Is There A School Finance Channel? Effects of Ambient Air Pollution on K-12 Education in USA

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Abstract

How pollution affects education is typically studied through the health aspects of pollution exposure, and its subsequent effects on academic performance. Other than the health channel, this paper proposes a financing channel of pollution's impact on education outcome. Financing of K-12 public education in USA is fairly decentralized, where local property tax is a major source of school revenue. Literature has shown that preference for air quality is capitalized in housing prices. School districts with better air quality are, therefore, endowed with higher tax base, and can generate more resources for K-12 education. Hence, public school funding across jurisdictions could be affected by pollution as well. This financing aspect of pollution and education nexus is generally not emphasized in literature. I analyze property tax revenue per pupil across school districts, and examine how that varies with pollution level. Panel fixed effect analysis for around 1000 metropolitan school districts from 1996 to 2008 academic years suggests that pollution has negative impact on per pupil property tax revenue.

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1 Introduction

The effect of air pollution on education outcome is generally modeled through health damage from pollution exposure, and its subsequent impact on academic performance. Epidemiological literature shows that children's exposure to air pollution increases illness and chronic disease (Schwartz, 2004). Economists follow this lead to relate school absenteeism and underperformance in class with illness and fatigue caused by pollution (Ham *et al.*, 2014). This paper asks the question whether there exists some other channels than health, through which pollution can affect education. One such channel, particularly in the USA context, can be the school finance channel. Public K-12 education financing in USA is fairly decentralized, where local property tax has traditionally been a major source of school revenue. Communities with larger property tax base can generate more revenue than poor communities, and thus expenditure per pupil can vary widely across school districts [1]. If housing prices, and thereby property tax base in the district are affected by pollution, then pollution may affect school finance as well. Investigating this financing aspect is important because if the finance channel is not accounted for, then pollution's true costs and abatement benefits could be understated. These numbers are critical for policy makers to decide on appropriate pollution control regulations, as well as to design equitable school finance policies. Therefore, the question asked in this paper has important policy implications.

Demand for better air quality is capitalized in housing prices, which suggests that

[1] For example, two large suburban school districts in Pittsburgh, PA Metropolitan Statistical Area - Gateway School District and Plum Borough School District, both had around 4300 students in 2002. However, with per pupil property tax revenue of $8,903, Gateway's current expenditure per pupil was $12,231 in 2002 academic year, while that of Plum Borough was only $8,428 with per pupil property tax revenue of $4,076.

improvement in air quality rises property values. In fact, a popular technique to measure willingness to pay for better air quality is to use hedonic housing price models, assuming that people will pay more for a housing unit in a less polluted area than for otherwise identical housing unit in a more polluted area (Harrison & Rubinfeld, 1978). Therefore, school districts with better air quality are endowed with higher tax base, and can generate more resources for K-12 education. Studies, investigating the nexus between pollution and education outcome, typically disregard this effect. Research in this area mostly focuses school absenteeism (Currie *et al.*, 2009b; Chen *et al.*, 2000), cognitive developments (Currie *et al.*, 2009a), and academic performance (Ham *et al.*, 2014) being affected by pollution. Ignoring a probable school finance effect is a gap in the existing literature, which this study intends to address.

The purpose of this paper is, therefore, to introduce and analyze the school finance channel of pollution. To establish the existence and magnitude of the school funding channel, I analyze per pupil property tax revenue and per pupil current expenditure across school districts, and examine how those vary with the level of air pollution. Among the six common air pollutants or criteria pollutants[2], for which The United States Environmental Protection Agency (EPA) sets National Ambient Air Quality Standards (NAAQS), I use ground level ozone (henceforth ozone), Nitrogen Dioxide (NO_2), coarse particulate metter (PM_{10}), and Sulfur Dioxide (SO_2) pollution levels in this paper. These pollutants are commonly used in both pollution-education and hedonic housing price literature. I match pollution monitor location coordinates with school district centroid coordinates, and identify all monitors located within 25 miles of each school district centroid. I then calculate annual pollution level for

[2]Six criteria pollutants are Ground-level Ozone, Particulate Matter (PM), Carbon Monoxide, Nitrogen Oxides, Sulfur Dioxide, and Lead

school districts by taking weighted average of monitor readings. My pollution measure is three-year average of annual pollution levels. It takes some time for change in housing prices to affect property tax revenue collection, and hence I use four year lag of pollution measures. Finally, I analyze school finance data in three-year intervals, so that the impact of change in pollution could channel in housing prices. Since housing prices are more likely to be affected in urban areas, my sample includes school districts located in cities and suburbs in metropolitan areas only. Using panel fixed effect analysis for around 1000 metropolitan school districts from 1996 to 2008 academic year, I found negative impact of pollution on property tax revenue per pupil.

My analysis suggests that in addition to conventional health channel, pollution also affects educational outcome through a school finance channel. Existing literature approaches the pollution education nexus through the health channel only, and to the best of my knowledge, school finance channel has not been critically emphasized in any other studies. Previous studies, in general, estimate empirical specifications of student achievements as dependent variable, and include pollution levels, socioeconomic and demographic characteristics, school characteristics, and expenditure per student as explanatory variables. However, these studies ignore the possibility that variation in instructional characteristics or expenditure per student in US school districts can be affected by pollution. Hence, the coefficient estimates of pollution variable are likely to be underestimated due to multicolinearity problem. Estimated benefits from air quality regulation could, therefore, be larger if this nexus between pollution and school resources is considered. This paper will advance the literature by introducing the school finance channel, and thereby providing a new perspective in the pollution education relationship.

I find that both current expenditure per pupil and property tax revenue increase (decrease) as pollution level decreases (increases) for all four pollutants. However, magnitude of effects varies by pollutants. A squared term of log of pollution, along with level form is included in regression analysis to examine whether effects are different at different levels of pollution. For ground level ozone and NO_2, it is found that marginal effects of change in pollution are higher at higher percentiles of pollution, while for PM_{10} and SO_2 marginal effects are higher at lower percentiles of pollution. At median level of pollution, property tax revenue per pupil increases from 0 to 114 dollars[3] for 5 log point decrease in pollution level for different pollutants. For the median school district with around 3880 students, this accounts for 0 to 442,000 dollar increase in property tax revenue, which is 1.7% of median instructional expenditure. Results for current expenditure per pupil are similar. When property tax revenue per pupil is controlled for as an independent variable in the current expenditure per pupil specification, the pollution coefficients become much smaller and/ or statistically insignificant. However, instead of property tax revenue per pupil if state revenue per pupil is controlled for, that doesn't change the original coefficient estimates by much. These suggest that the effect of pollution on current expenditure is primarily transmitted through property tax revenue.

The remainder of the paper is organized as following: section 2 presents literature review, section 3 provides model specification and empirical strategy, section 4 describes the data, section 5 provides baseline results, section 6 presents robustness check results, and finally section 7 outlines conclusion and plan for follow-up work.

[3] All dollar amounts are in constant 2009 prices unless otherwise mentioned.

2 Literature Review

The literature review in this paper is organized in two major parts. In the first part I discuss existing literature on education and pollution nexus to show that finance channel is generally overlooked. And, in the second part, I discuss several relevant literature to establish the school finance channel. This includes literature on how school resources affect student outcome, how property tax revenue affects school resources, how pollution affects housing value, and how housing value affects property tax revenue.

Studies that analyze pollution's effect on education through adverse health outcomes, can be categorized in three major groups. The first stream of literature shows that ambient air pollution increases school absenteeism (Ransom & Pope, 1992; Chen *et al.*, 2000; Gilliland *et al.*, 2001; Mohai *et al.*, 2011). A common concern for these studies is that poor households are located in more polluted areas (Pastor *et al.*, 2004), and they have limited access to preventive health care. As a result, confounding factors like family income are likely to affect both pollution exposure and delayed health recovery, causing longer school absenteeism. Studies exploit panel structure of data (Currie *et al.*, 2009b) or natural experiments (Ransom & Pope, 2013) to address such issues. Referring school absenteeism as a core impediment to learning, these studies claim that pollution adversely affects students' academic performance. Another stream of literature relates cognitive developments with prenatal or early childhood pollution exposure and demonstrates adverse impacts of pollution on infant health (Chay & Greenstone, 2003; Currie *et al.*, 2009a), education attainment (Isen *et al.*, 2015), and academic achievement (Sanders, 2012). These literature are built on the idea that early childhood events or events during fetal development in womb have long run impacts, and are important determinants of adult outcomes (Currie & Almond, 2011). A third stream of literature investigates pollution's impact on various standardized test scores and found negative associations between pollution and student performance (Ham *et al.*, 2014; Lavy *et al.*, 2014; Miller & Vela, 2013). Studies under this genre also show that academic outcomes are affected by school indoor air quality (Stafford, 2015; Haverinen-Shaughnessy *et al.*, 2011). Neither of the three major streams consider the likelihood that pollution can affect school inputs, which along with family background influences, peer influences, and innate abilities, is a common input in any standard education production function (Hanushek, 1979).

To formally develop the idea of a school finance channel of pollution, I first need to establish a link between school resources and student achievements, and then to show that school resources can vary with pollution levels across districts. In a meta-analysis of education production studies, Hedges *et al.* (1994) report a systematic positive relationship between school outcomes and resource inputs. Studies by Hanushek (1986, 1997), however, ruled out any strong or systematic relationship between student performance and school expenditure. Dewey *et al.* (2000), in another meta-analysis, argues that regression results suggesting ineffectiveness of school inputs on education attainment can be attributable to model misspecifications; and they conclude that school inputs have positive impact on learning. In a recent report, Baker (2012) reviews major studies on whether aggregate expenditure, and school resources that costs money, matter, and conclude that aggregate measures of per pupil spending, and schooling resources are positively associated with student outcomes. Several other studies show positive impacts of spending on pass rates and student test score (Papke, 2005; Sander, 1993, 1999; Taylor, 1998; Ludwig & Bassi, 1999); and positive effects of spending on high school graduation (Wilson, 2000).

Studies also demonstrate that instructional quality is an important determinant of student performance (Rockoff, 2004; Rivkin *et al.*, 2005; Koedel, 2008); and school quality positively affects student achievements (Eide & Showalter, 1998). Analyzing district level spending, Wenglinsky (1997) shows that higher instruction spending per pupil reduces pupil-teacher ratio and enhances test scores. All these studies suggest that school resources are important determinant of student educational achievements.

Second, I need a link between pollution and school resources. As mentioned earlier, the key element of this relationship is property tax revenue. The connection between school funding and property taxation is such that it is impossible for someone to ignore the role of property tax while studying school finance, and alternatively it is inevitable to consider school finance questions while studying property taxation (Kenyon, 2007). Property tax revenue accounts for nearly 36% of the total revenue for public elementary and secondary schools in 2011-12 (Snyder *et al.*, 2016). A dollar increase in property tax revenue per pupil rises total current expenditure and instructional expenditure per pupil by 59 cents and 39 cents respectively in elementary and secondary school districts at metropolitan areas [4]. With this strong reliance of school funding on property tax revenue, it now requires to show how pollution affects property values, and whether increase (decrease) in housing prices increase (decrease) property tax revenue in a jurisdiction.

Empirical investigation of the association between residential property values and air pollution dates back to Ridker & Henning (1967), who finds that owner occupied residential property values in St. Louis Metropolitan Statistical Area (MSA) are

[4] Author's estimate from panel fixed effect regression for 1865 metropolitan school districts from year 1992 to 2014.

positively associated with reduction in annual sulfation levels[5]. Anderson & Crocker (1971) extends this analysis for Kansas City and Washington D.C. in addition to St. Louis and concludes that pollution has a negative influence on residential property prices. Reviewing 37 studies that estimate marginal willingness to pay (MWTP) for reduction in pollution, measured as change in asset value of the house, Smith & Huang (1995) find that the range of MWTP lies between 0 to 98.52 (in constant 1982-84 dollars) for $1 \mu g/m^3$ reduction in total suspended particulates. The rationale behind these findings is well articulated and tested by Banzhaf & Walsh (2008) that better environmental amenities in a jurisdiction attracts people to move in, causing increase in demand for housing in that jurisdiction, and thus increases housing prices.

These hedonic analyses implicitly assume that that people can move freely across jurisdictions. In reality, however, there are costs of migration, and MWTP estimates for air quality are even higher when mobility costs are incorporated in analysis (Bayer *et al.*, 2009). This suggests that households are more likely to move among neighborhoods within a MSA rather than across different MSAs, causing property value differentials among neighborhoods in the MSA. Low income households living in a previously low environmental amenity neighborhood may not gain most from large improvements in air quality since their partial equilibrium gains can be offset by increase in housing prices (Sieg *et al.*, 2004). Despite these issues like who is benefited or whether to incorporate moving costs to estimate MWTP, there is general consensus that property values vary with pollution levels. Reduction in air pollution increases mean housing value (Chay & Greenstone, 2005), while opening of industrial plants causes decline in housing prices in surrounding areas (Currie *et al.*, 2015).

[5]Measured by an index indicating presence of SO_2, SO_3, H_2S, and H_2SO_4.

Next is to justify whether changes in property values due to environmental improvement or degradation affect property tax revenue collection. Lutz (2008) provides essential results in this regard. He studies how much property tax revenue rises, and how long it takes for property tax revenue to increase when housing prices rise. He finds that elasticity between house prices and property tax revenue is around 0.4, and it takes three years for housing price increase to influence property tax revenue. Hence, pollution affects property tax revenue collection. However, if there are assessment limits, then increase in housing prices due to improvement in air quality may not increase property tax revenue.

It is apparent from above discussion that school funding are linked with pollution level. Moreover, it is likely that better educators will accept teaching positions in financially affluent school districts where compensation and work conditions are better. Districts with higher property values essentially generate more resources for K-12 education, and can recruit more skilled educators. Lankford *et al.* (2002) finds that poor, nonwhite students are taught by lesser-qualified or less-skilled teachers in New York public schools. Clotfelter *et al.* (2006) reports similar results for North Carolina schools that lower qualified personnel serve high poverty schools since qualified educators find the combination of compensation and working conditions less attractive in those schools. Qualified educators could also have preference for socioeconomic and environmental amenities and may avoid school districts located in polluted areas. Studies show that teacher mobility and turnover in public schools are mostly attributable to teachers' preferences for race, socioeconomic mix, and achievements of students (Hanushek *et al.*, 2004; Clotfelter *et al.*, 2011). Pollution may impact residential sorting, and thereby influence more qualified teachers to stay in or leave a jurisdiction. However, such sorting channel is not the focus of this paper. Analyzing findings of relevant studies, what I have shown in this section is that apart from health related effects, pollution can also affect public education resources in the USA.

3 Model and Empirical Strategy

3.1 Theoretical Model

The relationship between pollution and education is usually studied using a education production function framework. Education outcome generally depends on student's health, family attributes like parents' income and education, school resources like teacher quality, class size etc., and socioeconomic characteristics of the jurisdiction. Incorporating these factors, I assume the following education production function:

$$Y = y(H, E, \vec{F}, S) \tag{1}$$

where, H is health, E is school resources, F is family attributes, and S is socioeconomic characteristics of the district. Education production function is non-decreasing in health and school resources, i.e. $y_H \geq 0$, and $y_E \geq 0$. For simplification, I assume that school resources are measured by level of current expenditure.

