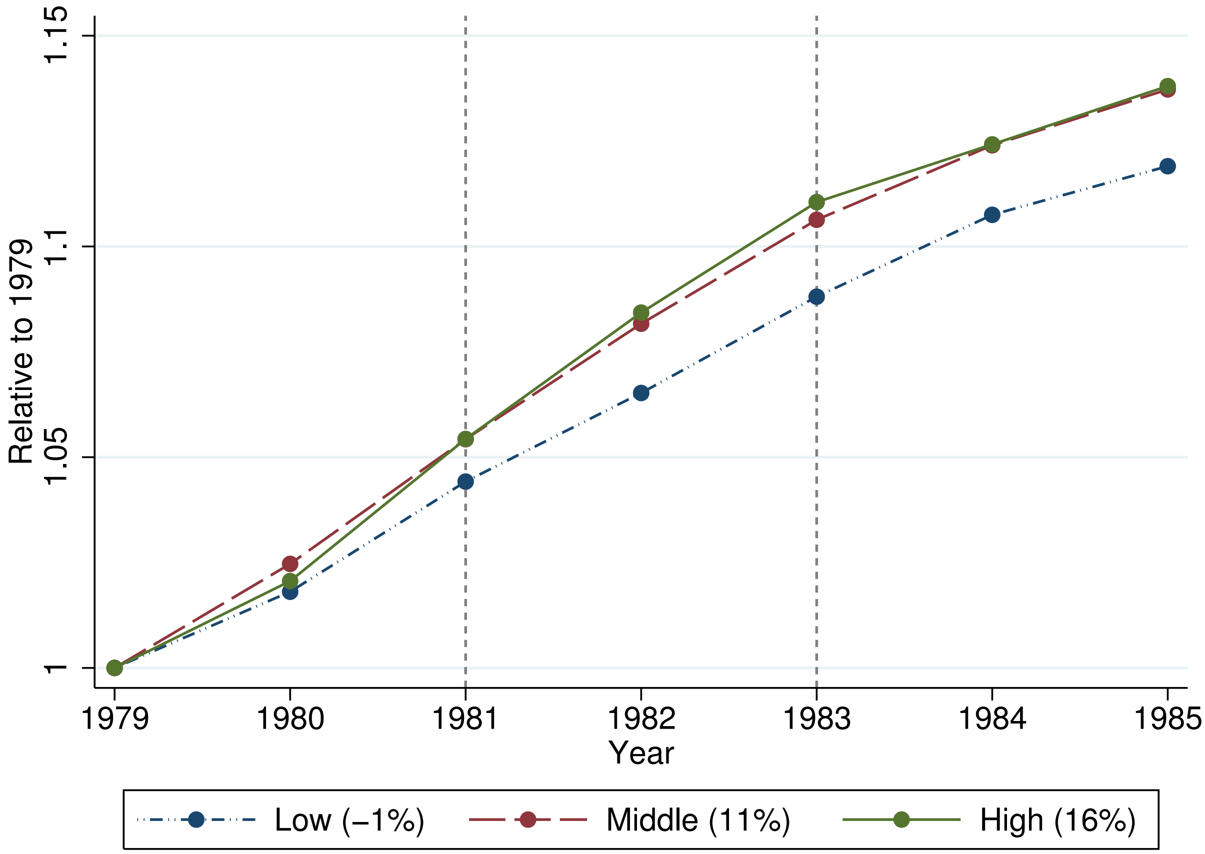
Notes: Graph is the annual geometric mean TSP level for an unbalanced panel of all sensors in the state of Texas, with quadratic fitted lines done separately for all years prior to 1983 and for 1983 and forward.

