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Which School Attributes Matter? The Influence of School District Performance and Demographic Composition on Property Values

John M. Clapp
University of Connecticut

Anupam Nanda
University of Connecticut

Stephen L. Ross
University of Connecticut

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341 Mansfield Road, Unit 1063
Storrs, CT 06269–1063
Phone: (860) 486–3022
Fax: (860) 486–4463
http://www.econ.uconn.edu/

Abstract

Increasing levels of segregation in American schools raises the question: do home buyers pay for test scores or demographic composition? This paper uses Connecticut panel data spanning seven years from 1994 to 2000 to ascertain the relationship between property values and explanatory variables that include school performance and school demographic attributes such as racial and ethnic composition. Census tract fixed effects are included to control for neighborhood unobservables, and assessed property values are shown to provide important additional controls. The study finds strong evidence that percent Hispanic and percent free lunch are important in determining housing prices, and no evidence that improved test scores lead to higher housing prices.

Journal of Economic Literature Classification: D1, D4, I2, R2, R5.

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I. Introduction

The U.S. educational system is characterized by tremendous diversity across school districts in school performance, socio-economic status, and racial and ethnic composition. The segregation of students by socio-economics status, race or ethnicity raises concerns about the extent of equality of opportunity in our society, and these concerns may be increasing in importance as a number of studies have documented growing levels of segregation in American public schools, e.g. Clotfelter, Ladd, and Vigdor (2003), Reardon and Yun (2003), and Frankenburg and Lee (2002). Moreover, racial segregation has been shown to be associated with lower outcomes for minority students (Hanushek, Kain, and Rivken, 2003; Mickelson, 2003; McHugh, 2003) and/or lower school quality (Freeman, Scafidi, and Sjoquist, In Press, 2005).

Many studies have examined property values in order to assess the value people place on the quality of local schools. Typically, property values from samples of housing transactions are regressed on some measure of school quality, such as standardized test scores. For example, Weimer & Wolkoff (2001) examine the capitalization of public school performance and tax costs by exploiting the imperfect congruence of the boundaries of public school districts and elementary enrollment areas with the boundaries of incorporated jurisdictions providing other public services. Their findings confirm the influence of school quality, especially elementary school, on house price. Similarly, Hayes & Taylor (1996), Bogart and Cromwell (1997), and Haurin and Brasington (1996) find a positive relationship between standardized test scores and housing prices using cross-sectional analysis. Ross and Yinger (1999) provide a review of the empirical literature on the capitalization of public service quality and property taxes into house price[3].

In addition to test scores, parents may care about other factors including the socio-economic and demographic composition of the student body, but only a small number of studies have examined this question. In a pioneering study, Clotfelter (1975) examines the effect of school desgregation on property values, finding that the schools with the greatest declines in segregation during the 1960-1970 period also experienced relative declines in house price. Norris (2002) examines this

[3] One limitation of this literature is that the price depends upon both supply and demand factors. In order to truly identify the effect of preferences a full hedonic demand function must be estimated. This has been made practical in a single market using the nonlinear identifying conditions discussed by Ekeland, *et al*. (2003); they generalize Epple (1987). Norris (2002) allows for simultaneity in his model but is forced to rely on troublesome identifying assumptions. In contrast, we rely on the assumption that prices describe a long-run equilibrium implying that our parameters reveal relationships in this equilibrium. We support this assumption by examining changes in housing prices over short and long time-frames.

question using a cross-sectional analysis for six Louisiana parishes. He finds that the representation of African-Americans in local schools either has no effect or leads to an increase in property values after controlling directly for the effect of test scores. Similarly, Weimer & Wolkoff (2001) examine the effect of the presence of low-income students on property values using the share of students who are eligible for the free-lunch program and find that the presence of such students raises property values. MacPherson and Sirmans (2001) study the effects of racial and ethnic minorities on growth in property values in two Florida cities. They find that an increase in percentage African-American has a significant negative effect whereas the percentage Hispanic has a very small positive effect in one city, a negative effect in the other. Brasington and Haurin (2004) find a significant negative effect of minorities on growth in house prices in Ohio.

This paper examines the effect of school performance as measured by student test scores and the effect of the socio-economic and demographic composition on local property values using a panel of housing transactions in the state of Connecticut between 1994 and 2000. In our sample we find zero effect for test scores and percent African-American, but find significantly negative effects for percent Hispanic, percent Non-English speaking students, and percent students qualifying for the free lunch program. Our short-run analyses consistently show that both the presence of Hispanic and Non-English speaking students lead to lower property values. In our long-run analysis, however, the effect of Hispanic and Non-English speaking appears to decline in importance being replaced by the share of Free lunch students. A plausible explanation is that Hispanic children are largely assimilated into the schools over five to seven years, and the negative effects of ethnic changes only persist if they are associated with persistently higher levels of poverty.

A common concern in studies of school quality capitalization is that school quality may be correlated with unobserved neighborhood characteristics. Bogart & Cromwell (2000) analyze the effect of a re-districting that changes the school of attendance for many neighborhoods and states that these changes have a substantial effect on house sales prices. Alternatively, Sandra Black (1999) addresses this concern by examining a sample of housing transactions that occur on the boundary between elementary school attendance zones within the same school district. She finds that specifications that control for neighborhoods using standard census variables overstate the importance of school quality by 30 to 40 percent when compared to a model that controls for neighborhood quality using boundary fixed effects. Similarly, Gibbons & Machin (2003) find a significant positive effect of primary school performance on local property prices in England. They control for neighborhood quality by estimating a smooth nonparametric housing price surface. The effect of school performance on property values is identified based on the deviations from the surface at attendance zone boundaries and the assumption that non-school neighborhood quality varies continuously over space.

While Black's empirical finding of bias from omitted neighborhood attributes is quite compelling, there are a number of reasons why empirical research on the capitalization of school quality should not rely exclusively on cross-sectional analyses across attendance zone boundaries. First, Cheshire & Sheppard (2002) argue that attendance zones may change and as a result parents along zone boundaries may discount differences in school quality by the likelihood of remaining in a specific zone. In support of this argument, they examine the capitalization of secondary school quality into housing price and find evidence that capitalization is smaller in areas where the housing supply is expanding. Similarly, Brasington (2002) finds that capitalization is smaller in outermost suburbs where presumably the elasticity of housing supply is higher. In addition, the effect of a school or district's performance and school demographics on housing prices may vary based on the types of individuals who are moving into a particular neighborhood. Analysis of this aspect of the problem requires information on the attributes of movers that may not be available for the short period covered by a cross-sectional analysis.

Our model controls for time-invariant neighborhood/census tract attributes using fixed effects. This paper complements previous analyses by Black (1999) and Gibbons & Machin (2003), but it has a key advantage in that the effect is driven by a complete sample of housing units rather than those that are located along the boundaries. However, we are limited to school variables at the district level; attendance zones are not available over time. In addition to controlling for neighborhood fixed effects, we use assessed property value to better control for neighborhood and property characteristics unobserved by econometrician but observed by the tax assessor. With town or tract fixed effects, the assessed value model is formally equivalent to a double differenced equation using repeat property transactions, but without the negative attributes of repeat sales models (Clapp and Giaccotto, 1992). In fact, we find that the estimates of property tax capitalization are substantially understated in models that control for neighborhood fixed effects, but do not control for unobserved differences between individual properties.