Existing literature treats H as function of pollution, and analyze the impact of pollution on Y through H. I extend this model by treating E as a function of pollution as well. For this, I need a functional specification for school resources, E, that incorporates property tax revenue. It is standard to assume that school resources are financed by local property tax revenue, which depends on property tax base and tax rate, and by state and federal government contributions. Since local governments, like school districts, are required to have a balanced budget, school resources, here, is equivalent to total revenue, and takes the following functional form:

$$E = e(T, R) = T + R = t(C, \gamma) + r(V, M) = t(C, \gamma) + r(V, m(V, T)) \tag{2}$$

where T is transfer from State and/ or Federal government, and R is local property tax revenue. T depends on some state specific characteristics γ, and business cycle C. T is non-decreasing during economic boom and decreasing during economic downturn. γ represents state policies, court litigation, etc. that affect elementary and secondary school funding. Property tax revenue R depends on property tax base V, and tax rate M. Local authorities usually adjust tax rates to generate desired level of revenue. Commonly tax rates are lower if tax bases are large, and vice versa. Tax rate also depends on state government contribution T. When T declines, local authorities increase M to offset the decrease in state contribution, and vice versa. Hence, $r_V \geq 0$, $r_M \geq 0$, $m_V \leq 0$, and $m_T \leq 0$.

Property tax base in a jurisdiction depends on pollution level, non environmental amenities, area specific characteristics, and business cycle or housing market trend. It takes the following functional form:

$$V = v(P, \vec{Z}, \theta, C) \tag{3}$$

where, $\vec{Z}$ is vector of non-environmental attributes, and θ is jurisdiction fixed effect. I assume that property values are non-increasing in pollution level, i.e. $v_P \leq 0$. The remaining argument of education production function, socioeconomic characteristics could also be affected by pollution level and other amenities since households sort according to their preferences. For example, wealthy people are likely to be sorted in areas that are less polluted since they can afford higher property prices in areas with better air quality.

Pollution, therefore, affects education through a direct health channel via pollution exposure, a school finance channel via air quality preference, and a sorting channel in respective jurisdictions. Total differentiating equation 1, after substituting in equations 2, and 3, and rearranging yields:

$$\frac{dY}{dP} = MPH\frac{\delta h}{\delta P} + MPE(\frac{\delta r}{\delta V}\frac{\delta v}{\delta P} + \frac{\delta r}{\delta M}\frac{\delta m}{\delta V}\frac{\delta v}{\delta P}) + MPS\frac{\delta s}{\delta P} \tag{4}$$

where MPH, MPE, and MPS are marginal products of health, school resources, and socioeconomic characteristics respectively. The first term in equation 4 denotes the health channel, the second term denotes the school finance channel, and the last term denotes a sorting channel. The school finance channel has two major components - MPE and $(\frac{\delta r}{\delta V}\frac{\delta v}{\delta P} + \frac{\delta r}{\delta M}\frac{\delta m}{\delta V}\frac{\delta v}{\delta P})$ or $\frac{dR}{dP}$. A good number of research estimate the first component of the school finance channel, MPE, and components of other channels - MPH, and MPS. I have already discussed the impact of school resources on education in previous section. Studies investigating MPH, show that health status affects academic achievements (Crump *et al.*, 2013; Crosnoe, 2006), and educational attainments (Haas & Fosse, 2008; Champaloux & Young, 2015). Studies looking at MPS, find that test scores are affected by school demographics and socioeconomic status (Sutton & Soderstrom, 1999), and neighborhood quality (Thompson, 2002; Ceballo *et al.*, 2004).

While examining the school finance channel in this paper, I do not intend to come up with new estimates for the marginal product of school resources. I will rather focus on the other component, $\frac{dR}{dP}$. As described in Lutz (2008), the first part of $\frac{dR}{dP}$, $(\frac{\delta r}{\delta V}\frac{\delta v}{\delta P})$ is the mechanical component, which refers that property tax revenue mechanically increases (decreases) as property value increases (decreases). The second part, $(\frac{\delta r}{\delta M}\frac{\delta m}{\delta V}\frac{\delta v}{\delta P})$ is the policy offset component that refers to any adjustment in tax rate to offset the mechanical change. Since $\frac{\delta r}{\delta V} \geq 0$, $\frac{\delta r}{\delta M} \geq 0$, $\frac{\delta m}{\delta V} \leq 0$, and $\frac{\delta v}{\delta P} \leq 0$, the sign and size of $\frac{dR}{dP}$ depend on respective magnitudes of mechanical and policy offset components. Changes due to mechanical component can be fully or partially offset by adjusting tax rates. $\frac{dR}{dP}$ is 0 if the effect is fully offset and less than 0 if partially offset. Data from my sample suggests that partial policy offset usually occurs in most cases (Figure 1).

Typical school year in USA begins from July and ends in June next year, i.e. 2007-08 school year is the time period from July 2007 to June 2008. Property values are assessed for tax purposes during the months of January to March of the preceding school year. For example, property tax assessment for 2007-08 school year took place in January 2007, during 2006-07 school year. At the beginning of the school year tax rates are adopted by the school district authorities, i.e. effective tax rates for 2007-08 school year was determined in August 2007. Tax bills are then sent to property owners during September to October, and taxes are due by December[6]. That's why property tax base for a jurisdiction at time t depends on lag values of pollution, and other attributes. Findings of Lutz (2008) also suggest lags in assessment of property values. Hence the property tax base in district j in state s at time t is:

$$V_{jst} = v(P_{j,s,t-k}, \vec{Z}_{j,s,t-k}, \theta_{j,s}, C_{t-k+1}) \tag{5}$$

[6]Property tax calender varies by state and county, and could be different for different jurisdictions.

where, t refers to current academic year, and $(t-k)$ denotes lag values with k being the appropriate lag. This is noteworthy that under this framework, property tax base is not affected by contemporaneous pollution, but depends on its lag values. On the contrary health is affected by current pollution level and may also be affected by lag pollution levels. Differentiating the education production function for individual i in district j in state s at time t, Y_{ijst}, with respect to $P_{j,s,t-k}$ yields:

$$\begin{aligned}\frac{\delta Y_{ijst}}{\delta P_{j,s,t-k}} = \frac{\delta Y_{ijst}}{\delta H_{ijst}}(\frac{\delta h}{\delta P_{j,s,t-k}}) + \frac{\delta Y_{ijst}}{\delta E_{jst}}(\frac{\delta r}{\delta V_{j,s,t}}\frac{\delta v}{\delta P_{j,s,t-k}} + \frac{\delta r}{\delta M_{j,s,t}}\frac{\delta m}{\delta V_{j,s,t}}\frac{\delta v}{\delta P_{j,s,t-k}}) \\ + \frac{\delta Y_{ijst}}{\delta S_{jst}}(\frac{\delta s}{\delta P_{j,s,t-k}})\end{aligned} \tag{6}$$

The term $(\frac{\delta r}{\delta V_{j,t}}\frac{\delta v}{\delta P_{j,t-k}} + \frac{\delta r}{\delta M_{j,t}}\frac{\delta m}{\delta V_{j,t}}\frac{\delta v}{\delta P_{j,t-k}})$ in equation 6 is the key component of the school finance channel, which can be retrieved from differentiating R_{jt} with respect to $P_{j,t-k}$. Local property tax revenue in jurisdiction j at time t is following:

$$\begin{aligned}R_{jst} &= r(V_{jst}, M_{jst}) \\ &= r(v(P_{j,s,t-k}, \vec{Z}_{j,s,t-k}, \theta_{js}, C_{t-k+1}), m(v(P_{j,s,t-k}, \vec{Z}_{j,s,t-k}, \theta_{js}, C_{t-k+1}), T_{j,s,t}))\end{aligned} \tag{7}$$

Following (Lutz, 2008), I consider $k = 4$. Property tax revenue at time t depends on property value at time $(t-3)$; and housing price at time $(t-3)$ is determined by housing market trend at time $(t-3)$, and pollution level and other arguments at time $(t-4)$. Since my pollution measure is 3-year average pollution level, for year t, the corresponding pollution data is average of periods $(t-4)$, $(t-5)$, and $(t-6)$.

3.2 Empirical Model

For baseline analysis I employ panel fixed effect regression approach to control for school district level unobserved heterogeneity. For current expenditure per pupil, I estimate the following equation:

$$\begin{aligned}E_{jst} = \gamma_0 + \gamma_1 \ln Pollution_{j,s,t-k} + \gamma_2 \ln Pollution_{j,s,t-k}{}^2 + \mathbf{State}'_{st}\, \boldsymbol{\gamma_3} \\ + \alpha_j + \lambda_t + \epsilon_{jt}\end{aligned} \tag{8}$$

where, E_{jst} is current expenditure per pupil in district j in state s at time t, and $pollution_{j,s,t-k}$ is 3-year average pollution level for district j in state s at time $(t-k)$. A square term of pollution is included in the model to control for non-linearity in pollution and school resource relationship. $\mathbf{State}_{st}$ includes state level characteristics and policy controls. α_j is school district fixed effect, λ_t is year fixed effect, and ϵ_{jt} is idiosyncratic error term. I assume that α_j is not orthogonal to $\mathbf{X}_{jt}$ for any t, where $\mathbf{X}$ is a vector representing explanatory variables in the model. A Hausman specification test confirms that random effect model is not consistent, i.e. α_j is not random. Therefore, time invariant district level characteristics such as district size and locale can not be controlled for in the model.

Controlling for other contemporaneous district level variables such as racial composition, poverty rate, and median household income may arise multicollinearity concerns, and hence are not included in the model. As discussed in the theoretical model section, pollution may affect sorting and thereby sociodemographic characteristics in the districts. Since past pollution can affect present pollution, the idiosyncratic error terms are not serially uncorrelated, i.e. $E[\epsilon_{jt}\epsilon_{js}] \neq 0, \forall\ t \neq s$. This assumption is tested using Wooldridge test for serial correlation in panel-data models, and the null hypothesis of no first-order autocorrelation is duly rejected. Idiosyncratic errors are also not homoskedastic, i.e. $E[\epsilon_j\epsilon'_j] \neq \sigma^2_\epsilon I_T$. This is confirmed by Breusch-Pagan test for heteroskedasticity, where the null hypothesis of constant variance is rejected.

Hence heterskedasticity and serial correlation robust standard errors are estimated using cluster option in Stata, where standard errors are clustered at school district level.

State level controls in equation 8 are state revenue as percentage of total K-12 revenue, and a state level index for average current expenditure per pupil. State share in K-12 revenue is a proxy for state policy regarding K-12 spending in the state. It is expected that higher the state share, lower the disparity across districts, and lower the average per pupil spending. An index of average spending per pupil is included in the model to control for the fact that current expenditure per pupil will be higher in school districts located in a state with higher average per pupil spending, and vice versa [7]. The index is calculated using the following formula[8]:

$$Index_{st} = \frac{y_{st} - y_{min,t}}{y_{max,t} - y_{min,t}} \tag{9}$$

where, y_{st} is average current expenditure per pupil in state s at time t, and $y_{max,t}$ and $y_{min,t}$ are the maximum and minimum average current expenditure per pupil at time t respectively. By construction, the index values range between 0 to 1, with 0 being the lowest average spending state and 1 being the highest. District level current expenditure per pupil are expected to be higher if index value is closer to 1, and lower if index value is closer to 0.

For property tax revenue per pupil, a similar model like equation 8 is estimated. It includes a new set of state level policy variables, district level controls, and a control

[7] For example, average current expenditure per pupil in Alabama was $9,275 in 2008, while that was $12,065 in Pennsylvania.

[8] This indexing formula is used by UNDP to calculate dimension indices for Human Development Index.

for state level housing market trend. The model is following:

$$\begin{aligned} R_{jst} = \beta_0 + \beta_1 \ln Pollution_{j,s,t-k} + \beta_2 \ln Pollution_{j,s,t-k}{}^2 + \mathbf{State}'_{st}\ \boldsymbol{\beta_3} \\ + \mathbf{Local}'_{j,s,t-k}\ \boldsymbol{\beta_4} + \mathbf{District}'_{jst}\ \boldsymbol{\beta_5} + \beta_6\ HPI_{s,t-k+1} + \alpha_j + \lambda_t + \epsilon_{jt} \end{aligned} \tag{10}$$

where, $\mathbf{State}_{st}$ includes state revenue as percentage of total K-12 revenue, and a state level index for average property tax revenue per pupil. Like the relationship described in equation 8, property tax revenue per pupil is expected to be higher if state revenue share is lower, and vice versa. The index for average property tax revenue serves similar purpose like the current expenditure index, and is calculated using the formula in equation 9. y in this case is the average property tax revenue per pupil.

$\mathbf{Local}_{j,s,t-k}$ includes public education related variables that might affect housing prices. These variables are measure for school quality, and school infrastructure facility at time $(t-k)$. Studies have shown that school quality affects housing prices (Bayer *et al.*, 2007; Weimer & Wolkoff, 2001). Ladd & Loeb (2013) suggests spending per pupil as one of the most common proxies for school quality. Here, I use variation in instructional spending per pupil as measure of school quality. In particular, I calculate per pupil instructional spending for a school district as percentage of median per pupil instructional spending across states[9]. Studies also find that increase in school facilities positively affects housing prices in the district (Cellini *et al.*, 2010). Here, I use capital outlay expenditure per pupil as proxy for school facilities.

$\mathbf{District}_{jst}$ includes variables that might effect property tax rate in the school

[9]Median values are obtained for each state for every academic year. For a school district located in New Jersey, the measure of school quality is per pupil current instructional expenditure of that school district as percentage of median per pupil current instructional expenditure of New Jersey.

district. These variables are total outstanding short and long term debts, and share of other local revenue in K-12 revenue of district j in state s at time t. School districts with larger debt to service may increase property tax revenue by increasing property tax rate. School districts can also diversify revenue generation by introducing other taxes like school district income tax (Ross & Nguyen-Hoang, 2013). It is expected that property tax rates would be lower if other local revenue share is higher, holding everything else constant. Finally, $HPI_{s,t-k+1}$ is the housing price index for state s at time $(t-k+1)$, which controls for overall housing market trend in the state. Controlling for HPI ensures that change in housing prices that affects property tax revenue in the model, is net of any economy wide housing market shock.

Identification in this model comes from within district variation in pollution level over time. The identification assumption is that correlation between the pollution variables and any unobservables that affect property tax revenue, is eliminated by controlling for district level unobserved time-invariant fixed effects along with relevant policy and economic variables as analyzed in the theoretical model. However, deviations from means remove useful time-invariant information as well. Several robustness checks are,therefore, performed to check the validity of baseline results. These tests and results are discussed in the Result section. The school finance channel component[10] is measured by the marginal effects of pollution on current expenditure and property tax revenue per pupil which are following:

$$\frac{\delta E_{jt}}{\delta \ln Pollution_{j,s,t-k}} = \gamma_1 + 2\gamma_2 \ln Pollution_{j,s,t-k} \tag{11}$$

$$\frac{\delta R_{jt}}{\delta \ln Pollution_{j,s,t-k}} = \beta_1 + 2\beta_2 \ln Pollution_{j,s,t-k} \tag{12}$$

[10] $\frac{\delta r}{\delta V}\frac{\delta v}{\delta P} + \frac{\delta r}{\delta M}\frac{\delta m}{\delta V}\frac{\delta v}{\delta P}$.

From equations 11 and 12, we see that marginal effects of pollution in my model specification varies with level of pollution. If sign of β_1 and sign of β_2 are same, then the effect of pollution will be higher for higher values of pollution. If signs of β_1 and sign β_2 are different then effect will vary at different level of pollution depending on respective sign and magnitudes of coefficients. I report marginal effects at 10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}, 60^{th}, 70^{th}, 80^{th}, and 90^{th} percentile values[11] of ozone, NO_2, PM_{10} and SO_2 concentrations.

4 Data

I obtain data from various sources. School district expenditure and revenue data are obtained from National Center for Education Statistics (NCES)'s Local Education Agency Finance Survey Data. Data for the academic years 1992 to 1994 are obtained from US Census Bureau's Government Finance Statistics data. All dollar values are converted in 2009 constant dollar by using Personal Consumption Expenditures Price Index (PCEPI) deflators. PCEPI data are obtained from Federal Reserve Bank of St. Louis website. School district characteristics are obtained from NCES's Local Education Agency Universe Survey Data. School district centroid coordiantes are obtained from NCES's Universe Survey Data and US Census Bureau's gazetteer files.

