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INCOME INEQUALITY, THE MEDIAN VOTER AND THE SUPPORT FOR PUBLIC EDUCATION*

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ABSTRACT: The financing of public education in the U.S. has traditionally been very decentralized, with nearly half of all revenues coming from localities. As a consequence, per-pupil spending has historically been closely tied to the characteristics of local districts. Wide differences in income or property wealth have produced significant variation in per-pupil spending across districts, prompting many states to enact sweeping finance reforms in recent decades. While much has been written about the relationship between income inequality and spending disparities *across* jurisdictions, less is known about the consequences of rising inequalities *within* school districts. Income inequality in U.S. districts has risen nearly 16 percent since 1969, at the same time districts have become more heterogeneous along other dimensions. The question of how these trends in within-district inequality have affected school financing has gone largely unexplored.

In this paper, we use a panel of 8,700 school districts from 1970-2000 to explore how rising within-district income inequality has affected support for education. We measure support in two ways—local tax dollars and student participation in public schools—and examine the impact of rising inequality on both per-pupil revenues and the fraction of students in private schools. We find that rising income inequality within districts actually *increases* local per-pupil spending, a finding consistent with a median voter model, in which rising income inequality in the top of the income distribution reduces the tax price of school spending to the median voter. Income inequality appears to have little impact on private schooling.

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I. INTRODUCTION

Traditionally, public elementary and secondary education has been highly decentralized in the United States, with a large proportion of funds coming from local sources. The local share of school revenues is dominated by the property tax, which accounts for more than 96 percent of locally raised revenues in independent school districts; this share is below 90 percent in only three states (Kentucky, Louisiana, and Pennsylvania). The historical consequence of a decentralized system of education finance and an overwhelming reliance on the property tax has been a close link between the wealth and/or income of a community, and its per-pupil funding of education.

That community characteristics are reflected in how well or how poorly local schools are financed is a surprise to no one. In the textbook economic model of local community formation (Tiebout 1956), families sort themselves into communities that provide the level of public goods they want. In this model, the end result is a series of communities with homogenous preferences for public goods. In the real world, however, there are numerous barriers to mobility that produce heterogeneity in tastes and characteristics in local populations. Because communities are heterogeneous, economists and social scientists have in recent years begun exploring in both empirical and theoretical work the impact of population heterogeneity on public finance in general and local school finance in particular.

Heterogeneity within school districts has risen markedly since 1970.[1] Districts have not only become more racially and ethnically diverse, but also more heterogeneous in age, educational attainment, native language and country of birth, religious preference, home

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[1] We show this to be true along a number of dimensions in a sample of 8,700 public school districts, in Section III.

ownership rates, and wealth. Inequality in income is another important form of rising population heterogeneity within school districts. Measured at the national level, household income inequality rose over 16 percent between 1969 and 1999 (as measured by the Gini coefficient); about three quarters of all U.S. school districts experienced a rise in income inequality to some degree over this period.[2]

A growing empirical literature in public economics seems to suggest that heterogeneity within jurisdictions tends to reduce the support for public programs. For example, Luttmer (1999) finds using data from the General Social Survey that while individual support for welfare redistribution *decreases* in the total number of area welfare recipients, support *increases* with the fraction of local recipients belonging to one's own racial group. Similarly, Alesina, Baqir and Easterly (1999) show in a cross-section of metropolitan areas in 1990 that expenditures on productive public goods like education, roads, libraries, sewers and trash pickup are negatively related to within-MSA ethnic fragmentation. The authors conclude that (p. 2) "...voters choose lower public goods when a significant fraction of tax revenues collected on one ethnic group are used to provide public goods shared with other ethnic groups." Alesina, Glaeser and Sacerdote (2001) argue that differences in U.S. and European support for welfare spending can be largely explained by interpersonal preferences—because welfare recipients in the United States are disproportionately black, the majority of (non-black) voters seem to be unwilling to support a generous system of redistribution.

Explanations for these findings have varied. Alesina, Baqir, and Easterly's model, for example, proposes that a voter's willingness to support public spending depends on how close

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[2] See http://www.census.gov/hhes/income/histinc/ie6.html (access date August 9, 2003) for Census data on nationwide household income inequality. We show in Section IIIC that rising income inequality has not been strictly a between-district phenomenon.

their preferred use of funds is to their anticipated use (that use preferred by the median voter). As preferences become more polarized, the typical voter becomes more likely to disagree with the median voter over the ultimate use of funds and chooses to reduce their support for public spending altogether. Here, the disagreement is not over the *level* of spending per se, but rather the *type* of spending. Initial support for local spending is negatively affected by anticipated discord over the use of tax dollars. Luttmer suggested a special case of this model involving interpersonal preferences, where a voter's support for a public program depends on the share of beneficiaries who come from the same socioeconomic or ethnic group.

[Briefly mention here median voter papers on welfare redistribution].

The link between income inequality and school finance has also received some attention. Epple and Romano (1996), for example, develop a theoretical model that shows how rising income inequality may be harmful for school spending. They describe this problem as the "ends against the middle," where high-income households oppose spending on public schools because of their high demand for private schools, and poorer families prefer lower taxes and expenditure in general. Goldin and Katz (1997) find some support for this model in their analysis of the development of secondary schooling in the United States. They find evidence that income inequality slowed the development of secondary schooling in some communities during the first half of the 20th century, in part due to the opposition of high- and low-income families to spending on public education.