The remainder of the paper is organized as follows: Section II provides methodology and intuition; Section III describes the data; and Section IV presents the findings in three major subsections covering a baseline analysis, an analysis in which the influence of longer run school changes are assessed across distinct time periods, and robustness checks. Finally, Section V summarizes and discusses of the major findings.

II. Methodology

The hedonic price function[4] can be defined as follows:

$$ln(P_{ijkt}) = \alpha + \delta Z_{kt} + \Gamma_{ijk} + \omega_t + \varepsilon_{ijkt} \tag{1}$$

where P_{ijkt} is the price of house *i* in neighborhood *j* in school district *k* at time *t*. Z_{kt} are the year-specific ($t^{th.}$) school/town ($k^{th.}$) level attributes, which includes school district performance as measured by standard test scores, socio-economic and demographic composition of the students, and local property tax rate. Γ_{ijk} is a term that captures non-school time-*invariant* observable attributes of the unit including the neighborhood and school district attributes. ε_{ijkt} is a time-*variant* unobservable that is assumed to be randomly distributed and uncorrelated with Z_{kt} and Γ_{ijk}. ω_t's are the time fixed effects like year, month and year-market interactions. Equation (1) is the baseline hedonic model.

The time-*invariant* unit attributes can be defined in a number of ways - each requiring a different set of assumptions. First, Γ_{ijk} may be specified simply as a function of observed housing unit attributes (X_i) and neighborhood attributes (W_j).

$$\Gamma_{ijk} = \beta X_i + \mu W_j \tag{2}$$

Equation (2) requires the assumption that unobserved unit, local public service, and neighborhood attributes are to be uncorrelated with X_i as well as W_j. This specification is comparable to the standard hedonic equation criticized by Black (1999); it uses neighborhood controls based on the decennial census.

If unobserved local public services or average neighborhood quality in the school district are correlated with observables, school district/town fixed effects (ν_k) are required to satisfy the assumption that the right hand side variables are orthogonal to ε_{ijkt}. Specifically,

$$\Gamma_{ijk} = \beta X_i + \mu W_j + \nu_k \tag{3}$$

Combining equation (1) and equation (3), we obtain:

$$ln(P_{ijkt}) = \alpha + \delta Z_{kt} + \beta X_i + \mu W_j + \nu_k + \omega_t + \varepsilon_{ijkt} \tag{4}$$

[4] This semi-log specification is standard in the literature.

Equation (4) is the school/town fixed effect model. This specification is closest to one in Black (1999) because it should eliminate any correlation between school performances at the specific scale measured and average neighborhood quality at that scale.

Unlike Black (1999), however, our analysis is at the school district level and the effect of schools may be identified by comparing sales at different times that occurred in different neighborhoods within the same school district. If housing appreciation rates vary across neighborhoods, a comparison of units that does not control for neighborhood unobservable attributes will have higher variance and attenuates estimates of the impact of school quality. This problem can be addressed by including a full set of neighborhood fixed effects (σ_j)[5].

$$\Gamma_{ijk} = \beta X_i + \sigma_j \quad (5)$$

Combining Equations (1) and (5), we obtain Equation (6) which is the tract fixed effect model:

$$ln(P_{ijkt}) = \alpha + \delta Z_{kt} + \beta X_i + \sigma_j + \omega_t + \varepsilon_{ijkt} \quad (6)$$

In addition, unobserved unit attributes or unobserved variation in neighborhood attributes that arise at a scale below the level of our neighborhood definition *j* may also lead to bias in the estimates. In this case, a standard approach is to estimate a repeat sales model that compares the differences in a unit's sales price between two time-periods to the changes in school district attributes in the same time-periods. Specifically, subtracting Equation (1) at time '*s*' from Equation (1) at time '*t*' we get:

$$ln(P_{ijkt}) - ln(P_{ijks}) = \delta(Z_{kt} - Z_{ks}) + (\omega_t - \omega_s) + (\varepsilon_{ijkt} - \varepsilon_{ijks}) \quad (7)$$

This is a standard way of controlling for unit fixed effects, but some serious concerns are associated with a sample of homes that sell two or more times. Previous research has found that houses selling repeatedly are typically older and smaller than houses that sell only once during a ten to twenty year sample period (Clapp, Giaccotto and Tirtiroglu, 1991). Moreover, the sample size is substantially reduced: we lost of almost 91 percent of the total observations when we identified repeat sales. Therefore, we do not pursue repeat sales model further.

[5] Note that the school district/town fixed effects (ν_k) is subsumed into the neighborhood fixed effects (σ_j) because census tracts do not to cross town/district boundaries in Connecticut.

An alternative to the repeat sales methodology is the assessed value (A_{ijks}) approach where the town assessor is assumed to have observed relevant unit and neighborhood attributes whether observed or unobserved by the econometrician and have provided an appraisal at least proportional to market value at the time of assessment (s).[6] Specifically,

$$\gamma \, ln(A_{ijks}) = \alpha + \delta Z_{ks} + \Gamma_{ijk} + \omega_s + \sigma_j + \varepsilon_{ijks} \tag{8}$$

Now, subtracting Equation (8) from Equation (1) yields

$$ln(P_{ijkt}) = \gamma \, ln(A_{ijks}) + \delta \, (Z_{kt} - Z_{ks}) + (\omega_t - \omega_s) + \sigma_j + (\varepsilon_{ijkt} - \varepsilon_{ijks}) \tag{9}$$

Equation (9) is the assessed value model. Note that this model includes tract fixed effects, σ_j , so that all parameters are identified based on within tract comparisons over time (mean differencing by tract). The differencing due to assessed value in equation (9) controls for location and house specific characteristics. Thus, the assessed value model is double differenced.

In summary, four models are estimated: the standard hedonic, equations (1) and (2); town fixed effects and tract fixed effects, equation (6); and the assessed value model with tract fixed effects, equation (9). We have estimated all the models (except for assessed value model) with robust (clustered by town or tract) standard errors[7].

III. Data Description and Summary Statistics

This study used a sample of sales of owner-occupied properties with one to four units[8] spanning over seven years from 1994 to 2000; the data are purchased from Banker and Tradesman for the state of Connecticut. The sample has 173,469 transactions for one to four unit owner-occupied

[6] See Clapp and Giaccotto (1992) for a comparison of assessed value and repeat sales models.
[7] See Bertrand, Duflow and Mullainathan (2002) and Kezdi (2003).