Following Murray *et al.* (1998) the sample includes only unified school districts i.e. districts offering both elementary and secondary education since there are cost differences between elementary and secondary education. School districts located in rural areas, and outside metropolitan areas are excluded since the desired effect is most likely to observe in urban metropolitan areas. School districts in large, mid-

[11]Percentile values are based on panel form.

size, and small cities and suburbs located in metropolitan areas constitute the sample. The sample is further restricted to regular local school districts or local school districts that are component of a supervisory union[12], and to school districts for which there were no significant boundary change. One concern in my analysis is existence of property tax limitations across states, which limits increase in assessed values of property in a jurisdiction. If there exists assessment limits then increase in property values due to decrease in pollution will not be reflected in property tax revenue. Hence, states that have statewide assessment limits are excluded. States with and without statewide assessment limit[13] are identified from Table 1 in Anderson *et al.* (2006). Finally there are some states that experience a major policy shift regarding K-12 education financing. For these states, the major share of K-12 financing has shifted from local property tax revenue to state revenue, and as a result property tax revenue per pupil has declined gradually (Figure 2). These states are excluded from the sample[14].

State level average current expenditure, property tax revenue, state revenue, total revenue, and student count is obtained from NCES's Digest of Education Statistics various issues. HPI data is obtained from Federal Housing Finance Agency. State level HPI is an all transaction index, estimated by using sales prices and appraisal data. The original index was a quarterly index, which is transformed in an annual index by averaging four quarterly values. Initial index value was 1980 quarter 1 = 100, which is transformed to 1995 = 100. A three-year lag value of HPI is used in

[12]School district that is a component of a supervisory union, shares superintendent and administrative services with other participating school district. 92% of the school districts in the sample are regular local school districts, and the rest are part of some supervisory union.

[13]States with statewide assessment limit are: Arkansas, Arizona, California, Colorado, Florida, Iowa, Maryland, Michigan, Minnesota, Montana, New Mexico, Oklahoma, Oregon, and Texas.

[14]States with major shift in K-12 financing policy are Arkansas, California, Idaho, Kansas,Michigan, Minnesota, Montana, New Hampshire, Oregon, Vermont, and Wisconsin.

regression analysis as per the setting of theoretical model.

Air pollution data and monitor location coordinates are obtained from United States Environmental Protection Agency (EPA) website. Pollution data for ozone, NO_2, PM_{10}, and SO_2 are available from 1990 onward. I calculate the distance between school district centroids and monitor locations by using respective latitude and longitude coordinates[15]. To get pollution measure for a school district, I consider all pollution monitors located within 25 miles of the school district centroid with at least 1 monitor located within 12 miles[16]. Average median distance of pollution monitors from district centroid is 10.8 miles, while average minimum distance is 5.6 miles. I then take weighted average of daily monitor readings. Inverse of squared distances of monitor locations from district centroid are used as weights, so that a closer monitor from district centroid is given a higher weight, and a distant monitor gets a relatively lower weight. Annual pollution measures are then calculated using EPA guidelines.

For ground level ozone, pollution measure is 3-year average of annual 4^{th} highest daily maximum 8-hour average. For NO_2, pollution measure is 3-year average of annual arithmetic mean of all of the reported 1-hour values. Pollution measure for PM_{10} is 3-year average of annual arithmetic mean, which is average of four quarterly means. And for SO_2, pollution measure is 3-year average of annual 99^{th} percentile of 1-hour daily maximum concentration. Details of pollution measure calculations are described in Table A1.

Since first year of pollution measure is 1990 calendar year (January 1990 to De-

[15]Stata's geodist command is used to calculate distances.

[16]Samples with smaller and larger distances than 12 miles are tested for sensitivity analysis.

cember 1990), corresponding first school year in data is 1996 (July 1995 to June 1996). This is because we assume 4-year lag in our model, that is pollution level of 1992 will affect property tax revenue in 1996. The 3-year average pollution level at 1992 is average pollution level of 1990, 1991, and 1992 calendar years. I consider 3-year intervals in finance data to allow effect of pollution change be transmitted in housing prices. Hence, school finance variables are of academic years 1996, 1999, 2002, 2005, and 2008. I restrict my analysis till academic year 2008 because of the impact of the great recession after 2008 (Figure 4). As discussed in the theoretical model, property tax revenue increases as state share in K-12 revenue decreases, and vice versa. After 2008 academic year, state revenue for K-12 education has started to decline as state government revenues got affected by the recession. Local school districts might respond by increasing tax rate to offset revenue loss. Since I can not distinguish between the mechanical component and policy offset component of change in property tax revenue, the sample is restricted till 2008 to avoid any spurious results. 2008 academic year's property tax revenue depends on housing prices of 2005, which is affected by average pollution levels of 2002, 2003, and 2004. Finally I estimate a balanced sample, and school districts for which data for all 5 periods are not available are excluded[17]. This is to ensure that results are not influenced by sudden inclusion or exclusion of school districts.

There are approximately 3000 regular elementary and secondary school districts located in cities and suburbs in metropolitan areas in the USA, for which finance data are available. Among them around 1000 are located in states with state wide assessment limits. Of the remaining 2000, my sample includes 485 to 940 school districts, depending on availability of pollution data for different pollutants. During

[17] An unbalanced sample with at least two years of data is later used to perform robustness check.

the period of analysis, school districts included in the sample generally show an increasing trend in property tax revenue and current expenditure, and a declining trend in level of air pollution. Average property tax revenue per pupil was \$5638 in 1996, which increases to \$7354 in 2008. Average current expenditure per pupil was \$9170 in 1996 academic year, which increases to \$12498 in 2008. Mean ozone pollution measure in 1992 was 86.3 *ppb*[18] which decreases to 82.5 *ppb* in 2004, while EPA standard for ground level ozone during that period was 0.08 *ppm* or 80.0 *ppb*. For NO_2, EPA standard is 53 *ppb*, and mean pollution measure decreases from 24 *ppb* in 1992 to 19 *ppb* in 2004. Mean PM_{10} measure in 1992 was 33 $\mu g/m^3$, which decreased to 25 $\mu g/m^3$ in 2008. EPA standard for PM_{10} pollution during that time period was 50 $\mu g/m^3$. Lastly, EPA standard for SO_2 is 75 *ppb*, and mean SO_2 pollution measure decreases from 92 *ppb* in 1992 to 58 *ppb* in 2004. SO_2 pollution level shows the largest decline from 1992 to 2004, followed by PM_{10}, NO_2, and ozone (Figure 5). Table 1 provides summary statistics of the key variables used in regression.

5 Results

A linear model, excluding log pollution squared term is first estimated for both current expenditure per pupil and property tax revenue per pupil. For the current expenditure regression, it appears that the coefficient of log pollution is not statistically different from 0 for NO_2, and SO_2 (Table 2). When a quadratic term of pollution is added in the model then the pollution coefficients γ_1 and γ_2 become jointly significant for all four pollutants (Table 4). γ_2 is individually significant for each pollutant as well. Similarly, for property tax revenue, pollution coefficients for SO_2 and PM_{10} are not statistically different from zero, but with the quadratic term, both β_1 and β_2 are

[18]EPA measure for ground level ozone is expressed in parts per million (*ppm*). Ozone pollution measure in this paper is transformed in parts per billion (*ppb*) for computational purposes.

jointly significant, and β_2 is also individually significant (Table 5). These results provide rationale for including a quadratic pollution term in the model.

5.1 Current Expenditure per Pupil

The coefficient of log pollution for current expenditure specification is positive, and the coefficient for the square term is negative for ozone and NO_2. For PM_{10} and SO_2, coefficient of the level term is negative and coefficient of the squared term is positive (Table 6). All pollution coefficients are statistically significant. This suggests that current expenditure per pupil increases with pollution up to certain initial level; and then decreases with pollution for ozone and NO_2. In other words, decrease in pollution in relatively more polluted area increases current expenditure per pupil more, compared to that in a less polluted area. The opposite is the case for PM_{10} and SO_2. For these pollutants, decrease in pollution in less polluted areas affects current expenditure more, than decrease in pollution in more polluted areas. These results go in line with the Banzhaf & Walsh (2008) rationale, since pollution decreases more in areas with high initial level of pollution[19] for ozone and NO_2. For PM_{10}, pollution increases in some districts with higher initial pollution, and for SO_2, the growth rates of pollution decrease are lower at higher initial level of pollution (Figure 6).

At 10^{th} percentile of ozone, 10 log point decrease[20] in pollution increases current expenditure per pupil by 144 dollars. Increases are 273 dollars and 376 dollars respectively at 50^{th} and 90^{th} percentiles. For NO_2, marginal effect at 10^{th} percentile is positive, i.e. decrease in NO_2 is associated with decrease in current expenditure.

[19] Compound growth rates of pollution are calculated for 1992 to 2004 time period, and are plotted against 1992 level of pollution to analyze this relationship.

[20] Marginal effects discussed in this section are for 10 log point change in pollution level, if not otherwise mentioned.

Marginal effects become negative from 30^{th} percentile, and are 90 dollars and 261 dollars respectively at 50^{th} and 90^{th} percentiles. For PM_{10}, marginal effects at 10^{th}, and 50^{th} percentiles are 198, and 102 dollars respectively, and not statistically significant at 90^{th} percentile. Finally for SO_2, 10 log point decrease in pollution increases current expenditure per pupil by 70 dollars at 10^{th} percentile, and 19 dollars at 50^{th} percentile. Marginal effects become positive after 60^{th} percentile of SO_2 pollution measure (Table 7).

Second, I investigate whether this variation in current expenditure is attributable to property tax revenue. The two major sources of K-12 revenue are property taxes, and state revenue are separately included in the current expenditure regression model to see whether their inclusion causes any changes to pollution coefficients. When property tax revenue per pupil is controlled for, the coefficients for pollution become much smaller (Table 8). Marginal effects at different percentiles also become smaller and/or statistically insignificant (Table 9). On the other hand, when state revenue per pupil is included in the model, the pollution coefficients remain almost unchanged (Table 10). These results suggest that the effect of pollution on current expenditure is primarily channeled through property tax revenue.

5.2 Property Tax Revenue per Pupil

Results for property tax revenue per pupil are similar to current expenditure per pupil analysis. The control variables, capital outlay expenditure, total debt outstanding, other local revenue share, annual housing price index, and property tax index show desired effects for almost every pollutant (Table 12). A 10 log point decrease in pollution increases property tax revenue per pupil by 102, 208, and 293 dollars at

10^{th}, 50^{th}, and 90^{th} percentiles of ozone pollution respectively. For NO_2, marginal effect at 10^{th} percentile is 66 dollars, and 228 and 416 dollars respectively at 50^{th} and 90^{th} percentiles. Marginal effects for PM_{10} are 102 and 38 dollars respectively at 10^{th} and 50^{th} percentiles, and not statistically significant beyond 50^{th} percentile. For SO_2, marginal effects are quite small, and statistically significant up to 40^{th} percentiles. A 10 log point decrease in SO_2 level increases property tax revenue per pupil by 40 dollars at 10^{th} percentile of SO_2 pollution (Table 13).

6 Robustness Checks

6.1 State-Year Fixed Effect and State Specific Time Trend

To check the validity of baseline results, a number robustness checks are conducted. I begin robustness check by including state-year fixed effects instead of state level controls in the property tax revenue model. The pollution coefficients with state-year fixed effect remain quite similar (Table 14). Marginal effects for ozone become larger at all percentile levels. Marginal effects for NO_2 and SO_2 remain almost similar (Table 15). Marginal effects for PM_{10}, however, become smaller and statistically insignificant after 20^{th} percentile. I then introduce state specific linear time trends instead of year fixed effects in the model. The coefficient estimates become smaller for ozone, and PM_{10}, remain similar for NO_2, and become slightly larger for SO_2 (Table 16). Marginal effects are also similar but become slightly smaller for ozone, NO_2, and SO_2. These results suggest that baseline results are mostly robust to state-year fixed effect and state specific linear time trend.

6.2 Lagged Dependent Variable

Next I substitute **Local** variables, i.e. school quality and capital outlay expenditure with four year lagged property tax revenue per pupil. This essentially introduces some sort of dynamic panel structure in analysis. Apart from being a substitute for school quality, lagged property tax revenue per pupil, to some extent, also accounts for district level unobserved characteristics, which could affect housing values. I also control for state-year fixed effects for this specification. With lagged property tax revenue in the model, pollution coefficients are quite similar to baseline model for ozone, NO_2, and SO_2. Pollution coefficients become much smaller for PM_{10} (Table 18). Marginal effects for PM_{10} become positive from 30^{th} percentile, and for the other pollutants remain similar to baseline analysis (Table 19).

6.3 Weighted Regression

School districts are different in size. Average number of pupil varies from 724 at 1^{st} percentile to 64627 at 99^{th} percentile[21]. Most school districts (about 40% of the sample) have student counts between 2,000 to 4,999. The second largest group, which is 21% of the sample, has average pupil count between 5,000 to 9,999, followed by 19% having pupil count from 1,000 to 1,999. Less than 2% of school districts has pupil count of 50,000 and more, and 4% of the school districts has pupil count of less than 1,000. My next robustness check involves school district size, and I perform weighted panel regressions, where weight is the average number of pupil in the school district. The pollution coefficients remain similar in weighted regressions (Table 20). Coefficient estimates for ozone, and NO_2 become smaller in magnitude, while coef-

[21]The largest school district in the sample in terms of student population is City of Chicago School District 299 in Illinois with average pupil count of 423,115. The smallest school district in the sample with average pupil count of 229 is Brooklyn Community Unit School District School 188, which is also in Illinois.

ficients for PM_{10} become larger. Coefficients for SO_2, however, become statistically insignificant. Marginal effects are similar as well, but lower in magnitude (Table 21). Despite differences in magnitude, the general findings of baseline regressions remain unchanged when weights are introduced.

School districts also differ in terms of share of property tax as revenue source. Median property tax share is 48% in my sample. Property tax share ranges from as low as 11% at 1^{st} percentile to as high as 85% at 99^{th} percentile[22]. The effect of pollution is likely to be more pronounced in school districts that have higher share of property tax revenue. For this reason, a weighted panel regression with weights being average property tax revenue share is performed. Pollution coefficients become slightly larger as expected (Table 22), and marginal effects remain similar to baseline analysis at different percentiles of pollution (Table 23).

6.4 Excluded Sample

Next, I investigate how change in pollution affects property tax revenue in school districts that are excluded because of assessment limit condition and K-12 financing policy shift. I expect very small or no effect of pollution in these school districts. I get much smaller coefficient estimates for this alternative sample (Table 24). Moreover, I get opposite signs of β_1 and β_2 for ozone, NO_2, and SO_2 compared to the baseline regression. Marginal effects turn out to be small, mostly positive, and statistically insignificant (Table 25). Hence, the public finance channel story doesn't fit for these excluded school districts as expected, and thereby provides support for validity of the baseline results.

[22] Camden City School District in New Jersey has the lowest share of property tax revenue of 3.1%, while Jericho Union Free School District in New York has the highest share of 86%.

6.5 Spurious Relationship

From Figure 5, we see that pollution measures show a declining trend during the analysis period. On the other hand, property tax revenue shows an increasing trend during the same period of time (Figure 4). A concern of spurious relationship between these variables is not unlikely. Since there are only 5 periods in data, cointegration tests for panel data are not feasible. Under the circumstances, I check whether pollution can explain state revenue per pupil, which also demonstrates an increasing trend like property tax revenue. According to the framework presented in this paper, pollution affects school resources through property tax revenue, and pollution doesn't affect state revenue. If statistically significant coefficients for pollution are obtained from the state revenue - pollution regression, then one can argue that pollution - property tax revenue relationship could be spurious. On the contrary, if coefficients are not statistically different from zero, then it can be argued that pollution and property tax revenue per pupil are not spuriously correlated. In this regression I control for state year fixed effect, and pollution coefficients for all pollutants are quite small and statistically insignificant (Table 26). This suggests that spurious relationship between pollution and property tax revenue is less likely.