Figure 2
Kernel Density for Texas Learning Index Math Scores



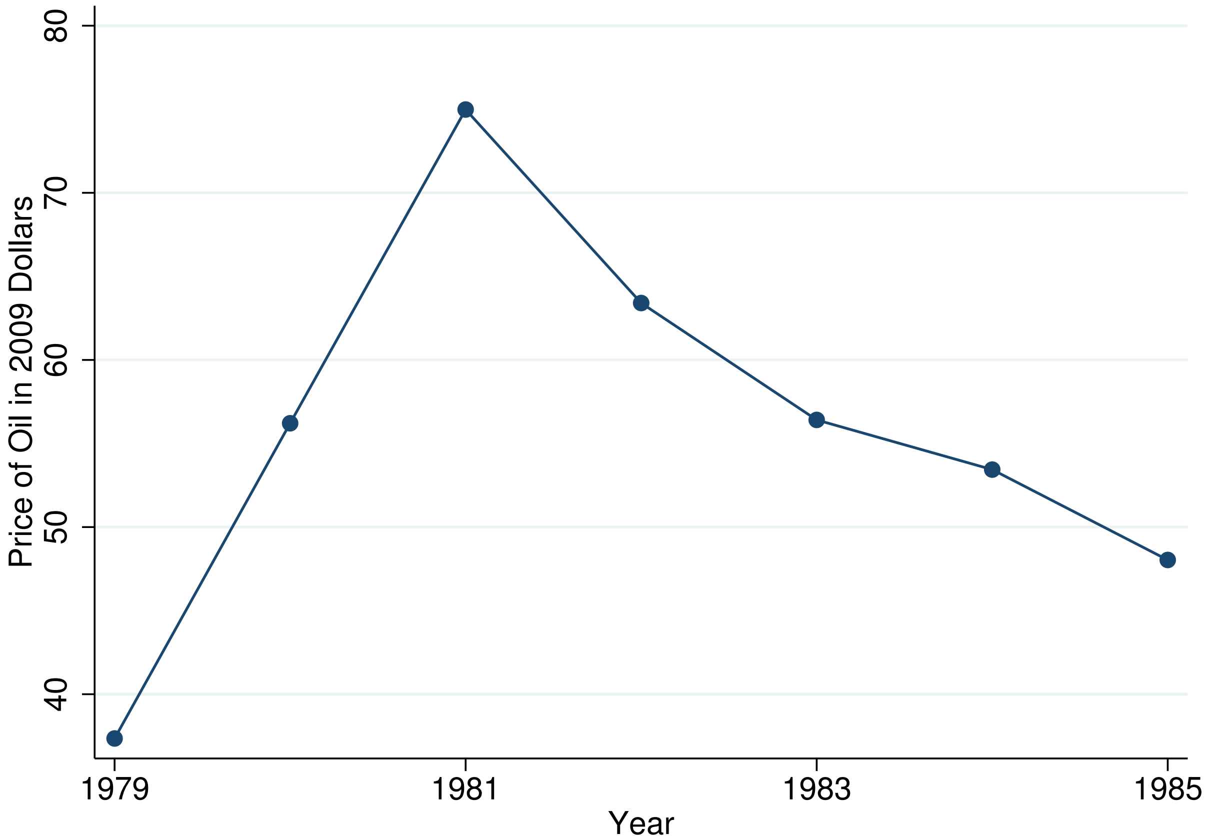
Notes: Kernel density calculated using a bandwidth of 2. Dashed line indicates the passing cutoff of 70.