[8] We include single-family, two-family, three-family, and residential condominiums. We compare results from the estimation with the sample that excludes the residential condominiums, an exclusion of about 13,500 transactions. We find no strong departure from the general tenor of the core results.

structures after any filtering to eliminate invalid or nonrepresentative transactions. Appendix A lists data filters, their effect on sample size and, if relevant, their effect on results. This data set contains information about the unit address, selling price, assessed value and sales date, as well as the detailed listing of the unit characteristics such as internal square footage, number of rooms, bedrooms, bathrooms, building age and lot size.[9]

Each property is geocoded to specific towns and census tracts. In Connecticut, towns and school districts share the same boundaries, i.e. they are co-determinous. The State of Connecticut School Profiles were used to obtain standardized eighth grade test scores in math, reading, and writing; as well as the percentage of students qualifying for the free lunch program, non-English speaking, blacks, and Hispanics for each of the 169 town/school districts in each year.[10] The property tax rate ("mill rate") for each town/school district in each year was obtained from State of Connecticut's Office of Policy Management, and an effective or equalized property tax rate (EPTR) is calculated using town and year specific comparisons of the assessed values and sales prices. Specifically, EPTR is the statutory mill rate times the ratio of average assessed values to average sales prices for each town in each year.[11]

This study uses the census tract as proxy for neighborhood.[12] Neighborhood fixed-effects are defined based on the 838 tracts in the State of Connecticut during the 1990 Decennial Census. The 1990 and 2000 censuses also are used to obtain median family income (*MFIT*), proportion of blacks in tract (*BlkTT*), proportion of Hispanics in tract (*HisTT*), proportion of owner occupied units in tract (*OWROCDT*), and proportion of married couple with children (*FamCHNT*) in each tract. The 1990 values are used as control variables in the simple pooled cross-sectional analysis, and the changes between 1990 and 2000 are used to capture changes in neighborhood racial and ethnic composition.

Finally, the specification includes both year and month fixed effects based on the sales date in the housing transaction record. Separate year fixed effects were estimated for each market or region

[9] Some observations have missing information on one or more housing attribute. These observations are retained in the sample and dummy variables are included to control for the fact that a specific attribute is missing.

[10] A few smaller towns have been consolidated into joint high school districts. The test scores for a consolidated district are used for the towns in that district. The number of transactions in these districts is small, and their exclusion has no effect on results.

[11] We use a standard functional form assumption for property tax capitalization (Yinger *et al.* 1988): EPTR = log [0.03+ {Mill rate * (ratio of assessed value to sales price)}/1000] where .03 is the assumed discount rate. It should be noted that the estimate of property tax capitalization varies monotonically with the discount rate assumption.

[12] Alternatively, census block groups might be used as a definition of neighborhood, but the house transaction data begins to get quite thin at that level of disaggregation.

in the state in order to account for the possibility that housing price appreciation varied regionally. The 10 Labor Market Areas (LMA's) in Connecticut are used to define markets or regions. LMAs are collections of towns defined by the State Department of Labor and are conceptually similar to the U.S. Census defined Metropolitan Statistical Areas (MSAs).[13]

Table 3.1 gives the summary statistics over all years of the variables that enter into regression analysis. The house sales price (dependent variable) and assessed value (independent variable) are listed as *Price variables*. The relationship between mean assessed value, \$130,880, and mean house sales price, \$202,011, reflects the legal mandate that properties be assessed at 70% of market value; revaluation lags account for the actual ratio of 64.8%.[14] Variables under the heading *Hedonic or house attributes,* indicate the number of rooms (5.5), bedrooms (2.4), bathrooms (2.0), age of the unit (36.1 years), and internal square footage (1,772).

The *Town/School district characteristics* panel shows that average mathematics (math), reading (read) and writing (write) scores are 125.694, 65.273 and 7.440 with standard deviations of 15.045, 4.996, and 1.099, respectively. This demonstrates substantial variation in school outcomes within the sample. The proportion of non-English speaking students (NEHL) is 11.9%, and the proportion of students qualifying for free lunch program (Free) is 20.9 percent, suggesting substantial difficulties in the production of favorable outcomes. Average property tax rate is \$31.259 per \$1000 of assessed house value for an effective tax rate of just over 2% of market value.

In the category of *Tract or Neighborhood attributes*, average tract median family income (*MFIT*) is \$57,220, indicating a substantial affluence in the tracts represented in the sample of housing sales; the 1995 median family income in the US was \$49,687 and in Connecticut it was \$62,157. In addition, the average percentage African-American is 5.8, average percent Hispanic population is 4.4, almost 73 percent of the housing units in tracts are owner-occupied, and 36.4 percent of families in these tracts are married with children.[15]

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[13] LMA has some key advantages over MSA: a.) the areas are consistent with town boundaries. b.) LMA provides complete coverage of all towns within the state, and c.) LMA is defined at a smaller scale and so, better representative of commuting and residential patterns in a small and densely populated state like Connecticut.

[14] In all assessed value models, we drop transactions in the assessment year. Previous research has shown that a short time for appreciation biases repeat sales models: E.g., one can obtain very large absolute values of appreciation rates when the time between sales is less than one year. Also, assessments were performed throughout the year and we cannot explicitly control for whether a transaction during the assessment year occurred prior to or after reassessment.

[15] All averages are taken over the sample of units, which disproportionately represents tracts that contain a large number of owner-occupied housing units and tracts in which such units sell more frequently.

Table 3.2 provides summary statistics in two different time-regimes i.e. 1994-1996 and 1998-2000 in order to illustrate the trends that have occurred in Connecticut over the period.[16] The sample period is characterized by recovery from declining prices, 1989-1993, so there is a relatively higher volume of housing transactions in 1998-2000 than in the 1994-96 period. Mean house price increases almost $15,000 or about 7 percent between the two periods while mean assessed value drops by $1,718. Compared to Table 3.2, we see that average test-scores improved by between one-half and one standard deviation for different tests over the timeframe. The state maintains that the test scores are comparable over time during this period, which suggests that student scores have been improving either due to improved education or increased parental and school district emphasis on testing. Free, NEHL, and BlkS fell between the two periods, whereas HisS increased by a small amount. These anomalies are due to the fact that the means are based upon the spatial distribution of housing transactions, which shifted towards more predominantly white school districts during the late 1990's. In fact, the proportional of African-American students in Connecticut schools increased by 0.5 percent per year during 1994-2000, compared to growth in total student population of 1.8 percent per year; the corresponding growth in Hispanic students was 4.0 percent per year. Thus, there was a very substantial shift towards Hispanics in many school districts.