6.6 Multiple Pollutants

I then check the impact of a pollutant on property tax revenue after controlling for other pollutants. Coefficient estimates for ozone is no longer statistically significant, when NO_2, or SO_2 only is controlled for. However, with PM_{10} only, ozone coefficients are statistically significant. With NO_2, PM_{10}, and SO_2 together, ozone coefficients are not significant again (Table 27). Coefficient estimates for NO_2, on the other hand, are significant with each and all pollutants together (Table 28). PM_{10} coefficients are significant as well for NO_2 only, SO_2 only, and for all pollutants together. PM_{10} coefficients, however, are not significant when only ozone is controlled for. (Table 29). And finally SO_2 coefficients are statistically significant for each and all pollutant controls (Table 30). These results suggest that except for ozone, baseline results are robust to different pollutant combinations for NO_2, PM_{10}, and SO_2. The statistical insignificance of ozone coefficients may be attributable to the fact that ground level ozone is a secondary pollutant, which created from chemical reactions of primary pollutants in presence of sunlight. Hence, when NO_2 and SO_2 are controlled for, which may contribute in ozone formation, the effect of ozone becomes smaller.

Next, I run a regression with all four pollutants in linear form. The coefficients of pollution in this regression provides an overall idea of how a certain pollutant affects property tax revenue on average, while other pollutants are controlled for. Pollution coefficients for all four pollutants are negative and statistically significant (Table 31). Ozone has the highest impact on property tax revenue per pupil, followed by NO_2, PM_{10}, and SO_2. 10 log point decrease in ozone increases property tax revenue per pupil by 277 dollars on average holding other pollutants constant. The increases are 63, 52, and 37 dollars respectively for NO_2, PM_{10}, and SO_2.

6.7 Sensitivity to Monitor Location Distance

I then check sensitivity in terms of monitor distance. My baseline analysis sample constitutes school districts that have at least one pollution monitor within 12 mile radius. Here I perform the baseline analysis for different samples with school districts that have at least one pollution monitor within 9 miles, 15 miles, and 20 miles radius respectively. Pollution coefficients become larger for 9 miles sample, and relatively smaller for 15 miles and 20 miles sample. However, overall direction and magnitude of results don't change a lot (Table 32, Table 33, Table 34, and Table 35). Marginal effects are also higher for 9 miles sample, and lower for 15 miles and 20 miles samples (Table 36, Table 37, Table 38, and Table 39).

6.8 Sensitivity to Sample Time Period and Lag Length

Next, I do sensitivity analysis for different time period in the sample. In baseline analysis I have 3-year intervals between observations. Here I check sensitivity for 4-year, 5-year, 6-year, and 12-year intervals[23]. For 4-year interval, time dimension is $T = 4$, for 5-year and 6-year it is $T = 3$, and for 12-year it is $T = 2$. To eliminate any sudden fluctuations in dependent variable, I take 3-year average of property tax revenue[24] for this specification. Pollution coefficients for all pollutants remain similar to baseline analysis with magnitudes being increased for larger time intervals (Table 40, 41, 42, and 43).

I assume $k = 4$ and use 4-year lagged pollution measure in baseline analysis. I now check sensitivity with 5-year lag, 6-year lag, and 7-year lag pollution variables. For this sensitivity analysis, I have to restrict sample from academic year 1999 to 2008 since corresponding 5-year lag pollution data is not available for academic year 1996. I get similar pollution coefficients like baseline model for ozone and NO_2 (Table 44, 45). Pollution coefficients for PM_{10} become statistically insignificant for different lag periods when the sample is restricted from 1999 to 2008 academic year (Table 46). Results for SO_2 are similar to baseline for 5-year lag, and become statistically

[23]For 4-year interval sample, academic years are 1996, 2000, 2004, and 2008. For 5-year interval, academic years in sample are 1997, 2002, and 2007. For 6-year interval, academic years are 1996, 2002, and 2008. Finally for 12-year interval, academic years in sample are 1996 and 2008.

[24]Property tax revenue per pupil in 1996 is average of property tax revenue per pupil in 1995, 1996, and 1997.

insignificant for 6-year and 7-year lag period (Table 47). These results suggest that baseline results for most of the pollutants (3 out of 4) are not sensitive to sample time period or different lag periods.

In the baseline analysis, I use a balanced sample. Now I check the sensitivity of baseline results by analyzing an unbalanced sample with at least 2 periods. I get coefficient estimates similar to baseline line results, except pollution coefficients for PM_{10} become statistically insignificant (Table 48). Other than PM_{10}, baseline results for other pollutants are pretty robust to unbalanced sample, which further validates the general findings of this paper.

6.9 Relative Pollution Measure

I then check robustness of baseline results with a different measure for pollution. I calculate pollution measures of the school district as percentage of median pollution level of the Core-Based Statistical Area (CBSA), and named it relative pollution. For this purpose, I only include CBSAs with at least 5 school districts in the sample, and control for CBSA-year fixed effects in regression. Unlike baseline analysis there is no quadratic term of pollution in this specification since pollution levels are already expressed as share of median pollution level. I find that 1 percentage point decrease in relative pollution increase property tax revenue per pupil by 13, 12, 3 dollars respectively for ozone, NO_2, and SO_2. These results reinforced the findings of baseline analysis. Coefficient for relative pollution is, however, not statistically different from 0 for PM_{10} (Table 49).

6.10 Geographic Cost Difference

The next robustness check involves the issue of geographic cost differentials, for which current expenditure may vary across school districts. To tackle this issue I substitute current expenditure per pupil with adjusted current expenditure by using comparable wage index (CWI). CWI takes into account a regional variation of salaries of college graduates who are not educators, and is used to adjust for geographic cost differences (Taylor & Glander, 2006). CWI data is obtained from NECS and Bush School of Government and Public Service website. Regressions results presented in Table 50, are similar to previous results. Marginal effects are not much different for ozone and SO_2. Marginal effects are, however, smaller for NO_2 and larger for PM_{10}. To further confirm this finding I consider log of pupil-teacher ratio as a measure of school resources. This is a non-monetary measure, and marginal effects from Table 53 suggests that pupil-teacher ratio decreases as pollution decreases. In particular 1 log point decrease in pollution decreases pupil teacher ratio by around 2.8 log points at median level of pollution for all pollutants. All these robustness check results supports the claim in this paper that pollution does have an impact on school resources.

7 Conclusion

The primary goal of this paper is to establish the school finance channel of ambient air pollution, which is generally not emphasized in literature. I argue that school resources have effects on student achievements, and allocation of school resources in a jurisdiction strongly depends on its property tax revenue. Property values in the jurisdiction affects property tax revenue collection, and pollution level affects property values. Hence, school resources are affected by pollution. The overall effect is, however, not one-to-one mechanical effect since it involves policy offsetting components like change in tax rate. Panel estimation results suggest that per pupil property tax revenue is affected by air pollution level, and thereby confirms existence of a school finance channel. However the effects are different for different pollutants, and different at different levels of pollution. A decrease in pollution level in relatively less polluted area is more effective in terms of increasing property tax revenue per pupil for PM_{10} and SO_2. In contrast, decrease in pollution shows a larger effect in more polluted areas for ground level ozone and NO_2.

This paper is the first in literature to show a link between air pollution and school resources. Such association could have critical policy implications. The results suggest that the effect of pollution on education outcome is not uni-dimensional. Children from poor households located in polluted areas are more exposed to air pollution, which directly affects their academic achievements. Moreover, schools in polluted areas have less resources, which affects education from another angle. The total effect of pollution on education is, therefore, higher than what we are commonly perceived of. Studies that treat pollution education nexus from a uni-dimensional perspective would recommend enhancing efforts to reduce pollution as standard policy. However, the way pollution affects education outcome is more complex and requires more than one policy actions.

To ensure environmental justice, and equity in school expenditure, a relevant policy action could be compensating the affected school districts. The analysis provided in this paper are partial equilibrium analysis, which are not sufficient to suggest appropriate policy recommendations. A general equilibrium analysis is required in this regard, which is one of my future research agendas. In this exercise, I focus on how change in pollution partially affects school district revenue and expenditure. In a general equilibrium framework it will be quite interesting to incorporate costs of pollution abatement, and to relate the costs with benefits from increase in school district revenue. On the other hand, more revenue from property taxes means less expenditure for other private goods, which could have interesting welfare dynamics. This paper brings all these issues to the table, which are future research questions to be addressed.

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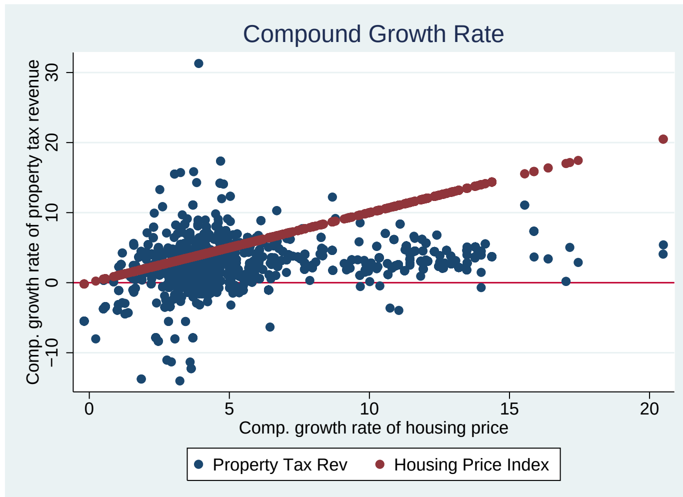
Figures and Tables

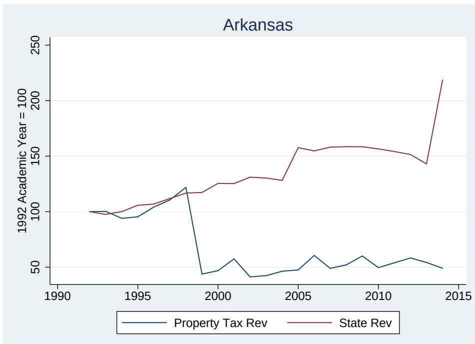
Figure 1: Policy Offsetting Effect



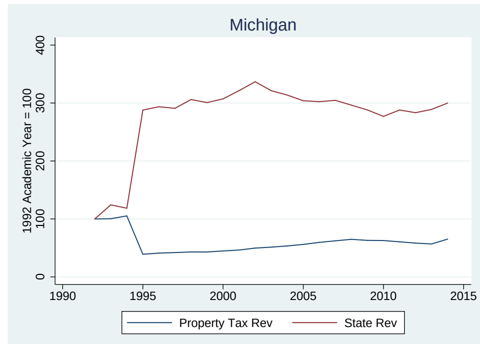
Note: To examine the policy offset effect, I compare compound growth rate of 3-digit ZIP code level Housing Price Index with compound growth rate of average property tax revenue per pupil at 3-digit ZIP code level, for academic years 2002, 2005, and 2008. Since I do not have school district level housing price data, 3-digit ZIP code level HPI is the closest approximate. If policy offset is 0, then compound growth rate of property tax revenue per pupil would coincide with red dots, where compound growth rate of property tax revenue per pupil equals compound growth rate of HPI. If policy offset is 1, i.e. full policy offset, then growth rates are 0 and will be on the horizontal red line. Growth rates in between the red dots and horizontal red line indicates partial policy offset.

Figure 2: Shift in State K-12 Financing Policy

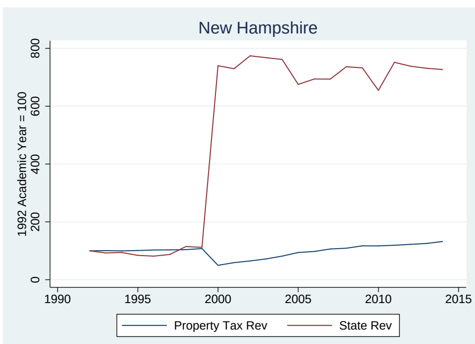
(a) Arkansas



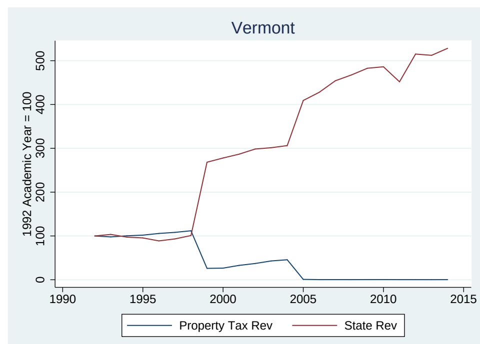
(b) Michigan



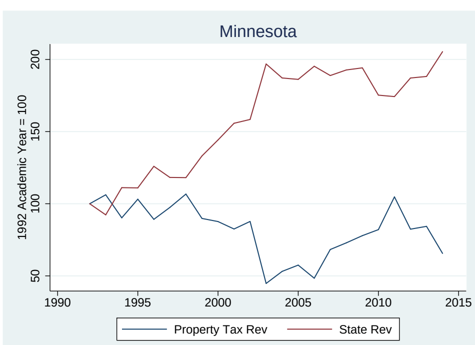
(c) New Hampshire



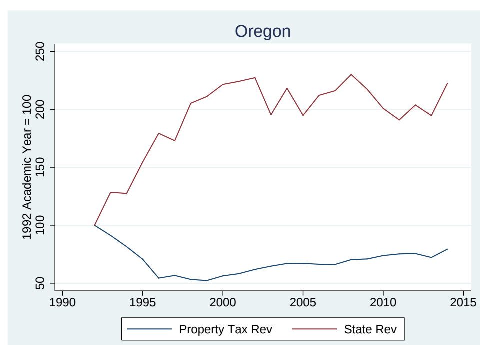
(d) Vermont



(e) Minnesota



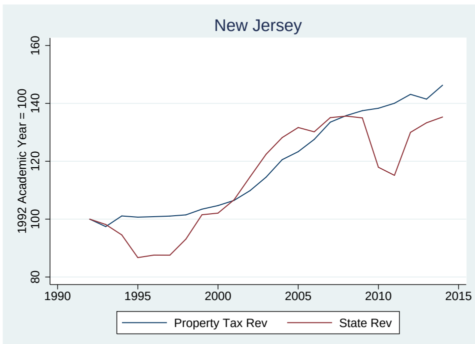
(f) Oregon



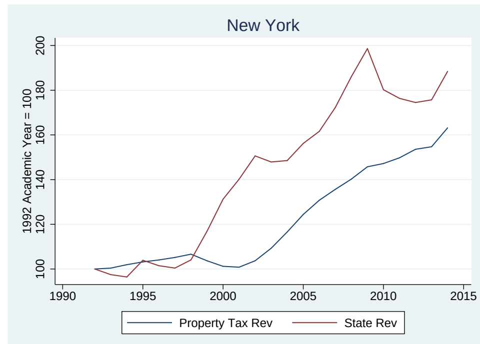
Note: Property tax revenue per pupil and state revenue per pupil are expressed as percentage of respective values in academic year 1992. Shift in state K-12 financing policy refers to the event, where trends in two variables deviate in opposite directions at some point of time, creating a large gap between them.