Figure 3
Texas Learning Index Math Scores By Pollution Change Tercile



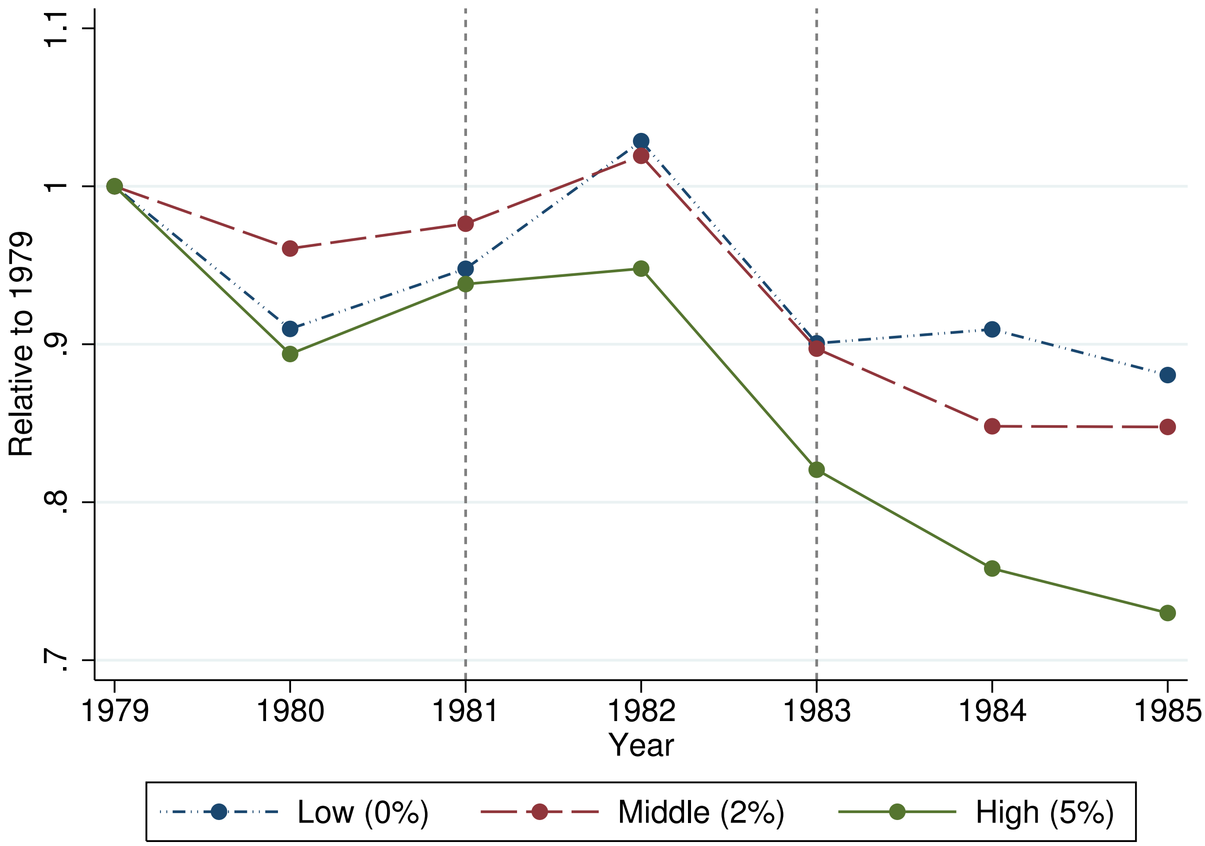
Notes: Counties are grouped into terciles by percentage change in total suspended particulates from 1981-1983 (see Section 4.1).

Figure 4
National Real price of Oil Over Time



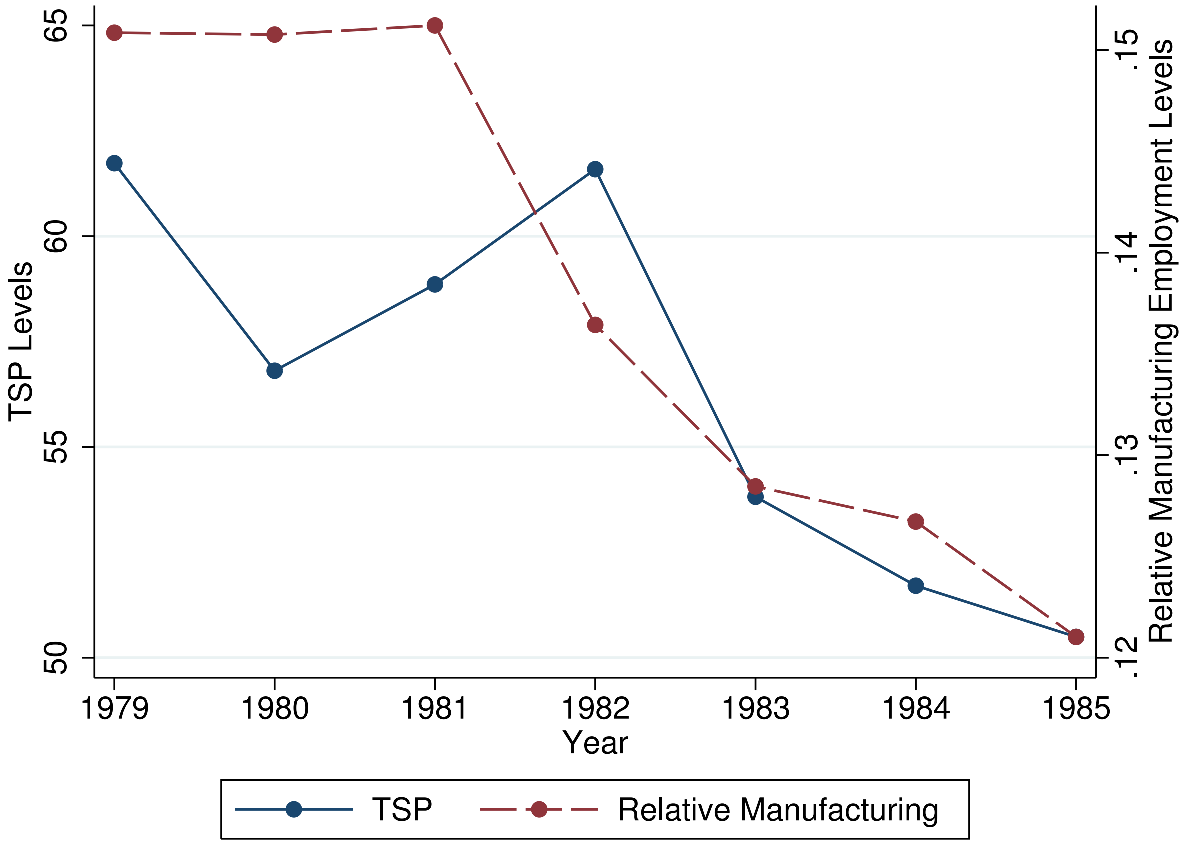
Notes: National oil price data are from United States Energy Information Administration. Oil prices adjusted to 2009 dollars using the Consumer Price Index.