IV. Results

4.1. Effect of School Attributes across Model Specifications

Table 4.1.1 presents the parameter estimates when we include math score in our estimation equation. Column (A) shows the traditional hedonic regression results where we do not control for the town or tract fixed effects, a pooled cross-sectional analysis. Column (B) presents the hedonic estimation after controlling for the town fixed effects, column (C) shows the hedonic estimation after controlling for the tract fixed effects, and column (D) presents the assessed value model with tract fixed effects. We have included the hedonic characteristics (such as number of rooms, bedrooms, age and square of the age of the unit in decades, and internal square footage),[17] town/school characteristics (such as math test-score, pupils qualifying for free lunch, proportion of blacks, Hispanics and the effective property tax rate, EPTR) and neighborhood or census tract characteristics (such as the median family income, the proportion of Blacks and Hispanics in

[16] A two-regime sample will be used in Section 4 to minimize the effect of noise in the measurement of school quality, property taxes, and other school variables and to focus on changes that occur over a longer period of time.
[17] To capture the non-linearity in Internal Square Footage, we have used a spline or piecewise variable. We selected to put the 'knot' at 2500 sq.ft.

tract, the proportion of units that are owner-occupied and the proportion of married couples with children).[18]

When comparing across the first three columns, the estimates suggest that one additional room is associated with an increase property value of between 2.6 to 2.9 percent; bedrooms do not add significantly to total rooms. Age of the building enters in quadratic form with the expected signs (decreasing at a decreasing rate). For example, a ten-year old house would be worth 6.1 to 6.8 percent less than a new house, but the size of this effect declines as the unit ages. Internal square footage is positively associated with the house sales price; a 10 percent increase in size adds 4.35 to 4.78 percent to value up to 2500 sq.ft. However, the effect is smaller (2.00 to 1.59 percent) for the floor sizes above 2500 sq. ft. In summary, the coefficients on the unit attributes are estimated fairly tightly and are quite stable across the different specifications. The reader should note that the estimated parameters on property characteristics for the assessed value model (column (D)) are not comparable because they only represent the deviation from the assessed value, which already considers property characteristics.

On the other hand, the estimated effects of school district attributes are much more sensitive to the specification. As found by Black (1999), the effect of test scores in a model that only controls for neighborhood observables (the hedonic baseline) is substantially overstated relative to fixed effects models. Specifically, in the baseline model, the effect of a one standard deviation increase in math score on property value is 11 percent, where a one standard deviation increase represents approximately a twelve percent change. The fixed effect models indicate small and statistically insignificant effects of test scores. The point estimates range from .3 to .6 percent, numbers that can be compared to Black's estimate of approximately 2.5 percent; Gibbons and Machin (2005) find .67% in England, versus .36% in Ohio (Brasington and Haurin, 2004). Thus, our point estimates are in the range of previous studies, and they suggest a small effect of school performance on house values.

Omitting demographic attributes does bias the estimated effects of test scores in some specifications (results not shown). In particular, the town fixed effects model without demographics shows that math scores have a 2.2% effect with a t-statistic of 2.4. However, the estimated math coefficient is small and insignificant in tract fixed effects and assessed value models.

[18] We include school spending in some models. It is always insignificant and never affects any of the results.

The baseline model suggests that percent non-English speaking and African-American are associated with higher property values, which is comparable to the surprising findings in earlier cross-sectional studies by Norris (2002) and Weimer & Wolkoff (2001). On the other hand, the effects of non-English speaking and Hispanic students on property values are significantly negative for the other three specifications that control for town, neighborhood, and unit unobservables. An interesting feature of our data is the possibilility of estimating the effects of the non-English speaking and free lunch school population separately from minority or ethnic identification.[19] The non-English speaking population and free lunch groups impose identifiable costs in the production of educational outcome; our double differenced model (last column) appears to be measuring these effects of -.64 and -.24 percent for a one percentage point change in composition.[20]

The positive effect of African-American students in the baseline model falls and becomes statistically insignificant in the town fixed effect, the neighborhood fixed effect and the assessed value models. Thus, we conclude that property values are not significantly influenced by racial integration or by school outcomes as measured by test scores, but they do respond negatively to percentages non-English speaking population, Hispanic and free lunch.

Our estimates of demographic effects using the assessed value model are comparable to the repeat sales estimates in Florida: a 1% increase in African-American population had a significant effect on growth in house prices ranging from -.1% to -.3% (MacPherson and Sirmans, 2001). For Hispanics, they found +.03% in Tampa and -.22% in Orlando. The absolute values of these estimates are somewhat lower than ours, but they did not control for tract fixed effects. Brasington and Haurin (2004) confirm this range of estimates; a one percent increase in racial/ethnic heterogeneity reduces growth in house prices by .27% in Ohio.

Finally, property taxes appear to be capitalized at an unusually high 55.6 percent rate in the baseline model, and at a much lower .9 percent rate for the town fixed effect model. The capitalization rate of about 22.8 percent in the assessed value model is more consistent with the existing literature. In Appendix B, we demonstrate that this is likely due to omitted variables bias in the models that ignore the location and structural attributes measured by the tax assessor. Thus, the assessed value model provides a valuable new method for measuring property tax capitalization, and generally improves controls in hedonic models.

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[19] The 2000 Census show that 18.4% of Connecticut's population speaks a language other than English at home; the percent Hispanic or Latino is only 9.4%. The next largest language group is Asian at 2.4%.
[20] The double differenced (assessed value) model will naturally reduce the positive correlation that exists between Free, NEHL, BlkS and HisS. We will present evidence on this below.

Table 4.1.2 and 4.1.3 presents estimation results with reading and writing scores respectively: Here, we only report the variables of specific interest, but specifications are the same as for math scores, and the trend of the estimates is very similar. The effect of a one standard deviation increase in reading scores is associated with an 8.6 percent increase in values in the baseline model, but statistically insignificant and small effects in the town and tract fixed effect, and 3.3 percent decrease in assessed value model. The negative effect of reading scores is an anomaly.[21] A similar pattern is observed in case of writing score, but the negative coefficient is small and insignificant. Finally, the impact of school demographic attributes and property taxes on property values are robust across the models that use mathematics, reading, and writing test scores as proxies for school quality.

4.2. Effect of School Attribute Changes across Time Periods

The fixed effect and assessed value models all have the advantage that they control for unobserved variables, which have been shown to be very important, by basing estimates on within town, neighborhood, or unit variation in house value. Such differencing/fixed effects approaches, however, dramatically decrease the variance of the unobservable, which can increase the attenuation bias that arises from variables that are measured with error. In this context, the results on standardized tests scores may vary over years due to cohort effects that have little to do with changes in overall school quality. Similarly, property taxes may experience temporary jumps from year to year based on a school district obtaining a grant or other temporary changes in the pattern of funding, but property tax changes are only capitalized into housing prices if they are expected to persist over time. In addition, year-to-year variation in house prices may be heavily influenced by short run dynamic changes in the housing market that may not be representative of the overall value that households place on school district attributes.

In order to address these concerns in next set of tables (4.2.1, 4.2.2, and 4.2.3), the seven-year span of the panel is divided into two time-regimes – 1994-1996 and 1998-2000. To estimate columns (A) – (C) in these three tables, all transactions in a time-period are assigned the average attributes for their school district over that three-year period, so the measurement error concern is addressed by the smoothing of town attributes over three year periods. The parameters in the two fixed effect models, columns (B) and (C), are identified by the changes from the first regime to the second. The assessed value model involves double differencing so smoothing takes a

[21] If the true coefficient is zero, then about 2.5 percent of estimated coefficients will be significant with the wrong sign. We tested the negative sign for interaction with non-English speaking, but it does not change.

somewhat different but comparable form. In equation (9) we have a year of assessment, s, and a year of sale, t: for each s and t, we average of the previous, current and next year values for the school district attributes, Z. The long run assessed value model addresses the concern about short run dynamics. This model (column (E)) is the same as column (D) except that it restricts the sample by dropping transaction within a one-year range of assessment year much as transactions in 1997 are dropped from the regime comparison.