Figure 3: No Shift in State K-12 Financing Policy

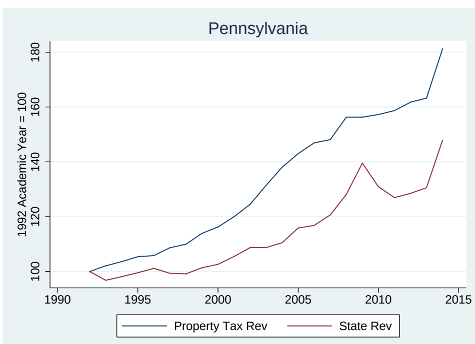
(a) New Jersey



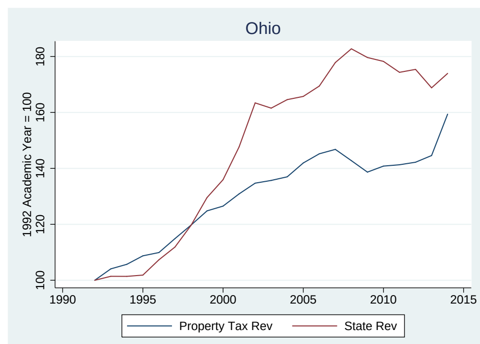
(b) New York



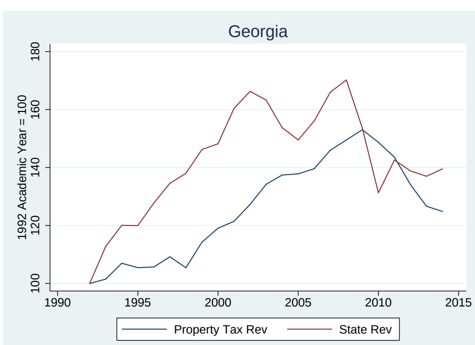
(c) Pennsylvania



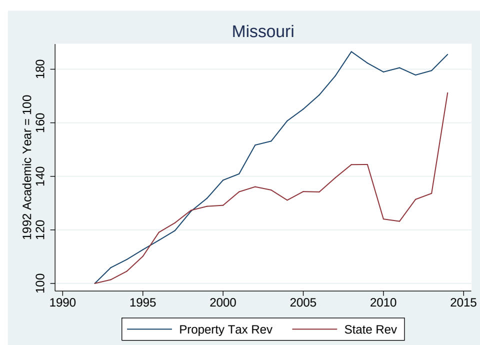
(d) Ohio



(e) Georgia



(f) Missouri



Note: There are no shifts in state K-12 financing policy if trends in two variables do not deviate significantly in opposite directions at some point of time.

Figure 4: Trend in Average School District Revenue per Pupil

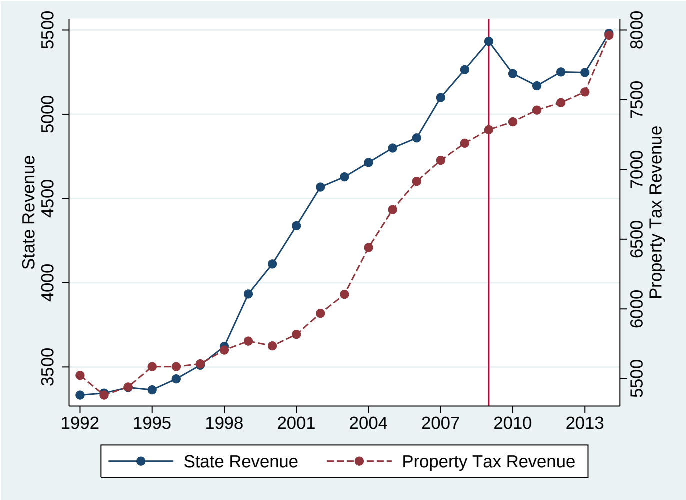
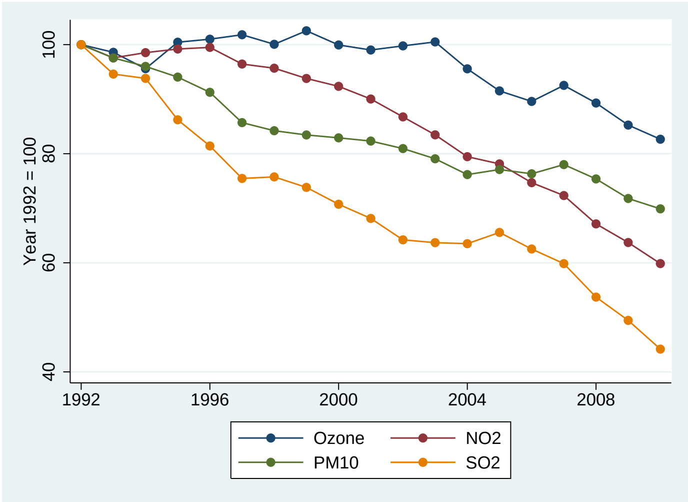


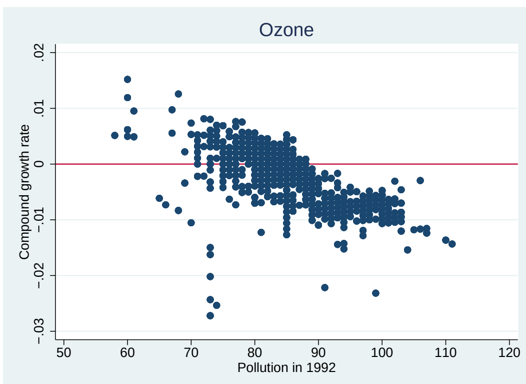
Figure 5: Trend in Average Pollution Level



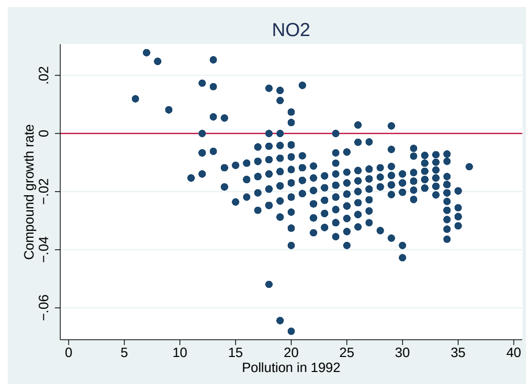
Note: Pollution levels are expressed as percentage of 1992 level of pollution.

Figure 6: Compound Growth Rate of Pollution - 1992 to 2004 and Initial Pollution Level

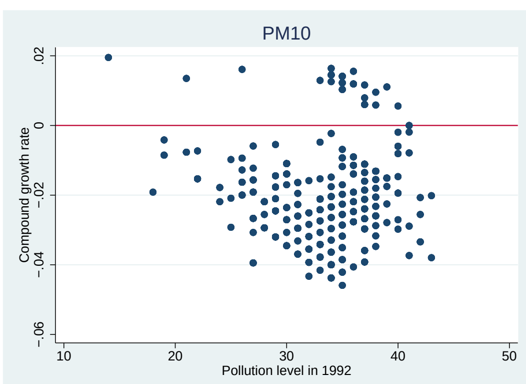
(a) Ozone



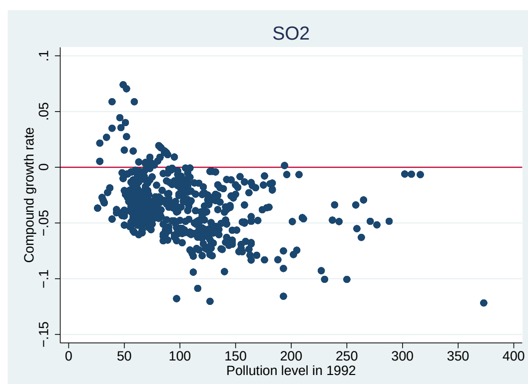
(b) NO_2



(c) PM_{10}



(d) SO_2



Note: Compound growth rates for the period 1992 to 2004 for each pollutant are plotted against pollution level at 1992.

Table 1: Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
Current Expenditure per Pupil	5030	10728.61	3769.63	4238.75	37030.79
Property Tax revenue per Pupil	5030	6390.01	4091.44	333.59	26446.41
School Quality Measure	5030	105.94	18.98	54.67	262.60
Cap-out Expenditure per Pupil	5030	1016.30	1496.23	0	38541.27
Other Local Revenue Share	5030	10.47	7.36	0	80.32
Total Debt per Pupil	5030	6195.28	5889.14	0	41126.63
Housing Price Index	5030	126.56	33.03	76.71	223.74
Avg. State Revenue Share	5030	44.36	7.71	27.99	70.15
Avg. Current Expenditure Index	5030	0.58	0.28	0	1
Avg. Property Tax Revenue Index	5030	0.57	0.23	0	1
Ozone Pollution	4700	85.51	7.68	44	111
NO_2 Pollution	2740	22.04	5.72	6	37
PM_{10} Pollution	2425	28.85	5.91	14	45
SO_2 Pollution	3685	72.57	40.19	16	373

Table 2: Current Expenditure per Pupil -Linear Model

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	-2,129***	18.37	-974.9***	-60.20
	(342.8)	(296.2)	(215.4)	(95.04)
State Share (%)	12.77*	36.57***	13.89	22.91***
	(7.638)	(10.42)	(9.663)	(8.773)
Expenditure Index	11,081***	12,714***	9,039***	11,494***
	(521.3)	(808.2)	(559.8)	(620.8)
Constant	11,932***	344.4	6,874***	1,924***
	(1,547)	(1,260)	(798.7)	(639.1)
Observations	4,700	2,740	2,425	3,685
R-squared	0.726	0.742	0.735	0.736
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Property Tax Revenue per Pupil - Linear Model

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	-1,583***	-1,339***	-344.8	-78.16
	(334.0)	(297.5)	(216.0)	(98.27)
School Quality	3.067	8.033**	2.473	6.798**
	(3.481)	(3.964)	(3.317)	(3.403)
Cap-out Expenditure	0.0494**	0.0529***	0.0782**	0.0634**
	(0.0228)	(0.0139)	(0.0347)	(0.0266)
Total debt	0.0456***	0.0557***	0.0474***	0.0427***
	(0.00512)	(0.00692)	(0.00689)	(0.00660)
Other Local Revenue Share (%)	-28.82***	-18.17***	-23.68***	-23.09***
	(5.894)	(5.530)	(5.610)	(4.512)
Housing Price Index	18.78***	19.32***	17.97***	17.28***
	(1.333)	(1.765)	(1.972)	(1.496)
State Share (%)	-0.493	35.40**	13.11	-6.851
	(8.202)	(14.77)	(9.753)	(10.76)
Property Tax Index	5,783***	8,447***	4,974***	5,656***
	(572.3)	(972.7)	(692.5)	(703.8)
Constant	7,628***	1,346	1,060	1,008
	(1,691)	(1,708)	(940.9)	(984.5)
Observations	4,700	2,740	2,425	3,685
R-squared	0.547	0.575	0.532	0.536
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Current Expenditure per Pupil Specification - Wald F-statistic

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Linear Model				
$\gamma_1 = 0$	38.57***	0.00	20.48***	0.40
	(0.000)	(0.951)	(0.000)	(0.527)
Quadratic Model				
$\gamma_1 = \gamma_2 = 0$	22.01***	12.44***	12.03***	6.70***
	(0.000)	(0.000)	(0.000)	(0.001)
γ_2=0	20.89***	23.98***	7.28***	13.38***
	(0.000)	(0.000)	(0.007)	(0.000)

Note: Null hypothesis are stated in the first column.
Prob > F in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Property Tax Revenue per Pupil Specification - Wald F-statistic

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Linear Model				
$\beta_1 = 0$	22.48***	20.28***	2.55	0.63
	(0.000)	(0.000)	(0.111)	(0.427)
Quadratic Model				
$\beta_1 = \beta_2 = 0$	19.1***	28.85***	2.33*	4.07**
	(0.000)	(0.000)	(0.099)	(0.018)
β_2=0	27.37***	38.57***	3.02*	7.08***
	(0.000)	(0.000)	(0.083)	(0.008)

Note: Null hypothesis are stated in the first column.
Prob > F in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Current Expenditure per Pupil Regression Results

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	49,030***	12,541***	-12,078***	-4,446***
	(11,070)	(2,521)	(4,166)	(1,215)
Log Pollution Squared	-5,810***	-2,207***	1,659***	515.2***
	(1,271)	(450.6)	(614.9)	(140.9)
State Share (%)	9.748	28.11***	14.27	16.47*
	(7.463)	(10.50)	(9.605)	(8.592)
Expenditure Index	10,898***	12,024***	9,094***	11,310***
	(520.2)	(783.3)	(557.2)	(626.9)
Constant	-100,376***	-16,272***	25,343***	11,537***
	(24,096)	(3,462)	(7,106)	(2,692)
Observations	4,700	2,740	2,425	3,685
R-squared	0.727	0.748	0.737	0.739
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Marginal Effects for Current Expenditure per Pupil

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-1,446***	588.6*	-1,976***	-697.8***
	(320.9)	(306.3)	(466.0)	(212.3)
20	-1,890***	36.14	-1,675***	-570.4***
	(329.3)	(304.2)	(369.3)	(182.5)
30	-2,318***	-454.8	-1,398***	-435.8***
	(362.6)	(335.8)	(290.3)	(153.5)
40	-2,457***	-681.2*	-1,143***	-316.8**
	(377.9)	(359.0)	(234.2)	(131.1)
50	-2,730***	-896.5**	-1,022***	-193.4*
	(412.8)	(384.9)	(217.2)	(113.1)
60	-2,865***	-1,298***	-793.0***	-68.32
	(431.9)	(440.9)	(208.9)	(103.4)
70	-3,129***	-1,666***	-578.8**	69.26
	(472.6)	(498.6)	(230.9)	(105.2)
80	-3,387***	-2,006***	-377.7	224.4*
	(515.6)	(555.6)	(271.9)	(122.0)
90	-3,764***	-2,616***	-97.11	487.0***
	(582.5)	(663.8)	(348.1)	(171.9)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Current Expenditure per Pupil With Control for Property Tax Revenue

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	27,139***	4,968**	-7,523**	-2,884**
	(10,095)	(2,299)	(3,477)	(1,138)
Log Pollution Squared	-3,239***	-785.3*	1,029**	334.3**
	(1,163)	(412.4)	(513.0)	(132.1)
Property tax revenue per pupil	0.424***	0.461***	0.365***	0.432***
	(0.0313)	(0.0343)	(0.0403)	(0.0338)
State Share (%)	40.64***	62.27***	29.63***	51.07***
	(6.882)	(9.546)	(8.943)	(7.786)
Expenditure Index	9,264***	9,985***	7,385***	9,771***
	(410.0)	(617.6)	(481.6)	(499.1)
Constant	-56,737***	-9,744***	15,477***	5,097**
	(21,855)	(3,042)	(5,952)	(2,580)
Observations	4,700	2,740	2,425	3,685
R-squared	0.769	0.799	0.774	0.783
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Marginal Effects for Current Expenditure per Pupil
After Controlling for Property Tax Revenue

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-996.1***	715.1***	-1,257***	-452.1**
	(269.9)	(272.7)	(396.3)	(195.6)
20	-1,244***	518.5*	-1,069***	-369.4**
	(288.1)	(273.4)	(317.4)	(167.4)
30	-1,482***	343.8	-897.8***	-282.1**
	(328.1)	(304.9)	(253.9)	(139.7)
40	-1,560***	263.2	-739.4***	-204.9*
	(344.7)	(327.2)	(209.7)	(118.2)
50	-1,712***	186.6	-664.6***	-124.8
	(381.3)	(351.8)	(196.5)	(101.0)
60	-1,787***	43.73	-522.6***	-43.62
	(400.7)	(404.4)	(190.1)	(91.70)
70	-1,934***	-87.23	-389.7*	45.66
	(441.3)	(458.2)	(207.0)	(93.95)
80	-2,078***	-208.1	-265.0	146.3
	(483.2)	(511.0)	(239.1)	(110.8)
90	-2,288***	-425.1	-90.95	316.8**
	(547.4)	(610.9)	(300.1)	(159.2)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Current Expenditure per Pupil With Control for State Revenue