Figure 5
Total Suspended Particulate Levels Relative to 1979 by Absolute Change in Manufacturing Employment Ratio



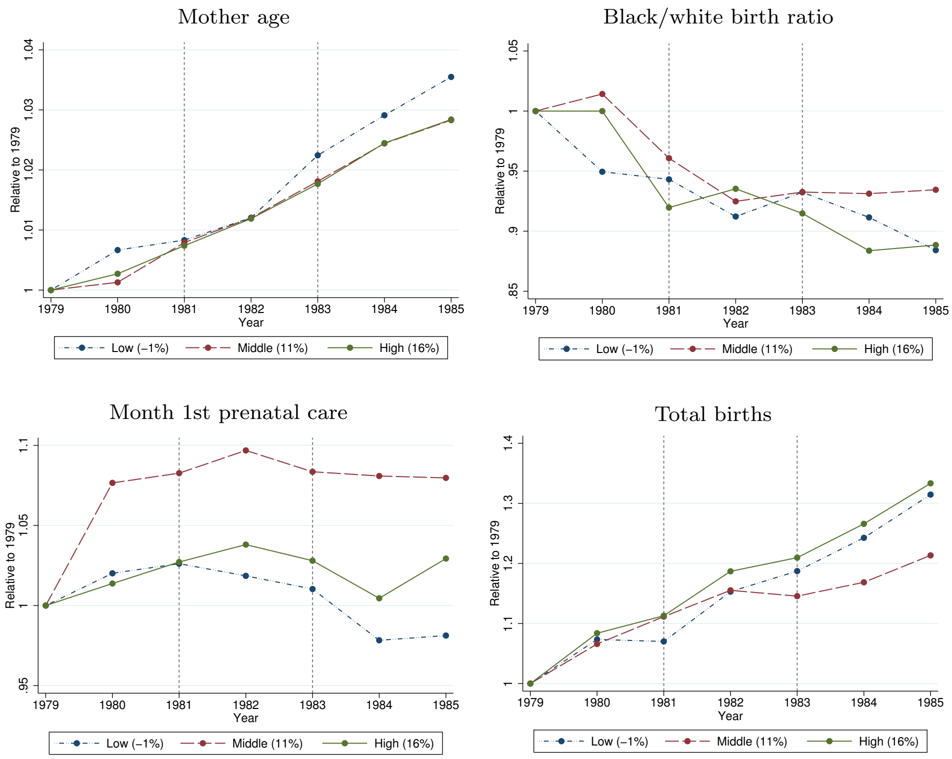
Notes: Data are the mean TSP and calculated instrument for a balanced panel of the 28 counties included in the analysis as described in Sections 3 and 4.1. Counties are grouped into terciles by absolute change in relative manufacturing employment from 1981-1983.