The results confirm that the estimates for test scores are overstated in the baseline model. In the four time smoothed fixed effects models, a one-standard deviation increase in math and write score is associated with negligible and statistically insignificant increases in housing prices, similar to the standard fixed effect model. The effect of changes in reading scores is also insignificant in the fixed effect models, but the negative relationship found in the earlier assessed value model persists here, as well. The key effect of reducing measurement error on the estimates is to increase the negative coefficients for the percent of property tax capitalization: See Appendix B for additional discussion. The estimated property tax capitalization rate increases from 22 to 36 percent for the assessed value model, and further increases to 61 percent when we restrict the sample in Column (E). This tells us that moving to longer run analysis by eliminated idiosyncratic year to year variation and dropping price comparisons of very short time spans brings the property tax capitalization closer to the 100 percent rate predicted by the theory. In many studies, estimated property tax capitalization rates may be lowered by expectations that some variation is temporary, and thus will not be borne by the homeowner over the long-run (See Yinger *et al*., 1988).

While the estimated parameters unit's physical attributes were suppressed from tables 4.2.1, 4.2.2, and 4.2.3, the shift to a regime-wise specification had virtually no effect on the unit attribute estimates.[22] But, the school district demographic attributes change in interesting ways. The free lunch has a significant positive sign in town and tract fixed effects models, as in Weimer and Wolkoff (2001), but this coefficient becomes insignificant in the double differenced model, Column (D). In the long run assessed value model the coefficient becomes negative. Subject to the robustness tests to be discussed below, we tentatively conclude that free lunch impairs the production of school outcomes primarily when poverty persists over longer periods of time.[23]

Hispanics have negative coefficients in the assessed value model, Column (D); the magnitude of the coefficients are cut by roughly one half (and become insignificant) in the long-run models.

[22] In fact, this finding is true throughout this paper.
[23] It is the intention of the free lunch program to increase productivity during the school day.

This makes sense if assimilation of children into the school system takes place over the five to seven years covered by our data. Rapid growth of the Hispanic school population (averaging 4 percent per year over our sample) was the main demographic issue addressed by Connecticut schools. The assimilation story is supported by the small and insignificant coefficients on percent black; the black school population was growing by only about .5 percent per year.

The results indicate an inability to separately estimate the effect of non-English speakers and Hispanics: simple correlation coefficients among the mean differenced variables are in the range of .4 to .5 for the samples used in Tables 4.2.1-3. The simple correlations between free lunch and Hispanics are about .25. Therefore, in our robustness tests, we will eliminate the non-English speaking variable but retain percent free and Hispanics.

4.3. Robustness Tests

The results from smoothed regime-wise analysis (section 4.2) suggest the importance of demographic variables in house price determination. The magnitudes of the demographic variables are different across specifications; free lunch and Hispanics are of particular concern. In this section, we attempt to see whether estimates are robust to non-linear patterns over the time period. Specifically, we examine whether demographic effects differ when we shift parameters on town variables based on the demographic structure of the towns. We categorize the towns based on percent minority (which is simply the sum of percent African-American and percent Hispanics). We divide the sample of towns into three parts: 0-5 percent minority, 5-15 percent minority and finally 15-over percent minority. We define an integrated town as one with a minority population of more than 15 percent.[24] We interact these three classification dummies with all demographic and test score variables except the one of interest. For example, the non-linear part of column (A), Table 4.3.1, reports the results for math score (-.037) when the other reported variables are interacted with the minority dummies whereas the linear column contains no interactions.[25] The regressions contain all hedonic, tract and year controls used in the previous tables.

The results show that the major findings of the assessed value models are robust to non-linear specifications. The double differencing moves two important coefficients in the expected direction: math test score changes from significant with the wrong sign in part (A) to insignificant; the effective property tax rate (EPTR) moves from insignificant to significant and in

[24] See Ondrich, Ross and Yinger (2003) which uses similar racial thresholds.

[25] We tested for non-linear effects of school district variables on house prices, but the results were not stable across our different specifications and modeling approaches. As a result, we focus on robustness of linear terms in Table 4.3.1.

the range of previous findings. These results confirm those in the earlier tables: the assessed value model appears capable of controlling most unobservables.

School outcomes as measured by math scores have no significant effect on house values in any of the assessed value models, and the percent of the school population that is black is likewise insignificant. Free lunch has no significant effect in the short run, but persistent poverty in the schools has a long-term negative effect on house values. A one percent increase in the Hispanic enrollment generally has a negative effect on house prices ranging from .5 percent in the long run model to about 1.3% in short run models.[26] It is plausible that assimilation of Hispanic children into the school system will, over time, reduce or eliminate the effect; i.e., given enough time, the Hispanic coefficient should tend to become small or even positive, similar to the coefficient on percent African-American.[27]

We replicated table 4.3.1 with non-English speaking (NEHL) instead of Hispanics (results not shown). The effect of NEHL has the same sign, but smaller magnitude, than Hispanics for the tract fixed effects and assessed value models. For the long run assessed value model, the coefficient on NEHL (-0.687) is the same magnitude as the Hispanic coefficient, and it is statistically significant (t-value of -1.96).

V. Conclusions

This paper uses a panel of school districts to examine the effects of school district outputs and demographic composition on housing prices after controlling for the influence of unobserved neighborhood attributes with fixed effects and assessed value (double differencing) models. In general, we find that people in the state of Connecticut during the study period seem to be more concerned about the changes in socio-economic and demographic attributes over time than the changes in test scores when deciding how much to pay for homes. We find no evidence that test scores have a significant positive effect on property values in Connecticut, but we find strong evidence for the influence of some school demographic characteristics.

Specifically, the analysis suggests that demographic attributes like percent free lunch (indicator of poverty), non-English speaking students (indicator of immigration), and Hispanic representation have negative effects on house prices in Connecticut. The high correlation between changes in

[26] The long run coefficients do not achieve significance in our sample, but additional years of data are likely to fully identify this coefficient.
[27] These findings are consistent with an earlier study by Clapp and Ross (2004), which found that the housing market adjusted relatively quickly to LMA wide changes in the demand for housing.

these variables prevents us from precisely identifying the individual effect of non-English speaking and Hispanics. When we eliminate the non-English speaking variable and add non-linear effects, a one percentage point increase in Hispanics reduces house prices by about 1.25 percent in the short run, and by about half that amount in the longer run model. A plausible explanation for the differences between the short and long run models is that Hispanic children are largely assimilated into the schools over five to seven years. Free lunch students have no significant effect in the short run and negative effects of about .8 percent over five to seven years. While the free lunch program may increase productivity during the school day, persistent high levels of poverty are associated with higher costs of producing educational outcomes and appear to overwhelm any mitigating effects of the program.