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	43,457***	12,387***	-11,589***	-4,411***
	(9,456)	(2,454)	(3,902)	(992.5)
Log Pollution Squared	-5,177***	-2,192***	1,615***	519.7***
	(1,086)	(435.7)	(578.0)	(114.9)
State revenue per pupil	0.365***	0.364***	0.246***	0.349***
	(0.0582)	(0.0436)	(0.0396)	(0.0424)
State Share (%)	-29.20***	-16.55	-8.953	-21.89***
	(7.733)	(10.39)	(9.072)	(8.259)
Expenditure Index	8,915***	10,166***	8,030***	9,213***
	(601.7)	(739.8)	(550.0)	(638.0)
Constant	-86,544***	-14,071***	24,904***	12,995***
	(20,531)	(3,359)	(6,641)	(2,266)
Observations	4,700	2,740	2,425	3,685
R-squared	0.778	0.790	0.769	0.783
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: Marginal Effects for Current Expenditure per Pupil After Controlling for State Revenue

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-1,523***	516.3*	-1,755***	-630.6***
	(297.8)	(280.1)	(428.2)	(178.1)
20	-1,919***	-32.37	-1,461***	-502.1***
	(305.0)	(270.2)	(339.2)	(154.6)
30	-2,300***	-519.9*	-1,192***	-366.3***
	(332.0)	(296.9)	(268.0)	(131.9)
40	-2,424***	-744.7**	-943.0***	-246.3**
	(344.4)	(318.5)	(220.2)	(114.6)
50	-2,667***	-958.6***	-825.5***	-121.8
	(372.8)	(343.3)	(207.2)	(101.0)
60	-2,787***	-1,357***	-602.7***	4.377
	(388.4)	(397.5)	(205.3)	(93.77)
70	-3,023***	-1,723***	-394.2*	143.2
	(421.9)	(453.8)	(230.0)	(95.03)
80	-3,253***	-2,060***	-198.4	299.7***
	(457.4)	(509.4)	(270.5)	(107.5)
90	-3,589***	-2,666***	74.72	564.6***
	(513.0)	(615.0)	(343.3)	(146.0)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Property Tax Revenue per Pupil Regression Results

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	40,600***	12,401***	-7,870*	-2,301***
	(7,937)	(2,190)	(4,381)	(832.5)
Log Pollution Squared	-4,791***	-2,411***	1,125*	260.9***
	(915.8)	(388.2)	(647.6)	(98.06)
School Quality	3.173	8.993**	1.744	6.334*
	(3.462)	(3.995)	(3.305)	(3.363)
Cap-out Expenditure	0.0486**	0.0511***	0.0791**	0.0625**
	(0.0227)	(0.0141)	(0.0348)	(0.0265)
Total debt	0.0453***	0.0531***	0.0467***	0.0423***
	(0.00508)	(0.00687)	(0.00677)	(0.00656)
Other Local Revenue Share (%)	-28.49***	-16.02***	-24.10***	-23.49***
	(5.829)	(5.636)	(5.627)	(4.499)
Housing Price Index	18.41***	15.38***	17.94***	16.56***
	(1.323)	(1.869)	(1.969)	(1.497)
State Share (%)	-3.757	32.22**	12.09	-8.079
	(8.084)	(14.14)	(9.875)	(10.84)
Property Tax Index	5,761***	8,887***	4,832***	5,832***
	(574.1)	(948.7)	(689.9)	(699.1)
Constant	-84,985***	-17,710***	13,812*	5,772***
	(17,178)	(3,439)	(7,488)	(2,045)
Observations	4,700	2,740	2,425	3,685
R-squared	0.550	0.588	0.534	0.538
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Marginal Effects for Property Tax Revenue per Pupil

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-1,023***	-655.7**	-1,023**	-403.1***
	(275.8)	(263.8)	(481.7)	(150.4)
20	-1,390***	-1,259***	-818.0**	-338.6**
	(290.4)	(254.6)	(379.4)	(133.2)
30	-1,742***	-1,795***	-630.4**	-270.4**
	(318.7)	(276.5)	(296.0)	(117.6)
40	-1,857***	-2,043***	-457.3*	-210.2**
	(330.4)	(294.7)	(237.4)	(107.1)
50	-2,083***	-2,278***	-375.6*	-147.6
	(356.1)	(315.7)	(220.2)	(100.6)
60	-2,193***	-2,717***	-220.4	-84.33
	(370.0)	(362.3)	(213.9)	(99.36)
70	-2,411***	-3,119***	-75.23	-14.66
	(399.1)	(411.1)	(240.1)	(104.4)
80	-2,624***	-3,490***	61.11	63.91
	(429.5)	(459.6)	(285.6)	(117.1)
90	-2,935***	-4,156***	251.3	196.9
	(476.7)	(552.2)	(368.1)	(149.9)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Property Tax Revenue per Pupil Regression With State-Year Fixed Effect

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	33,158***	14,355***	-9,788**	-3,265***
	(10,332)	(2,547)	(4,292)	(928.5)
Log Pollution Squared	-4,115***	-2,738***	1,461**	375.8***
	(1,189)	(453.3)	(638.0)	(108.0)
School Quality	3.869	9.198**	2.343	6.520*
	(3.584)	(4.063)	(3.494)	(3.480)
Cap-out Expenditure	0.0437*	0.0447***	0.0690*	0.0576**
	(0.0242)	(0.0139)	(0.0385)	(0.0278)
Total debt	0.0462***	0.0537***	0.0514***	0.0437***
	(0.00524)	(0.00691)	(0.00667)	(0.00685)
Other Local Revenue Share (%)	-29.70***	-15.78***	-25.14***	-23.09***
	(6.177)	(6.058)	(5.849)	(4.599)
Housing Price Index	5.907**	-4.068**	5.954***	14.98***
	(2.366)	(1.942)	(1.669)	(1.235)
Constant	-60,635***	-11,734***	20,664***	10,962***
	(22,444)	(3,619)	(7,180)	(2,044)
Observations	4,700	2,740	2,425	3,685
R-squared	0.589	0.618	0.595	0.564
Number of District	940	548	485	737
State-Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Marginal Effects for Property Tax Revenue per Pupil - State Year Fixed Effect

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-2590.465***	-473.063	-890.708*	-530.253***
	(353.613)	(307.234)	(462.025)	(178.075)
20	-2905.020***	-1158.413***	-624.863*	-437.332***
	(365.214)	(300.643)	(366.016)	(158.696)
30	-3207.990***	-1767.446***	-381.198	-339.145**
	(396.263)	(329.294)	(291.160)	(140.847)
40	-3306.552***	-2048.311***	-156.296	-252.314**
	(409.900)	(351.580)	(243.853)	(128.203)
50	-3500.204***	-2315.469***	-50.020	-162.260
	(440.840)	(376.903)	(232.843)	(119.262)
60	-3595.348***	-2813.599***	151.597	-71.033
	(457.782)	(432.320)	(236.846)	(115.532)
70	-3782.399***	-3270.168***	340.197	29.342
	(493.864)	(489.849)	(268.121)	(118.204)
80	-3965.290***	-3691.580***	517.359	142.528
	(532.090)	(546.864)	(314.770)	(129.121)
90	-4232.228***	-4448.042***	764.460*	334.130**
	(591.929)	(655.428)	(396.228)	(161.448)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 16: Property Tax Revenue per Pupil - State Specific Time Trend

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	20,740***	12,243***	-6,335*	-3,003***
	(7,786)	(2,305)	(3,706)	(855.7)
Log Pollution	-2,516***	-2,293***	892.0	349.4***
	(897.9)	(411.6)	(546.5)	(100.6)
School Quality	4.902	9.826**	3.690	7.034**
	(3.594)	(3.966)	(3.422)	(3.420)
Cap-out Expenditure	0.0480**	0.0498***	0.0713*	0.0612**
	(0.0230)	(0.0135)	(0.0365)	(0.0267)
Total debt	0.0462***	0.0540***	0.0465***	0.0425***
	(0.00507)	(0.00680)	(0.00643)	(0.00661)
Other Local Revenue Share (%)	-29.47***	-16.98***	-24.49***	-23.30***
	(6.129)	(5.858)	(5.660)	(4.520)
Housing Price Index	12.66***	10.05***	11.04***	13.07***
	(0.781)	(1.079)	(1.206)	(0.795)
State Share (%)	-43.15***	-19.12	-25.03***	-32.41***
	(6.799)	(12.33)	(9.526)	(7.926)
Property Tax Index	5,673***	6,820***	5,314***	5,583***
	(435.4)	(714.0)	(558.7)	(485.1)
Constant	-39,534**	-14,561***	13,174**	8,552***
	(16,864)	(3,480)	(6,322)	(1,910)
Observations	4,700	2,740	2,425	3,685
R-squared	0.570	0.602	0.575	0.554
Number of District	940	548	485	737
Year Fixed Effect	No	No	No	No

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Marginal Effects for Property Tax Revenue per Pupil - State Specific Time Trend

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-1120.952***	-177.356	-903.682**	-460.912***
	(255.695)	(244.921)	(415.680)	(152.880)
20	-1313.307***	-751.412***	-741.395**	-374.534***
	(269.428)	(240.001)	(329.073)	(134.601)
30	-1498.578***	-1261.544***	-592.648**	-283.260**
	(297.397)	(270.738)	(257.941)	(117.940)
40	-1558.850***	-1496.799***	-455.355**	-202.542*
	(309.009)	(293.578)	(206.719)	(106.492)
50	-1677.271***	-1720.574***	-390.478**	-118.828
	(334.688)	(318.995)	(190.811)	(99.085)
60	-1735.453***	-2137.812***	-267.399	-34.025
	(348.490)	(373.368)	(181.917)	(97.267)
70	-1849.838***	-2520.239***	-152.267	59.284
	(377.487)	(428.674)	(200.715)	(102.210)
80	-1961.678***	-2873.218***	-44.117	164.500
	(407.800)	(482.769)	(236.868)	(115.289)
90	-2124.915***	-3506.839***	106.727	342.612
	(454.710)	(584.561)	(304.688)	(149.309)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Property Tax Revenue per Pupil - Dynamic Panel Specification

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	37,270***	11,027***	-5,619*	-1,744**
	(9,296)	(1,852)	(3,301)	(729.2)
Log Pollution Squared	-4,537***	-2,085***	873.1*	199.7**
	(1,074)	(330.2)	(490.5)	(85.12)
Lagged Property Tax Revenue	0.379***	0.563***	0.510***	0.595***
	(0.123)	(0.0344)	(0.0457)	(0.0323)
Total debt	0.0434***	0.0458***	0.0453***	0.0399***
	(0.00472)	(0.00576)	(0.00574)	(0.00554)
Other Local Revenue Share (%)	-35.80***	-14.39***	-22.95***	-20.61***
	(10.02)	(4.799)	(5.174)	(3.879)
Housing Price Index	3.264*	-4.630***	3.980***	3.995***
	(1.800)	(1.593)	(0.949)	(0.916)
Constant	-72,079***	-10,284***	11,337**	6,148***
	(19,858)	(2,558)	(5,516)	(1,620)
Observations	4,700	2,740	2,425	3,685
R-squared	0.652	0.712	0.686	0.683
Number of District	940	548	485	737
State-Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Marginal Effects for Property Tax Revenue per Pupil - Dynamic Panel

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-2144.73***	-262.83	-302.49	-291.43**
	(326.09)	(254.30)	(359.13)	(138.96)
20	-2491.54***	-784.64***	-143.63	-242.06*
	(346.45)	(252.60)	(285.85)	(123.98)
30	-2825.58***	-1248.34***	1.97	-189.90*
	(382.06)	(272.97)	(228.87)	(110.33)
40	-2934.25***	-1462.18***	136.36	-143.77
	(396.36)	(288.24)	(192.83)	(100.83)
50	-3147.76***	-1665.58***	199.87	-95.93
	(427.60)	(305.56)	(184.30)	(94.37)
60	-3252.66***	-2044.85***	320.35*	-47.46
	(444.25)	(343.63)	(186.70)	(92.06)
70	-3458.89***	-2392.46***	433.05**	5.86
	(479.06)	(383.51)	(209.72)	(94.81)
80	-3660.54***	-2713.32***	538.92**	65.99
	(515.30)	(423.35)	(244.66)	(103.95)
90	-3954.85***	-3289.26***	686.57**	167.78
	(571.24)	(499.89)	(306.28)	(129.92)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 20: Property Tax Revenue per Pupil Regression Results - Weighted by Pupils

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	24,659**	6,283**	-10,788**	-663.0
	(9,975)	(2,774)	(4,409)	(1,040)
Log Pollution Squared	-2,937**	-1,214**	1,587**	60.81
	(1,160)	(548.9)	(647.1)	(122.3)
School Quality	7.323**	10.67**	7.269**	10.74***
	(3.466)	(4.321)	(3.659)	(3.939)
Cap-out Expenditure	0.0281	0.0376	0.0484	0.0388
	(0.0188)	(0.0237)	(0.0322)	(0.0246)
Total debt	0.0288***	0.0206	0.0171	0.0238**
	(0.00825)	(0.0134)	(0.0114)	(0.0101)
Other Local Revenue Share (%)	-19.35***	-8.211	-18.63**	-18.35***
	(6.664)	(9.522)	(8.367)	(6.997)
Housing Price Index	13.70***	10.81***	7.015***	15.24***
	(2.526)	(3.521)	(2.599)	(1.836)
State Share (%)	-12.15	-5.794	-7.513	-19.08
	(14.84)	(19.61)	(16.80)	(16.96)
Property Tax Index	2,971***	3,931**	2,264***	3,917***
	(813.8)	(1,634)	(767.8)	(784.9)
Constant	-50,057**	-6,897*	19,966**	2,806
	(21,337)	(4,100)	(7,901)	(2,504)
Observations	4,700	2,740	2,425	3,685
R-squared	0.519	0.544	0.524	0.533
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Marginal Effects for Property Tax Revenue per Pupil - Weighted by Pupils

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-543.0	-292.1	-975.9**	-223.9
	(352.4)	(493.6)	(479.7)	(199.3)
20	-779.5**	-596.0	-834.8*	-200.1
	(360.8)	(571.6)	(432.8)	(166.9)
30	-1,007***	-734.8	-445.6	-182.5
	(390.4)	(614.2)	(321.8)	(148.4)
40	-1,154***	-990.6	-210.4	-169.2
	(418.8)	(700.7)	(278.2)	(138.8)
50	-1,367***	-1,222	8.644	-155.3
	(469.8)	(785.4)	(263.7)	(133.8)
60	-1,437***	-1,433*	112.7	-146.3
	(488.4)	(866.6)	(267.2)	(133.6)
70	-1,574***	-1,628*	311.2	-131.6
	(527.3)	(943.7)	(291.3)	(138.5)
80	-1,773***	-1,893*	498.0	-114.4
	(588.2)	(1,052)	(331.0)	(151.6)
90	-2,028***	-2,055*	759.0*	-85.95
	(671.7)	(1,119)	(404.3)	(185.7)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22: Property Tax Revenue per Pupil Regression Results - Weighted by Property Tax Share

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	42,409***	12,603***	-12,977**	-2,619**
	(9,924)	(2,723)	(5,459)	(1,015)
Log Pollution Squared	-5,022***	-2,391***	1,876**	294.7**
	(1,137)	(469.2)	(805.8)	(120.3)
School Quality	12.47***	21.36***	7.529*	16.81***
	(4.479)	(4.680)	(4.084)	(4.065)
Cap-out Expenditure	0.0596**	0.0620***	0.0933**	0.0736**
	(0.0262)	(0.0150)	(0.0372)	(0.0303)
Other Local Revenue Share (%)	-33.69***	-19.79***	-25.32***	-27.53***
	(7.645)	(6.160)	(6.445)	(5.219)
Total debt	0.0498***	0.0565***	0.0492***	0.0490***
	(0.00553)	(0.00704)	(0.00724)	(0.00719)
Housing Price Index	18.91***	14.98***	18.48***	17.16***
	(1.471)	(2.169)	(2.181)	(1.650)
State Share (%)	1.989	54.75***	8.834	1.083
	(10.39)	(18.02)	(12.60)	(14.07)
Property Tax Index	7,141***	11,116***	5,827***	7,164***
	(720.0)	(1,179)	(893.4)	(877.1)
Constant	-89,580***	-21,204***	22,242**	5,083**
	(21,648)	(4,463)	(9,384)	(2,545)
Observations	4,700	2,740	2,425	3,685
R-squared	0.609	0.648	0.591	0.602
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 23: Marginal Effects for Property Tax Revenue per Pupil - Weighted by Property Tax Share