Figure 6
Mean Total Suspended Particulates vs. Mean Manufacturing Percentages



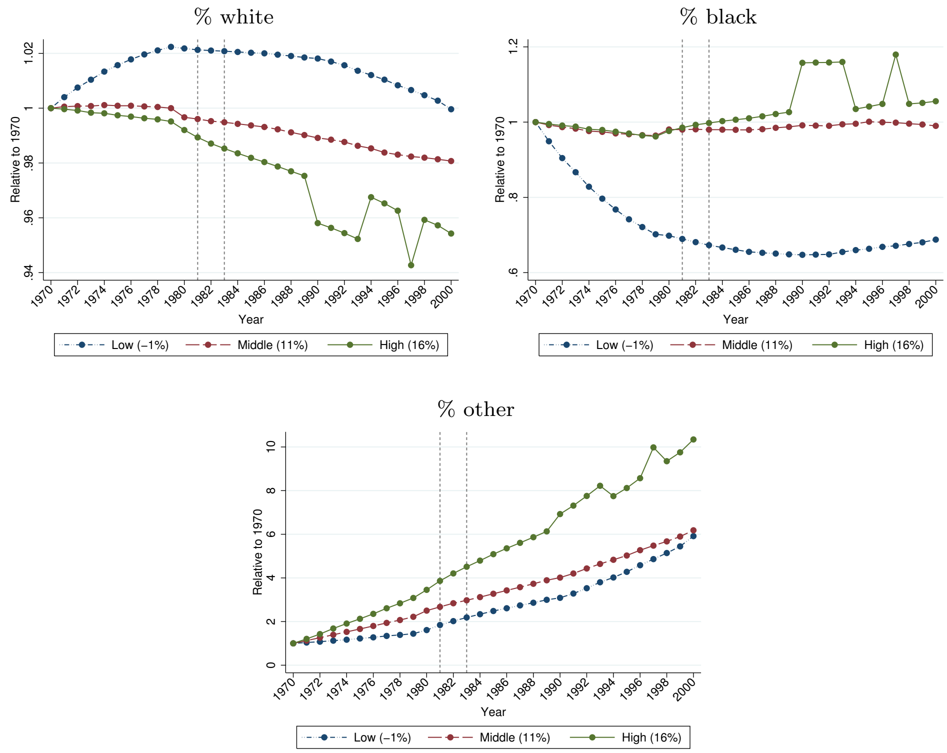
Notes: Data are the mean TSP and calculated instrument for a balanced panel of the 28 counties included in the analysis as described in Sections 3 and 4.1.

Figure 7
Mother Characteristics Relative to 1979



Notes: Mother characteristic data from the National Bureau of Economic Research natality data files as described in Section 3. Counties are grouped into terciles by percentage changes in TSPs from 1981-1983.

Figure 8
Population Characteristics Relative to 1979



Notes: Population characteristic data from the National Cancer Institute, and are derived from intercensus population estimates provided by the Census Bureau (see Section 3). Counties are grouped into terciles by percentage changes in TSPs from 1981-1983.

Table A-1

Ambient TSPs and Relative Manufacturing Employment: Additional Weather Variables

	(1)	(2)	(3)	(4)	(5)
Manufacturing Ratio	0.8236***	0.8461***	0.8395***	0.7734***	0.7220***
	(0.2252)	(0.2315)	(0.2250)	(0.2451)	(0.2320)
Population Density	3.9232**	4.0325***	3.8979**	3.5422**	2.8236**
	(1.4856)	(1.4323)	(1.4961)	(1.3165)	(1.3719)
Days with Rain	−0.1297**	−0.1238*	−0.1170*	−0.1056*	−0.1063*
	(0.0578)	(0.0611)	(0.0580)	(0.0538)	(0.0536)
Avg. Yearly Temp.	0.3385	0.3762	0.2803	−0.5869	−0.9263
	(0.4144)	(0.3968)	(0.4154)	(0.6601)	(0.6999)
Avg. Yearly Humidity		−2.1047	−1.9771	0.2847	0.2751
		(1.5931)	(1.6125)	(2.2899)	(2.3158)
Days with Snow			−0.1082	−0.1126	−0.1334
			(0.1301)	(0.1327)	(0.1408)
Days with Fog				−0.0782*	−0.0874*
				(0.0425)	(0.0444)
Avg. Yearly Windspeed					1.7915*
					(0.9827)
Observations	196	196	196	196	196