We find no significant effect of percent African-American students on property values. Our analysis suggests that cross-sectional studies, such as Norris (2002), may be biased towards finding a positive relationship between race and property values. The different results for blacks and Hispanics are likely the result of the seven-year period in Connecticut: black students grew by only .5 percent per year, on average, whereas Hispanic students grew by fully 4 percent per year, whereas the total school population grew by 1.8 percent per year.

Our methodology also confirms earlier findings by Black (1999): cross-sectional studies that do not control for unobservable components of neighborhood quality overstate the influence of test scores on property values. Our data indicate that a one-standard-deviation or twelve percent increase in mathematics test scores is associated with no significant change in Connecticut property values. However, the estimated effects of unit attributes on housing price are very robust and consistent with earlier studies.

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Appendix A: Data Filters

About 82,000 observations with missing tract number had no significant influence on estimated parameters when included in the town fixed effects equation.[28] Approximately, 10,000 observations are deleted because assessed value is missing. All core specifications that do not include assessed value were rerun with the larger sample. The deletion of these observations had no substantive effect on the results reported in this paper. Additional observations were deleted due to unreasonable values for age (negative values), price (below 10,000), assessed value (below 10,000), internal square footage (below 400 sq.ft.), and number of rooms and bedrooms (if the number are 0 or more than 40, or number of rooms is less than number of bedrooms). Finally, houses older than 100 years are also excluded from the sample.

Items		Number of Observations
Raw Data Set		**446,327**
Usage other than Single-Family, Two-Family, Three-Family, Condominiums, Residential Dwelling 1-3 units	less:	71,140
Missing Tract number	less:	166,014
Units owner-occupied <= 0 in tracts	less:	1,740
House Sales Price < $10,000	less:	4,842
Assessed Value < $10,000	less:	3,060
Internal Square Footage <= 400 sft, Number of Bedrooms > Number of Rooms, Units built before year 1600, Unit Age > 100 years	less:	12,395
Price per square foot, Ratio of Sales price and assessed value beyond 3 std. Dev. Limit	less:	3,550
Any missing Assessed Value	less:	10,117
Regression Sample		**173,469**

[28] Another 84,000 with missing tract numbers were also missing house attribute data.

Appendix B
Sources of bias in Estimated EPTR Coefficients

We simplify notation in the text in order to focus on econometric issues. In particular, we assume that individual property variables indexed by *i* vary at the sub-tract and sub-town level rather than make this explicit.

Definitions:

Let *i* index individual properties.
Let *t* index time. An *i* index without a t indicates that the observation is purely cross sectional, occurring at the earliest time, t_0.
Let *n* index the municipality/ school district.
Let Z_{it} = the unobserved local public services that vary within the municipality, at the property level, and over time.
Let Z'_{it} =the pure time series part of Z_{it}; Z'_{it} =0 at t_0.
Let $EPTR_{it}$ = the effective tax rate.
Let $EPTR'_{it}$ =the pure time series part of $EPTR_{it}$; $EPTR'_{it}$ =0 at t_0.
Let AV_i = assessed value that varies at the property level but not over time.
Let X_i = all other variables in the model.
Let $\ln P_{it}$ =log of sales price.
Let b(x,y) = the slope of the regression of x on y.

The model:

$$\begin{aligned}
&\ln P_{it} = \beta_0 X_i - \beta_1 EPTR_{it} + \beta_2 Z_{it} + \beta_3 AV_i + \varepsilon_{it} \\
&\beta_k > 0, k = 1,2,3. \\
&EPTR_{it} = EPTR_i + EPTR'_{it} \\
&Z_{it} = Z_i + Z'_{it} \qquad\qquad \text{(A1)} \\
&b(Z_i, Z'_{it}) > 0 \\
&b(Z_{it}, EPTR_{it}) > 0 \\
&b(AV_i, EPTR_{it}) > 0
\end{aligned}$$

The last two inequalities hold for the *i* and *t* components separately. The first inequality holds because properties with a relatively high Z at time t_0 are likely to have a relatively high Z at any later time, even if Z grows at a slower rate than those properties with a low Z at time t_0.

If we estimate the model with $EPTR_{nt}$ instead of $EPTR_{it}$, and with municipality dummies included in X (fixed effects) we will get unbiased estimates because β_1 will be identified by changes over time within municipalities. Therefore, we turn to possible bias when we ignore the joint effect of Z_{it} over space and time (i.e., the part of Z_{it} that cannot be controlled by fixed effects and time dummies).

Main result:

Estimate the model omitting Z and AV: then $-\hat{\beta}_1$ is biased upward; but if we omit only Z, the bias is reduced. These results follow from standard omitted variables reasoning.

Extended Model:

These results can be extended with the following assumptions:

$$\beta_1 = \beta_2$$
$$Z_i = gAV_i$$
$$Z_{it} = gAV_i + Z'_{it}$$
$$b(Z_{it}, EPTR_{it}) = 1$$
$$b(Z'_{it}, EPTR_{it}) < .5$$
$$b(gAV_i, EPTR_{it}) > .5$$

All would seem to be reasonable. In particular, there is much more cross sectional variation in Z than there is time variation. The assumption that there is a proportional relationship over space between AV and Z (second equation) is artificial: any sufficiently strong positive relationship gives the result.
Now when we estimate the model without Z but with AV we get:

$$E[-\hat{\beta}_1] = -\beta_1 + \beta_2 b(Z'_{it}, EPTR_{it}) = -\beta_1(1 - b(Z'_{it}, EPTR_{it}))$$

i.e., the true parameter multiplied by some number between .5 and 1.0.
This is considerably reduced from the bias when AV is also omitted:

$$E[-\hat{\beta}_1] = -\beta_1 + \beta_1 + \beta_3 b(AV_i, EPTR_{it}) = 0 + \beta_3 b(AV_i, EPTR_{it}) > 0$$

Errors-in-Variables Model

We could also consider the effects of errors in measurement of EPTR.[29] Specifically, the true variable is at the individual property level, $EPTR_{it}$, but we actually observe the municipality variable, $EPTR_{nt}$., an average over individual properties. Then the first equation in (A1) would be modified as follows:

$$\ln SP_{it} = \beta_0 X - \beta_1 EPTR_{nt} + \beta_2 Z_{it} + \beta_3 AV_i - \beta_1(EPTR_{it} - EPTR_{nt}) + \varepsilon_{it} \qquad \text{(A2)}$$

The presence of the unobservable attenuates the estimate of the β_1 coefficient. This explains the fact that $-\hat{\beta}_1$ is closer to zero than the theoretical value of -1 in our double differenced equations.

[29] AV may be measured with error also, but Clapp and Giaccotto (1992) show that this is small in Connecticut.