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-1,347***	-654.7**	-1,553***	-474.5***
	(337.5)	(320.5)	(599.3)	(173.5)
20	-1,726***	-1,218***	-1,212***	-401.6***
	(346.3)	(302.9)	(469.3)	(151.9)
30	-1,971***	-1,476***	-898.7**	-336.8**
	(362.8)	(308.0)	(361.5)	(135.2)
40	-2,210***	-1,955***	-609.9**	-289.6**
	(386.0)	(338.0)	(283.0)	(125.2)
50	-2,328***	-2,390***	-341.8	-225.2*
	(399.6)	(383.7)	(246.3)	(115.5)
60	-2,559***	-2,789***	-91.52	-149.1
	(429.9)	(436.1)	(257.7)	(111.1)
70	-2,784***	-2,976***	27.61	-81.62
	(463.3)	(463.3)	(278.0)	(114.4)
80	-3,005***	-3,331***	255.1	20.52
	(498.9)	(517.9)	(335.5)	(130.7)
90	-3,327***	-3,969***	572.4	162.7
	(554.9)	(623.9)	(440.1)	(168.7)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: Property Tax Revenue per Pupil Regression - Excluded Sample

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	-9,178***	-5,359***	-4,514***	439.6
	(2,364)	(962.2)	(1,189)	(428.5)
Log Pollution Squared	1,107***	939.1***	659.7***	-88.62
	(263.8)	(160.1)	(174.7)	(58.90)
School Quality	6.878**	6.895	9.687**	13.50***
	(3.190)	(4.380)	(3.741)	(4.124)
Cap-out Expenditure	0.0247**	0.0123	0.0241	-0.0140
	(0.0105)	(0.0147)	(0.0157)	(0.0174)
Total debt	0.0346***	0.0328***	0.0290***	0.0299***
	(0.00457)	(0.00684)	(0.00619)	(0.00676)
Other Local Revenue Share (%)	-24.60***	-24.19***	-20.85***	-23.86**
	(7.497)	(8.890)	(7.437)	(11.78)
Housing Price Index	0.446	1.267*	0.968	-0.300
	(0.645)	(0.757)	(0.752)	(1.101)
State Share (%)	5.153	8.449	7.732	0.967
	(9.470)	(13.51)	(11.05)	(14.19)
Property Tax Index	6,127***	8,482***	8,028***	7,714***
	(956.6)	(1,246)	(1,185)	(1,403)
Constant	18,824***	6,532***	6,607***	-1,123
	(5,056)	(2,036)	(2,115)	(1,334)
Observations	2,445	1,345	1,815	995
R-squared	0.369	0.335	0.294	0.318
Number of District	489	269	363	199
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Marginal Effects for Property Tax Revenue per Pupil - Excluded Sample

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-38.33	-691.7***	-628.7***	-15.00
	(256.5)	(256.7)	(213.2)	(141.2)
20	230.4	-402.2*	-435.3**	-40.36
	(216.6)	(233.0)	(180.7)	(127.2)
30	353.5*	-151.4	-320.4*	-99.99
	(202.5)	(219.4)	(166.0)	(97.92)
40	470.1**	69.85	-214.8	-144.5*
	(192.4)	(214.0)	(156.5)	(81.95)
50	553.6***	267.7	-70.74	-185.4**
	(187.3)	(214.7)	(151.1)	(74.99)
60	607.6***	359.4*	59.15	-227.0***
	(185.1)	(216.8)	(154.4)	(77.63)
70	686.3***	530.2**	214.6	-277.0***
	(183.5)	(223.6)	(167.8)	(92.37)
80	835.6***	965.6***	320.2*	-315.9***
	(185.6)	(255.5)	(181.7)	(109.6)
90	998.0***	1,372***	479.3**	-369.4***
	(195.4)	(299.2)	(208.1)	(137.8)
Observations	2,445	1,345	1,815	995

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 26: Spurious Regression Check - State Revenue

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	2,073	96.01	-598.3	1,410
	(11,196)	(2,850)	(6,345)	(1,060)
Log Pollution Squared	-163.2	0.271	90.03	-181.8
	(1,283)	(519.5)	(936.5)	(120.5)
Constant	-2,046	3,056	4,634	1,738
	(24,435)	(3,933)	(10,745)	(2,325)
Observations	4,700	2,740	2,425	3,685
R-squared	0.414	0.417	0.343	0.424
Number of District	940	548	485	737
State-Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 27: Property Tax Revenue - All Pollutant Regression - Ozone

	(1) NO_2	(2) PM_{10}	(3) SO_2	(4) All
Log Ozone	-8,355	33,758**	30,227	-11,735
	(28,409)	(14,938)	(23,452)	(32,640)
Log Ozone Squared	590.1	-4,049**	-3,683	1,015
	(3,180)	(1,692)	(2,645)	(3,653)
Log NO_2	-1,057***			-486.3
	(305.7)			(368.7)
Log PM_{10}		-268.3		-481.8*
		(218.5)		(273.6)
Log SO_2			-66.77	-367.6**
			(102.9)	(145.9)
Constant	26,889	-68,560**	-60,120	36,277
	(63,133)	(33,017)	(52,119)	(72,352)
Observations	2,625	2,235	3,495	1,405
R-squared	0.588	0.544	0.546	0.575
Number of District	525	447	699	281
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 28: Property Tax Revenue - All Pollutant Regression - NO_2

	(1) Ozone	(2) PM_{10}	(3) SO_2	(4) All
Log NO_2	12,582***	8,364***	14,699***	9,121***
	(2,200)	(2,535)	(2,507)	(2,507)
Log NO_2 Squared	-2,395***	-1,620***	-2,781***	-1,715***
	(385.3)	(442.2)	(440.2)	(442.9)
Log Ozone	-2,946***			-2,619***
	(437.6)			(632.1)
Log PM_{10}		-453.1*		-450.1*
		(274.3)		(270.4)
Log SO_2			-44.34	-315.6**
			(117.9)	(139.0)
Constant	-4,431	-9,471**	-20,840***	2,670
	(3,908)	(3,850)	(4,014)	(5,142)
Observations	2,625	1,545	2,525	1,405
R-squared	0.601	0.570	0.587	0.583
Number of District	525	309	505	281
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 29: Property Tax Revenue - All Pollutant Regression - PM_{10}

	(1) Ozone	(2) NO_2	(3) SO_2	(4) All
Log PM_{10}	-5,896	-22,607***	-13,176**	-17,867***
	(4,636)	(6,330)	(5,169)	(6,477)
Log PM_{10} Squared	838.8	3,280***	1,894**	2,572***
	(684.4)	(926.3)	(759.5)	(945.2)
Log Ozone	-1,939***			-2,315***
	(437.0)			(632.8)
Log NO_2		-653.8**		-427.0
		(319.9)		(352.6)
Log SO_2			-331.8***	-367.9**
			(113.4)	(147.9)
Constant	19,641**	39,955***	24,436***	43,574***
	(8,272)	(10,812)	(8,902)	(11,281)
Observations	2,235	1,545	1,945	1,405
R-squared	0.543	0.574	0.547	0.581
Number of District	447	309	389	281
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 30: Property Tax Revenue - All Pollutant Regression - SO_2

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) All
Log SO_2	-1,583*	-4,584***	-2,936***	-2,849**
	(890.4)	(1,202)	(1,124)	(1,440)
Log SO_2 Squared	176.4*	519.6***	303.9**	287.3*
	(105.3)	(141.7)	(132.5)	(168.0)
Log Ozone	-2,451***			-2,438***
	(409.4)			(635.1)
Log NO_2		-1,392***		-680.2*
		(331.2)		(371.0)
Log PM_{10}			-492.2*	-538.1*
			(255.9)	(279.3)
Constant	15,655***	11,792***	8,482***	21,030***
	(2,868)	(3,380)	(2,834)	(4,831)
Observations	3,495	2,525	1,945	1,405
R-squared	0.546	0.576	0.546	0.577
Number of District	699	505	389	281
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 31: Property Tax Revenue - All Pollutant Regression

	(1) Property Tax Revenue
Log Ozone	-2,776***
	(635.3)
Log NO_2	-630.9*
	(325.6)
Log PM_{10}	-522.3*
	(272.7)
Log SO_2	-369.2**
	(145.9)
School Quality	1.483
	(4.293)
Cap-out Expenditure	0.0183
	(0.0205)
Total debt	0.0583***
	(0.00865)
Other Local Revenue Share (%)	-8.526
	(6.282)
Housing Price Index	19.20***
	(2.378)
State Share (%)	4.407
	(15.24)
Property Tax Index	7,086***
	(1,016)
Constant	17,001***
	(3,517)
Observations	1,405
Number of District	281
R-squared	0.576
Year Fixed Effect	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 32: Minimum Monitor Distance Robustness Check - Ozone

	(1) 12 miles	(2) 9 miles	(3) 15 miles	(4) 20 miles
Log Ozone	40,600***	45,482***	38,069***	40,248***
	(7,937)	(10,055)	(7,264)	(6,537)
Log Ozone Squared	-4,791***	-5,350***	-4,504***	-4,741***
	(915.8)	(1,151)	(840.5)	(758.8)
Constant	-84,985***	-95,214***	-79,704***	-84,517***
	(17,178)	(21,920)	(15,692)	(14,096)
Observations	4,700	3,735	5,145	5,530
R-squared	0.550	0.545	0.551	0.545
Number of District	940	747	1,029	1,106
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 33: Minimum Monitor Distance Robustness Check - NO_2

	(1) 12 miles	(2) 9 miles	(3) 15 miles	(4) 20 miles
Log NO_2	12,401***	12,512***	10,734***	10,917***
	(2,190)	(2,974)	(1,720)	(1,644)
Log NO_2 Squared	-2,411***	-2,492***	-2,127***	-2,062***
	(388.2)	(516.6)	(308.0)	(295.2)
Constant	-17,710***	-15,754***	-14,903***	-15,805***
	(3,439)	(4,602)	(2,759)	(2,607)
Observations	2,740	2,115	3,140	3,675
R-squared	0.588	0.597	0.595	0.595
Number of District	548	423	628	735
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 34: Minimum Monitor Distance Robustness Check - PM_{10}

	(1) 12 miles	(2) 9 miles	(3) 15 miles	(4) 20 miles
Log PM_{10}	-7,870*	-9,721*	-6,459	-6,334*
	(4,381)	(5,102)	(4,198)	(3,809)
Log PM_{10} Squared	1,125*	1,383*	918.4	884.0
	(647.6)	(750.3)	(620.6)	(565.8)
Constant	13,812*	16,942*	10,603	9,390
	(7,488)	(8,670)	(7,173)	(6,473)
Observations	2,425	1,880	2,765	3,305
R-squared	0.534	0.506	0.543	0.563
Number of District	485	376	553	661
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 35: Minimum Monitor Distance Robustness Check - SO_2

	(1) 12 miles	(2) 9 miles	(3) 15 miles	(4) 20 miles
Log SO_2	-2,301***	-2,696***	-1,826**	-1,683**
	(832.5)	(893.3)	(744.2)	(688.3)
Log SO_2 Squared	260.9***	296.3***	210.8**	199.5**
	(98.06)	(104.1)	(89.17)	(83.09)
Constant	5,772***	8,001***	3,982**	3,821**
	(2,045)	(2,213)	(1,774)	(1,612)
Observations	3,685	2,935	4,215	4,730
R-squared	0.538	0.530	0.555	0.554
Number of District	737	587	843	946
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 36: Monitor Distance Robustness Check Marginal Effects - Ozone

Percentiles	(1) 12 miles	(2) 9 miles	(3) 15 miles	(4) 20 miles
10	-1,023***	-996.0***	-941.9***	-813.1***
	(275.8)	(329.7)	(274.9)	(253.6)
20	-1,390***	-1,405***	-1,404***	-1,299***
	(290.4)	(327.2)	(294.5)	(276.7)
30	-1,742***	-1,669***	-1,626***	-1,534***
	(318.7)	(338.0)	(312.0)	(294.5)
40	-1,857***	-1,927***	-1,843***	-1,762***
	(330.4)	(357.1)	(333.3)	(315.3)
50	-2,083***	-2,179***	-2,055***	-1,985***
	(356.1)	(382.6)	(357.3)	(338.1)
60	-2,193***	-2,302***	-2,159***	-2,095***
	(370.0)	(397.2)	(370.1)	(350.2)
70	-2,411***	-2,546***	-2,364***	-2,310***
	(399.1)	(429.4)	(396.8)	(375.1)
80	-2,624***	-2,783***	-2,564***	-2,521***
	(429.5)	(464.4)	(424.6)	(400.8)
90	-2,935***	-3,131***	-2,857***	-2,828***
	(476.7)	(520.2)	(467.5)	(440.3)
Observations	4,700	3,735	5,145	5,530

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 37: Monitor Distance Robustness Check Marginal Effects - NO_2

	(1)	(2)	(3)	(4)
Percentiles	12 miles	9 miles	15 miles	20 miles
1bn0	-655.7**	-983.9***	-784.2***	-253.3
	(263.8)	(369.9)	(242.4)	(227.6)
20	-1,259***	-1,608***	-1,317***	-769.5***
	(254.6)	(336.2)	(243.6)	(229.7)
30	-1,795***	-1,892***	-1,790***	-1,228***
	(276.5)	(336.5)	(264.2)	(250.6)
40	-2,043***	-2,418***	-2,008***	-1,440***
	(294.7)	(363.3)	(278.9)	(265.2)
50	-2,278***	-2,661***	-2,413***	-1,641***
	(315.7)	(385.6)	(313.0)	(281.4)
60	-2,717***	-3,114***	-2,602***	-2,016***
	(362.3)	(439.8)	(331.2)	(316.5)
70	-3,119***	-3,530***	-2,957***	-2,360***
	(411.1)	(499.9)	(368.5)	(352.8)
80	-3,490***	-3,913***	-3,284***	-2,678***
	(459.6)	(561.5)	(405.7)	(388.8)
90	-4,156***	-4,602***	-3,872***	-3,248***
	(552.2)	(681.4)	(477.0)	(457.7)
Observations	2,740	2,115	3,140	3,675

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 38: Monitor Distance Robustness Check Marginal Effects - PM_{10}

	(1)	(2)	(3)	(4)
Percentiles	12 miles	9 miles	15 miles	20 miles
1bn0	-1,023**	-1,299**	-781.0*	-951.4**
	(481.7)	(584.3)	(411.1)	(403.8)
20	-818.0**	-1,048**	-699.4*	-790.6**
	(379.4)	(464.7)	(364.3)	(315.7)
30	-630.4**	-817.1**	-546.2*	-643.2***
	(296.0)	(365.8)	(284.5)	(245.2)
40	-457.3*	-604.2**	-404.9*	-573.8***
	(237.4)	(292.8)	(228.5)	(218.4)
50	-375.6*	-406.5	-273.6	-442.8**
	(220.2)	(255.0)	(204.7)	(187.0)
60	-220.4	-222.0	-211.3	-320.8*
	(213.9)	(257.7)	(206.1)	(189.1)
70	-75.23	-49.08	-92.80	-206.7
	(240.1)	(293.1)	(231.1)	(218.1)
80	61.11	33.50	18.55	-152.3
	(285.6)	(318.5)	(274.5)	(238.6)
90	251.3	341.2	173.9	1.511
	(368.1)	(441.1)	(353.4)	(310.7)
Observations	2,425	1,880	2,765	3,305

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 39: Monitor Distance Robustness Check Marginal Effects - SO_2