Notes: Estimated standard errors, clustered on county, are displayed in parentheses. Results are for a balanced panel of counties from 1979-1985. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. Total number of counties is 28. Weather data are assigned to counties based on the methodology discussed in Section 3.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A-2
OLS and IV of TLI Math Score Using Student-level, Uncollapsed Data

	(1) TLI OLS	(2) TLI IV	(3) Passrate OLS	(4) Passrate IV
TSP	−0.0297**	−0.1104**	−0.0010**	−0.0035**
	(0.0119)	(0.0418)	(0.0004)	(0.0015)
Income (YOB)	0.3255	1.2820	0.0094	0.0403
	(0.7637)	(0.8720)	(0.0267)	(0.0314)
Income (YOT)	−1.7849***	−1.7217***	−0.0596***	−0.0577***
	(0.4948)	(0.4457)	(0.0190)	(0.0178)
Male	1.8231***	1.8233***	0.0477***	0.0477***
	(0.0802)	(0.0803)	(0.0030)	(0.0030)
Black	−8.0857***	−8.0838***	−0.2182***	−0.2182***
	(0.2204)	(0.2207)	(0.0065)	(0.0065)
Hispanic	−4.0730***	−4.0716***	−0.1008***	−0.1007***
	(0.1817)	(0.1822)	(0.0054)	(0.0054)
Asian	1.9241***	1.9250***	0.0232***	0.0232***
	(0.1768)	(0.1777)	(0.0052)	(0.0052)
Special Ed	−13.6415***	−13.6416***	−0.3650***	−0.3650***
	(0.4406)	(0.4404)	(0.0131)	(0.0130)
Free/Reduced Lunch	−1.8638***	−1.8644***	−0.0463***	−0.0463***
	(0.1891)	(0.1894)	(0.0047)	(0.0048)
Pupil/Teacher Ratio	−0.0455	−0.0616	−0.0012	−0.0017
	(0.0668)	(0.0695)	(0.0023)	(0.0024)
% School Black	−0.7736	−0.0676	−0.0203	0.0016
	(4.0753)	(3.8910)	(0.1306)	(0.1251)
% School Hispanic	2.9755	2.7598	0.2232*	0.2162
	(4.4676)	(4.6236)	(0.1272)	(0.1368)
% School Free Lunch	−1.1013	−0.9446	−0.0445*	−0.0395
	(1.0873)	(1.0615)	(0.0233)	(0.0235)
Days with Rain	−0.0080*	−0.0120**	−0.0002	−0.0003*
	(0.0044)	(0.0051)	(0.0002)	(0.0002)
Avg. Yearly Temp.	−0.1656	−0.1862	−0.0042	−0.0047
	(0.1545)	(0.1594)	(0.0053)	(0.0053)
Pop. Density (YOB)	0.6173	0.2598	0.0172	0.0059
	(0.3769)	(0.4619)	(0.0123)	(0.0183)
Pop. Density (YOT)	−0.8288**	−0.7948**	−0.0266**	−0.0256**
	(0.3493)	(0.3497)	(0.0103)	(0.0101)
Observations	572,438	245,408	252,366	240,751
Angrist-Pischke F for TSPs		18.61		18.61
Angrist-Pischke F for Income		186.16		186.16
Kleibergen-Paap F		9.63		9.63
Stock-Wright p-value		0.0024		0.0068

Notes: Data are collapsed on school, year of birth, year of test, and student demographic cells and weighted accordingly (see Section 5). All regressions control for school and year of birth by year of test fixed effects. Covariates are described in Section 3. Estimated standard errors, clustered on county, are displayed in parentheses. Results are for a balanced panel of schools corresponding to birth cohorts 1979-1985 and test years 1994-2002. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. Total number of counties is 28. YOB and YOT indicate "year of birth" and "year of test", respectively. Per capita income is in tens of thousands of dollars, and density is in hundreds of people per square mile.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A-3
OLS and IV of TLI Math Score Using Collapsed Data Without Weights