Table 3.1: Summary Statistics: All Years

Variable (Description)	**N**	**Mean**	**Std. Dev.**
Price Variables:			
Price (House Sales Price (000 omitted) ; tax and inflation adj. to 1994 prices)	173,469	202.011	262.674
AssValT (Assessed House Value (000 omitted))	173,469	130.880	121.699
Hedonic or House Attributes:			
Room (Number of Rooms)	173,469	5.506	3.549
Bed (Number of Bedrooms)	173,469	2.430	1.757
Bath (Number of Bathrooms)	139,376	1.987	0.889
AgeT (Age of the Building in number of decades)	173,469	3.609	2.820
Internal Square Footage in 1000s	130,142	1.772	1.068
Town/School District Attributes:			
Math (Average Math Exam Score)[30]	173,469	125.964	15.045
Read (Average Read Exam Score)	173,469	65.273	4.996
Write (Average Write Exam Score)	173,469	7.440	1.099
Free (Percent of Students qualifying for the Free Lunch Program)	173,469	20.88	21.456
NEHL (Percent of Non-English speaking students)	173,469	10.988	13.494
BlkS (Percent of Black students)	173,469	12.091	16.230
HisS (Percent of Hispanic Students)	173,469	10.093	13.291
Mill Rate (property tax rate in dollars per $1,000 assessed valuee)	173,469	31.259	13.430
Tract or Neighborhood Attributes:			
MFIT (Median Family Income in 10,000s)	173,469	5.722	2.142
BlkTT (Percent of Blacks in Tract)	173,469	5.798	12.393
HisTT (Percent of Hispanics in Tract)	173,469	4.387	7.519
OWROCDT (Percent of Owner-occupied Units in Tract)	173,469	73.089	19.773
FamCHNT (Percent of Married couples with Children in Tract)	173,469	36.407	7.253

[30] All the test scores are standardized when estimating the regression equation to facilitate the one-standard deviation change interpretation. All other town/ school district variables are divided by 100.

Table 3.2: Summary Statistics: 3-Year Regimes

	1994-1996			1998-2000		
Variable	**N**	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**
Price	55,043	196.334	234.997	88,708	210.388	287.050
AssValT	55,043	132.033	125.144	88,708	130.315	121.280
Math	55,043	122.029	15.795	88,708	128.585	14.088
Read	55,043	63.780	4.869	88,708	66.124	4.938
Write	55,043	6.613	1.039	88,708	7.828	0.883
Free	55,043	21.286	20.602	88,708	20.840	22.237
NEHL	55,043	11.629	13.190	88,708	10.804	13.672
BlkS	55,043	12.972	16.331	88,708	11.694	16.156
HisS	55,043	10.090	12.733	88,708	10.271	13.669
Mill Rate	55,043	32.270	14.568	88,708	30.986	12.767

Table 4.1.1: Math Score Comparison

Regressand: ln(house sales price)

Regressors	(A) Hedonic Baseline (eqn. 1)	(B) Hedonic: Town FE (eqn. 4)	(C) Hedonic: Tract FE (eqn. 6)	(D) Assessed Value (eqn. 9)
ln(AssValT)				0.756 (55.50)
Hedonics:				
Room	0.029 (10.78)	0.026 (10.30)	0.027 (11.20)	0.009 (5.29)
Bed	0.005 (1.23)	0.004 (1.01)	0.003 (0.97)	0.001 (0.12)
AgeT	-0.061 (-11.45)	-0.063 (-13.76)	-0.068 (-15.29)	-0.017 (-4.96)
AgeT-squared	0.002 (3.31)	0.0016 (3.77)	0.002 (5.15)	0.001 (0.76)
Internal Square Footage[31] *< 2500*	0.435 (25.92)	0.478 (30.76)	0.462 (31.01)	0.148 (13.77)
Internal Square Footage >= 2500	0.200 (4.21)	0.153 (3.56)	0.159 (3.65)	-0.017 (-0.70)
Town/School:				
Math	0.110 (7.79)	0.006 (0.78)	0.006 (0.81)	0.003 (0.35)
Free/100	-0.573 (-7.31)	0.071 (1.08)	0.047 (0.75)	-0.241 (-2.11)
NEHL/100	0.511 (3.74)	-0.363 (-2.15)	-0.366 (-2.24)	-0.635 (-3.04)
BlkS/100	0.380 (5.67)	0.112 (0.60)	0.145 (0.79)	0.069 (0.19)
HisS/100	0.252 (1.37)	-0.653 (-2.23)	-0.688 (-2.43)	-0.802 (-2.23)
EPTR	-0.556 (-8.33)	-0.009 (-0.24)	0.011 (0.33)	-0.228 (-4.06)
Tract:				
MFIT	0.079 (14.21)	0.059 (10.52)		
BlkTT	-0.472 (-5.70)	-0.523 (-7.88)		
HisTT	-0.645 (-5.89)	-0.824 (-8.71)		
OWROCDT	0.024 (0.51)	0.015 (0.44)		
FamCHNT	-0.368 (-2.92)	-0.098 (-1.00)		
FE Dummies?	No	Town	Tract	Tract
Adj. R^2	0.6833	0.3771	0.7145	0.4440
N	173,469	173,469	173,469	154,056

[31] Note we have specified a spline here. Also note that in the regression we put logarithm of internal square footage.

Table 4.1.2: Read Score Comparison

Regressand: ln(house sales price)

Regressors	**(A)** **Hedonic Baseline (eqn. 1)**	**(B)** **Hedonic: Town FE (eqn. 4)**	**(C)** **Hedonic: Tract FE (eqn. 6)**	**(D)** **Assessed Value (eqn. 9)**
ln(AssValT)				0.756 (55.64)
Read	0.086 (6.28)	-0.002 (-0.27)	-0.003 (-0.35)	-0.033 (-4.01)
Free/100	-0.570 (-7.03)	0.068 (1.03)	0.044 (0.70)	-0.247 (-2.18)
NEHL/100	0.566 (4.08)	-0.355 (-2.10)	-0.358 (-2.18)	-0.695 (-3.22)
BlkS/100	0.303 (4.65)	0.086 (0.46)	0.116 (0.63)	0.014 (0.04)
HisS/100	0.096 (0.53)	-0.640 (-2.21)	-0.676 (-2.41)	-0.879 (-2.46)
EPTR	-0.566 (-8.25)	0.076 (0.21)	0.010 (0.30)	-0.227 (-4.08)
Adj. R^2	0.6828	0.4272	0.7160	0.4444
N	173,469	173,469	173,469	154,056