Percentiles	(1) 12 miles	(2) 9 miles	(3) 15 miles	(4) 20 miles
10	-403.1***	-525.0***	-292.9**	-242.1**
	(150.4)	(168.7)	(124.7)	(114.5)
20	-338.6**	-453.5***	-240.8**	-182.1*
	(133.2)	(151.3)	(109.8)	(97.68)
30	-270.4**	-366.0***	-185.7*	-134.1
	(117.6)	(133.4)	(96.97)	(87.11)
40	-210.2**	-300.1**	-144.8	-91.18
	(107.1)	(123.3)	(90.20)	(80.73)
50	-147.6	-222.3*	-93.39	-49.13
	(100.6)	(116.2)	(86.00)	(78.03)
60	-84.33	-161.7	-41.45	0.820
	(99.36)	(115.0)	(87.23)	(79.84)
70	-14.66	-77.43	10.24	50.43
	(104.4)	(119.8)	(93.70)	(86.69)
80	63.91	21.00	75.22	112.7
	(117.1)	(133.7)	(107.7)	(100.8)
90	196.9	165.2	177.5	207.0
	(149.9)	(165.4)	(138.3)	(129.3)
Observations	3,685	2,935	4,215	4,730

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 40: Property Tax Revenue - Different Time Sample - Ozone

	(1) 4-year	(2) 5-year	(3) 6-year	(4) 12-year
Log Pollution	40,604***	57,176***	80,618***	127,912***
	(8,412)	(12,360)	(13,409)	(19,705)
Log Pollution Squared	-4,810***	-6,738***	-9,391***	-15,156***
	(971.0)	(1,423)	(1,541)	(2,282)
Constant	-85,650***	-118,871***	-172,160***	-273,969***
	(18,209)	(26,776)	(29,169)	(42,774)
Observations	3,756	2,808	2,820	1,880
R-squared	0.549	0.598	0.583	0.613
Number of District	939	936	940	940
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 41: Property Tax Revenue - Different Time Sample - NO_2

	(1) 4-year	(2) 5-year	(3) 6-year	(4) 12-year
Log Pollution	16,918***	13,519***	15,568***	16,606***
	(2,444)	(2,501)	(2,562)	(3,382)
Log Pollution Squared	-3,225***	-2,493***	-2,987***	-3,276***
	(432.1)	(450.1)	(459.2)	(611.1)
Constant	-23,337***	-18,098***	-22,807***	-33,791***
	(3,789)	(3,783)	(4,070)	(5,811)
Observations	2,184	1,629	1,644	1,096
R-squared	0.602	0.621	0.620	0.650
Number of District	546	543	548	548
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 42: Property Tax Revenue - Different Time Sample - PM_{10}

	(1) 4-year	(2) 5-year	(3) 6-year	(4) 12-year
Log Pollution	-9,601**	-9,664**	-10,838**	-10,132*
	(4,252)	(4,646)	(4,372)	(5,533)
Log Pollution Squared	1,397**	1,367**	1,604**	1,536*
	(630.7)	(686.1)	(648.2)	(831.7)
Constant	16,335**	16,313**	19,137**	12,726
	(7,260)	(7,973)	(7,497)	(10,307)
Observations	1,932	1,446	1,455	970
R-squared	0.525	0.588	0.559	0.602
Number of District	483	482	485	485
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 43: Property Tax Revenue - Different Time Sample - SO_2

	(1) 4-year	(2) 5-year	(3) 6-year	(4) 12-year
Log Pollution	-2,914***	-1,862**	-2,672***	-3,669***
	(813.9)	(914.6)	(867.6)	(1,343)
Log Pollution Squared	318.6***	220.2**	308.3***	413.3***
	(94.19)	(107.5)	(101.2)	(151.3)
Constant	6,798***	5,641***	6,309***	4,459
	(1,988)	(2,170)	(2,201)	(4,659)
Observations	2,948	2,181	2,211	1,474
R-squared	0.540	0.576	0.563	0.568
Number of District	737	727	737	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 44: Property Tax Revenue - Different Lag Period - Ozone

	(1) Baseline	(2) 5-year Lag	(3) 6-year Lag	(4) 7-year Lag
Log Pollution	29,031***	31,841***	37,930***	44,399***
	(8,061)	(8,960)	(7,559)	(6,992)
Log Pollution Squared	-3,507***	-3,840***	-4,531***	-5,228***
	(924.8)	(1,016)	(865.3)	(805.2)
Constant	-60,268***	-66,170***	-79,141***	-94,236***
	(17,669)	(19,830)	(16,627)	(15,235)
Observations	3,744	3,744	3,744	3,744
R-squared	0.570	0.572	0.572	0.572
Number of District	936	936	936	936
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 45: Property Tax Revenue - Different Lag Period - NO_2

	(1) Baseline	(2) 5-year Lag	(3) 6-year Lag	(4) 7-year Lag
Log Pollution	13,814***	12,944***	13,585***	14,549***
	(2,281)	(2,233)	(2,430)	(2,871)
Log Pollution Squared	-2,571***	-2,460***	-2,650***	-2,879***
	(402.4)	(398.2)	(432.0)	(507.7)
Constant	-24,190***	-22,508***	-21,208***	-20,809***
	(3,700)	(3,616)	(3,844)	(4,313)
Observations	2,152	2,152	2,152	2,152
R-squared	0.611	0.609	0.613	0.617
Number of District	538	538	538	538
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 46: Property Tax Revenue - Different Lag Period - PM_{10}

	(1) Baseline	(2) 5-year Lag	(3) 6-year Lag	(4) 7-year Lag
Log Pollution	-4,330	-2,920	-7,298	-7,054
	(4,594)	(4,554)	(4,576)	(5,240)
Log Pollution Squared	571.9	379.3	1,051	1,057
	(683.4)	(672.9)	(672.1)	(767.1)
Constant	7,697	5,134	12,388	11,483
	(7,679)	(7,749)	(7,981)	(9,157)
Observations	1,916	1,916	1,916	1,916
R-squared	0.501	0.499	0.500	0.499
Number of District	479	479	479	479
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 47: Property Tax Revenue - Different Lag Period - SO_2

	(1) Baseline	(2) 5-year Lag	(3) 6-year Lag	(4) 7-year Lag
Log Pollution	-1,773**	-1,457*	-1,293	-1,316
	(849.1)	(787.1)	(794.1)	(900.8)
Log Pollution Squared	196.6*	144.1	135.1	138.0
	(100.9)	(91.19)	(93.53)	(104.3)
Constant	2,565	2,142	1,584	1,744
	(2,122)	(2,048)	(1,958)	(2,226)
Observations	2,912	2,912	2,912	2,912
R-squared	0.558	0.559	0.558	0.558
Number of District	728	728	728	728
Year Fixed Effect	Yes	Yes	Yes	Yes

Note: State, Local, and District controls are not reported.
Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 48: Property Tax Revenue per Pupil - Unbalanced Panel

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	38,542***	9,593***	-4,545	-1,432**
	(6,631)	(2,441)	(2,918)	(640.4)
Log Pollution Squared	-4,552***	-1,883***	622.4	162.4**
	(769.7)	(425.5)	(436.6)	(76.71)
School Quality	2.793	9.397**	3.506	6.390**
	(3.331)	(3.841)	(2.940)	(3.212)
Cap-out Expenditure	0.0477**	0.0533***	0.0650**	0.0580**
	(0.0216)	(0.0133)	(0.0286)	(0.0248)
Total debt	0.0431***	0.0503***	0.0476***	0.0417***
	(0.00500)	(0.00661)	(0.00579)	(0.00607)
Other Local Revenue Share (%)	-27.90***	-17.50***	-25.34***	-22.52***
	(5.646)	(5.403)	(4.933)	(4.285)
Housing Price Index	18.60***	16.27***	17.77***	17.49***
	(1.220)	(1.780)	(1.787)	(1.429)
State Share (%)	-1.859	38.04***	14.67*	2.243
	(7.856)	(13.79)	(7.859)	(9.392)
Property Tax Index	5,904***	8,993***	5,378***	6,306***
	(556.9)	(935.5)	(604.6)	(653.6)
Constant	-80,678***	-14,556***	7,992	3,065*
	(14,282)	(3,773)	(4,891)	(1,587)
Observations	5,070	3,034	3,683	4,175
R-squared	0.553	0.585	0.532	0.538
Number of District	1,055	640	857	890
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 49: Property Tax Revenue per Pupil - CBSA Relative Pollution Level

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Relative Pollution	-13.43**	-11.69**	1.295	-3.135**
	(5.452)	(5.467)	(6.130)	(1.384)
School Quality	4.591	7.763*	1.868	7.087**
	(3.912)	(4.143)	(3.637)	(3.591)
Cap-out Expenditure	0.0458*	0.0384***	0.0759*	0.0569*
	(0.0267)	(0.0135)	(0.0393)	(0.0304)
Total debt	0.0428***	0.0513***	0.0477***	0.0412***
	(0.00504)	(0.00658)	(0.00668)	(0.00640)
State Share (%)	53.81***	68.66***	15.61	53.39***
	(15.10)	(20.37)	(16.60)	(17.19)
Other Local Revenue Share (%)	-27.80***	-18.18***	-21.17***	-20.96***
	(6.587)	(6.084)	(5.761)	(4.558)
Housing Price Index	-0.494	-3.519	-1.640	-3.324
	(4.379)	(5.626)	(5.941)	(4.722)
Property Tax Index	10,759***	13,099***	8,009***	10,840***
	(1,166)	(1,686)	(1,544)	(1,351)
Constant	-693.8	-2,873	283.1	-1,797
	(1,568)	(2,287)	(1,738)	(1,791)
Observations	4,100	2,550	2,120	3,325
R-squared	0.643	0.669	0.615	0.639
Number of District	820	510	424	665
CBSA-Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 50: Adjusted Current Expenditure per Pupil Regression Results

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	62,748***	10,877***	-7,515*	-2,923**
	(9,996)	(2,354)	(4,435)	(1,202)
Log Pollution Squared	-7,337***	-1,954***	980.8	315.7**
	(1,147)	(421.2)	(654.7)	(139.7)
State Share (%)	5.438	26.66***	8.487	12.68
	(7.287)	(9.906)	(9.570)	(8.570)
Expenditure Index	10,395***	11,047***	8,016***	11,054***
	(491.0)	(714.6)	(541.3)	(585.2)
Constant	-132,978***	-15,478***	16,473**	6,722**
	(21,753)	(3,253)	(7,522)	(2,659)
Observations	4,700	2,740	2,425	3,685
R-squared	0.868	0.881	0.876	0.876
Number of District	940	548	485	737
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school district
*** p<0.01, ** p<0.05, * p<0.1

Table 51: Marginal Effects for Adjusted Current Expenditure per Pupil

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	-1,446***	588.6*	-1,976***	-697.8***
	(320.9)	(306.3)	(466.0)	(212.3)
20	-1,890***	36.14	-1,675***	-570.4***
	(329.3)	(304.2)	(369.3)	(182.5)
30	-2,318***	-454.8	-1,398***	-435.8***
	(362.6)	(335.8)	(290.3)	(153.5)
40	-2,457***	-681.2*	-1,143***	-316.8**
	(377.9)	(359.0)	(234.2)	(131.1)
50	-2,730***	-896.5**	-1,022***	-193.4*
	(412.8)	(384.9)	(217.2)	(113.1)
60	-2,865***	-1,298***	-793.0***	-68.32
	(431.9)	(440.9)	(208.9)	(103.4)
70	-3,129***	-1,666***	-578.8**	69.26
	(472.6)	(498.6)	(230.9)	(105.2)
80	-3,387***	-2,006***	-377.7	224.4*
	(515.6)	(555.6)	(271.9)	(122.0)
90	-3,764***	-2,616***	-97.11	487.0***
	(582.5)	(663.8)	(348.1)	(171.9)
Observations	4,700	2,740	2,425	3,685

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 52: Pupil Teacher Ratio Regression Results

	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
Log Pollution	-1.269***	0.158**	1.551***	-0.0997***
	(0.347)	(0.0742)	(0.137)	(0.0355)
Log Pollution Squared	0.165***	-0.0227*	-0.231***	0.00950**
	(0.0398)	(0.0130)	(0.0204)	(0.00428)
State Share (%)	0.00215***	0.00172***	0.00207***	0.00209***
	(0.000283)	(0.000392)	(0.000359)	(0.000326)
Pupil Teacher Ratio Index	0.649***	0.777***	0.578***	0.697***
	(0.0173)	(0.0244)	(0.0204)	(0.0199)
Constant	4.967***	2.281***	-0.00159	2.827***
	(0.758)	(0.109)	(0.230)	(0.0749)
Observations	47,305	27,565	30,175	35,560
R-squared	0.171	0.165	0.133	0.181
Number of School	9,461	5,513	6,035	7,112
Year Fixed Effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered by school
*** p<0.01, ** p<0.05, * p<0.1

Table 53: Marginal Effects for Pupil Teacher Ratio

Percentiles	(1) Ozone	(2) NO_2	(3) PM_{10}	(4) SO_2
10	2.780***	2.792***	2.808***	2.799***
	(0.00183)	(0.00436)	(0.00274)	(0.00206)
20	2.786***	2.796***	2.820***	2.794***
	(0.00134)	(0.00324)	(0.00178)	(0.00148)
30	2.795***	2.797***	2.827***	2.790***
	(0.000765)	(0.00271)	(0.00123)	(0.00116)
40	2.799***	2.800***	2.831***	2.787***
	(0.000542)	(0.00173)	(0.00100)	(0.000992)
50	2.804***	2.802***	2.832***	2.785***
	(0.000459)	(0.00107)	(0.000972)	(0.000925)
60	2.808***	2.803***	2.831***	2.784***
	(0.000591)	(0.00136)	(0.00108)	(0.000917)
70	2.813***	2.804***	2.828***	2.781***
	(0.000857)	(0.00230)	(0.00131)	(0.00103)
80	2.818***	2.805***	2.823***	2.779***
	(0.00118)	(0.00400)	(0.00166)	(0.00135)
90	2.827***	2.805***	2.814***	2.776***
	(0.00192)	(0.00518)	(0.00240)	(0.00237)
Observations	47,305	27,565	30,175	35,560

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A1: Pollution Measures

Pollutant	Measure	Rules
Ozone	Annual 4^{th} highest daily maximum	1. 75% of the days within ozone monitoring season at least 135 days. 2. 75% of the hourly averages for the 8-hour period are available at least 18 observations per day; or if the daily maximum 8-hour average concentration for the day is greater than the level of the standard (0.075 ppm). 3. 8-hour average to be reported to the 3rd decimal place; additional digits to the right of the 3rd decimal place shall be truncated. 4. 3-year average of annual 4th highest daily maximum 8-hour average shall be reported to 3 decimal places; digits to the right of the 3rd decimal place shall be truncated. *Source: Federal Register Vol. 73 No. 60 pp. 16511 – 16512.*
NO_2	Annual arithmetic mean of all of the reported 1-hour values	1. At least 75% of the hours in the year are reported (at least 180 days – in line with 98^{th} percentile criteria). 2. Annual mean shall be rounded to the nearest whole number. *Source: Federal Register Vol. 75 No. 26 pp. 6532 – 6534.*
PM_{10}	Annual arithmetic mean of 4 quarterly means concentrations	1. 75% of the scheduled PM_{10} samples per quarter – at least 11 days. 2. Quarterly average must be rounded to nearest 10^{th}. 3. Annual average must be rounded to nearest 10^{th}. 4. 3-year average shall be rounded to nearest integer. *Source: Federal Register Vol. 52 No. 126 pp. 24667 – 24669.*
SO_2	99^{th} percentile of 1-hour daily maximum concentration	1. 4 quarters are complete 75% (at least 50%) of sampling days for each quarter (at least 45 days). 2. 75% of hourly concentration value (at least 18 observations). 3. 99^{th} percentile are not rounded. 4. 3-year average is rounded to nearest whole number. *Source: Federal Register Vol. 75 No. 119 pp. 35596 – 35597.*