	(1) OLS 1979-1985	(2) OLS 1979-1981	(3) OLS 1981-1983	(4) IV 1981-1983	(5) OLS 1983-1985
TSP	0.0056	0.0066	−0.0556***	−0.1812***	0.0151
	(0.0126)	(0.0117)	(0.0167)	(0.0511)	(0.0263)
Income (YOB)	0.1481	1.1116	0.2372	2.2085***	−0.7779
	(0.7023)	(3.1508)	(0.7987)	(0.7679)	(1.8306)
Income (YOT)	−3.0521***	−9.3105***	−1.0864	−1.1868	−0.5134
	(0.4771)	(2.1349)	(1.1554)	(1.1114)	(0.4104)
Male	2.3468***	3.0533***	2.4348***	2.4346***	1.5781***
	(0.0893)	(0.1027)	(0.1021)	(0.1026)	(0.1028)
Black	−7.8485***	−9.6615***	−7.6298***	−7.6263***	−5.9194***
	(0.2222)	(0.2315)	(0.2543)	(0.2558)	(0.2533)
Hispanic	−3.7465***	−4.9064***	−3.4633***	−3.4640***	−2.6384***
	(0.2043)	(0.2741)	(0.2120)	(0.2115)	(0.1825)
Asian	2.4561***	3.2276***	2.3626***	2.3601***	1.9702***
	(0.1550)	(0.2762)	(0.1592)	(0.1585)	(0.2400)
Special Ed	−13.1852***	−15.8753***	−12.9707***	−12.9712***	−10.5202***
	(0.3981)	(0.3689)	(0.4684)	(0.4688)	(0.4699)
Free/Reduced Lunch	−1.7206***	−2.0981***	−1.7203***	−1.7198***	−1.3802***
	(0.1611)	(0.1994)	(0.1765)	(0.1764)	(0.2094)
Pupil/Teacher Ratio	−0.0551	0.0306	−0.0985	−0.1164	−0.0565
	(0.0709)	(0.1116)	(0.1000)	(0.1016)	(0.0685)
% School Black	−2.9793	−3.2261	−2.8720	−2.3403	−8.5417
	(2.7836)	(9.9386)	(5.9358)	(5.9795)	(6.7719)
% School Hispanic	−6.5354**	−4.4887	4.6727	4.2318	1.0747
	(2.6129)	(7.1703)	(5.3513)	(5.3697)	(7.3993)
% School Free Lunch	0.0479	0.3157	−0.0818	0.0379	−2.0068
	(1.0975)	(1.8310)	(1.9572)	(1.9474)	(1.6632)
Days with Rain	−0.0108	−0.0317***	−0.0141**	−0.0227**	0.0187
	(0.0068)	(0.0092)	(0.0063)	(0.0099)	(0.0121)
Avg. Yearly Temp.	0.0463	−0.2225	−0.1042	−0.1114	0.1433
	(0.1068)	(0.2176)	(0.1736)	(0.2097)	(0.1466)
Pop. Density (YOB)	1.7953***	2.4160**	−0.2347	−0.7416	0.1529
	(0.4819)	(1.1676)	(0.4796)	(0.8360)	(0.5814)
Pop. Density (YOT)	−2.1182***	−2.2374	−0.8490	−0.8294	−0.2699
	(0.4656)	(1.4009)	(0.5466)	(0.5084)	(0.4461)
Observations	56,816	24,455	26,692	26,692	23,116
Angrist-Pischke F for TSPs				14.20	
Angrist-Pischke F for Income				136.35	
Kleibergen-Paap F				7.23	
Stock-Wright p-value				0.0589	

Notes: Data are collapsed on school, year of birth, year of test, and student demographic cells (see Section 5) but regressions are done without weights. All regressions control for school and year of birth by year of test fixed effects. Covariates are described in Section 3. Estimated standard errors, clustered on county, are displayed in parentheses. Results are for a balanced panel of schools corresponding to birth cohorts 1979-1985 and test years 1994-2002. Included counties are those with a population centroid within 20 miles of a pollution sensor with at least 26 valid readings per year and non-missing covariates, excepting Harris county as noted in Section 3. Total number of counties is 28. YOB and YOT indicate "year of birth" and "year of test", respectively. Per capita income is in tens of thousands of dollars, and density is in hundreds of people per square mile.

* significant at 10%; ** significant at 5%; *** significant at 1%