Table 4.1.3: Write Score Comparison

Regressors	**(A)** **Hedonic Baseline (eqn. 1)**	**(B)** **Hedonic: Town FE (eqn. 4)**	**(C)** **Hedonic: Tract FE (eqn. 6)**	**(D)** **Assessed Value (eqn. 9)**
ln(AssValT)				0.756 (55.54)
Write	0.064 (8.43)	-0.00004 (-0.01)	-0.0002 (-0.05)	-0.007 (-1.15)
Free/100	-0.663 (-8.48)	0.069 (1.05)	0.046 (0.72)	-0.248 (-2.13)
NEHL/100	0.513 (3.75)	-0.353 (-2.10)	-0.357 (-2.18)	-0.625 (-2.98)
BlkS/100	0.284 (4.41)	0.092 (0.49)	0.124 (0.68)	0.076 (0.21)
HisS/100	0.065 (0.37)	-0.635 (-2.18)	-0.670 (-2.37)	-0.796 (-2.23)
EPTR	-0.580 (-8.79)	0.008 (0.22)	0.010 (0.31)	-0.230 (-4.12)
Adj. R^2	0.6827	0.4272	0.7160	0.4444
N	173,469	173,469	173,469	154,056

Table 4.2.1: Regime-wise Math Score Comparison

Regressand: ln(house sales price)

Regressors	**(A) Pooled Hedonic: Baseline 1994-96 & 1998-00**	**(B) Smoothed Estimates: Town FEs (eqn. 4)**	**(C) Smoothed Estimates: Tract FEs (eqn. 6)**	**(D) Smoothed Estimates: Assessed Value (eqn. 9)**	**(E) Smoothed Estimates: Assessed Value (eqn. 9)**
Math	0.127 (23.51)	-0.011 (-0.74)	-0.026 (-1.31)	-0.003 (-0.15)	-0.004 (-0.20)
Free/100	-0.502 (-14.48)	0.360 (1.81)	0.346 (2.77)	0.032 (0.21)	-0.737 (-3.10)
NEHL/100	0.539 (12.16)	-0.521 (-1.70)	-0.346 (-1.23)	-0.190 (-0.58)	-0.592 (-1.63)
BlkS/100	0.461 (20.03)	-0.121 (-0.27)	-0.028 (-0.11)	0.055 (0.11)	0.190 (0.29)
HisS/100	0.360 (5.16)	-0.973 (-1.41)	-1.523 (-4.19)	-1.243 (-2.50)	-0.506 (-1.03)
EPTR	-0.796 (-28.33)	-0.120 (-1.38)	-0.121 (-1.68)	-0.363 (-4.51)	-0.614 (-5.81)
Adj. R^2	0.6954	0.3772	0.7160	0.4440	0.4510
N	173,469	143,751	143,751	154,056	117,934

Table 4.2.2: Regime-wise Read Score Comparison

Regressand: ln(house sales price)

Regressors	**(A) Pooled Hedonic: Baseline 1994-96 & 1998-00**	**(B) Smoothed Estimates: Town FEs (eqn. 4)**	**(C) Smoothed Estimates: Tract FEs (eqn. 6)**	**(D) Smoothed Estimates: Assessed Value (eqn. 9)**	**(E) Smoothed Estimates: Assessed Value (eqn. 9)**
Read	0.088 (18.15)	-0.0008 (-0.05)	0.007 (0.42)	-0.046 (-2.74)	-0.054 (-2.76)
Free/100	-0.542 (-15.04)	0.353 (1.77)	0.326 (2.63)	0.037 (0.25)	-0.725 (-3.08)
NEHL/100	0.582 (12.94)	-0.556 (-1.80)	-0.469 (-1.79)	-0.203 (-0.62)	-0.565 (-1.52)
BlkS/100	0.368 (16.76)	-0.095 (-0.21)	0.083 (0.34)	-0.032 (-0.07)	0.110 (0.17)
HisS/100	0.170 (2.30)	-0.998 (-1.45)	-1.547 (-4.27)	-1.466 (-2.91)	-0.80 (-1.51)
EPTR	-0.788 (-27.93)	-0.113 (-1.32)	-0.114 (-1.60)	-0.347 (-4.36)	-0.599 (-5.69)
Adj. R^2	0.6950	0.3772	0.7160	0.4444	0.4510
N	173,469	143,751	143,751	154,056	117,934

Table 4.2.3: Regime-wise Write Score Comparison

Regressand: ln(house sales price)

Regressors	(A) Pooled Hedonic: Baseline 1994-96 & 1998-00	(B) Smoothed Estimates: Town FEs (eqn. 4)	(C) Smoothed Estimates: Tract FEs (eqn. 6)	(D) Smoothed Estimates: Assessed Value (eqn. 9)	(E) Smoothed Estimates: Assessed Value (eqn. 9)
<u>*Write*</u>	0.098 (24.05)	0.003 (0.31)	0.000 (0.04)	0.004 (0.55)	0.008 (0.93)
Free/100	-0.618 (-18.62)	0.351 (1.74)	0.325 (2.63)	0.032 (0.21)	-0.735 (-3.12)
NEHL/100	0.587 (13.03)	-0.551 (-1.77)	-0.465 (-1.74)	-0.191 (-0.58)	-0.605 (-1.67)
BlkS/100	0.429 (19.05)	-0.088 (-0.19)	0.054 (0.22)	0.068 (0.14)	0.216 (0.33)
HisS/100	0.166 (2.37)	-0.999 (-1.44)	-1.566 (-4.20)	-1.248 (-2.52)	-0.506 (-1.02)
EPTR	-0.818 (-29.20)	-0.112 (-1.31)	-0.110 (-1.54)	-0.363 (-4.51)	-0.614 (-5.80)
Adj. R^2	0.6995	0.3772	0.7160	0.4444	0.4510
N	173,469	143,751	143,751	154,056	117,934

Table 4.3.1: Robustness of Findings to Non-Linear Town Controls – Smoothed Analysis[32]
Regressand: ln(house sales price)

	(A)[33] Hedonic Tract Fixed Effect		**(B)[34] Assessed Value Model**		**(C)[35] Assessed Value Model (Long Run)**	
	Linear	Non-Linear	Linear	Non-Linear	Linear	Non-Linear
<u>*Math*</u>	-0.032 (-1.71)	-0.037 (-1.96)	-0.003 (-0.19)	-0.005 (-0.30)	-0.005 (-0.23)	0.004 (0.20)
Free/100	0.351 (2.82)	0.315 (2.43)	0.022 (0.15)	0.069 (0.44)	-0.801 (-3.39)	-0.786 (-3.00)
BlkS/100	0.030 (0.13)	0.013 (0.05)	0.101 (0.21)	0.077 (0.20)	0.324 (0.53)	0.173 (0.44)
HisS/100	-1.671 (-4.99)	-1.545 (-4.46)	-1.315 (-2.81)	-1.208 (-2.47)	-0.684 (-1.50)	-0.474 (-1.04)
EPTR	-0.119 (-1.65)	-0.101 (-1.30)	-0.358 (-4.53)	-0.331 (-4.22)	-0.592 (-5.60)	-0.498 (-4.98)
N	143,751	143,751	154,056	154,056	117,934	117,934

[32] All the 18 models exclude percent Non-English Speakers due to correlation with percent Hispanic students. Non-linear specification includes interacted terms with percent minority categories (5-15 percent and 15-100 percent).
[33] Sample size is after dropping transactions in 1997.
[34] Sample size is after dropping transactions in assessment year.
[35] Sample size is after dropping transactions within one year of assessment year.