Although the rise in income inequality over the past 30 years has helped spark research in the real consequences of population heterogeneity, this is by no means a new topic in public finance. Over 20 years ago, Meltzer and Richard (1981) examined the impact of income inequality on the size of government within a median voter framework. The authors note that in the standard median-voter model, since the tax price to the decisive voter is the ratio of the median to mean income, a rise in income inequality coming from an expansion of incomes at the top of the distribution will reduce the cost of raising funds and lead to an expansion in the size of government.

In this paper, we use the demographic characteristics from a national panel of 8,700 unified school districts in 1970, 1980, 1990, and 2000 to explore how rising within-district income inequality has affected local support for public education. We measure support for education in two ways—local tax dollars and student participation in public schooling—and examine the impact of income inequality (and other forms of population heterogeneity) on both local education revenues per student and the fraction of students within district boundaries who enroll in private schools. We utilize a within-group estimator that holds constant the permanent unobserved characteristics of school districts and examines whether changing within-district support for schools over time is correlated with changes over time in population heterogeneity. Because school spending varies considerably across states and time, we also hold constant changes in spending that are common to all districts in a state for a given year.

In contrast with much of the recent theoretical and empirical work, suggesting a negative link between income inequality and public finance, we find results consistent with the median voter model. First, we find that rising income inequality within a school district actually increased the level of real per-pupil expenditure at the local level. In more detailed models, we find that increases in inequality in the top of the income distribution (which reduce the tax price) increased spending but changes in inequality that occur due to falling incomes at the bottom of the distribution (which increases the tax price) reduced spending. Interestingly, changes in income inequality at both the bottom and top of the distribution that produce equivalent changes in aggregate income, had similar but opposite signed effects on local finance, again a result predicted by the median voter model. We also find that increased heterogeneity in race and schooling reduce per-pupil expenditure somewhat; greater racial heterogeneity within a school district also tends to increase the proportion of children who enroll in private schools. Income inequality appears to have little impact on private schooling.

This paper is organized as follows. In Section II, we argue that despite opportunities to migrate between jurisdictions (a key assumption of the Tiebout hypothesis), communities in practice are in fact quite heterogeneous. Given that perfect stratification of households is rare, we explore some of the ways in which heterogeneity might affect support for schools by presenting a simple median voter model of school spending; we also briefly review other literature on this subject. Section III describes our empirical model and data. Section IV presents our results, and Section V concludes.

II. HETEROGENEITY AND COLLECTIVE CHOICE

A. Tiebout Sorting and Population Heterogeneity

Before we address why heterogeneity within a community might affect the demand for local public goods, a prerequisite question might be: why would local communities have heterogeneous populations? The benchmark local public finance theory of community formation—that of Tiebout (1956)—largely ignores heterogeneity within jurisdictions by assuming that households costlessly sort into homogeneous communities that offer their preferred level of public services.[3] Multiple jurisdictions, together with zoning regulations and a

[3] We emphasize that perfect Tiebout sorting implies homogeneity in *preferences* for public spending, not necessarily in observed characteristics (see Hamilton (1976), Epple and Platt (1998)). In practice, however, demand for education spending appears to be strongly correlated across households with similar

property tax, create an efficient "market" for public goods in which each household exactly satisfies their demand for public services, and (through the capitalization of taxes and benefits into property values) faces a "price" commensurate with their level of demand for those services.[4]

The Tiebout model predicts homogeneity of preferences within local communities. In practice, we do not observe preferences but instead, correlates of preferences, such as income, wealth, age, race, education, etc. Even with this noisy measure of preferences, communities are often much more heterogeneous than the Tiebout model might predict.[5] Labor market decisions, moving costs, government interventions into the housing market, infrequent entry and exit of governments, the bundling of public services, and imperfect information about communities all act as barriers to perfect sorting across jurisdictions. Communities also seem to be willing to tolerate some heterogeneity in the population in return for economics of scale in the production of public goods; Alesina, Baqir, and Hoxby (2000) find evidence for such a tradeoff in U.S. school districts, municipalities, and special districts over the 1960—1990 period.

Yet even as Tiebout "market imperfections" have mitigated over time, communities remain significantly less homogeneous than one would expect.[6] In a recent paper, Rhode and

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observed characteristics. [Briefly mention empirical work on the demand for public spending on education, relationship with income].

[4] Hamilton (1975) introduced the idea of municipal zoning into the original Tiebout model. Zoning acts not only as a barrier to entry (resulting in an inelastic supply of housing in the locality) but also as a tool in which municipalities can indirectly set the tax price that households pay for local services.

[5] In the words of Oates (1981), "the pure [Tiebout] model … involves a set of assumptions so patently unrealistic as to verge on the outrageous."

[6] Rhode and Strumpf (2003) argue that improvements in transportation and communications technology have contributed to large reductions in moving costs over time; Fischel (2001) claims that the suburbanization of America has minimized the importance of labor market decisions and commuting costs in household location decisions, and increased households' ability to sort among jurisdictions.

Strumpf (2003) document a persistent *decline* in stratification by race, income, education, and age (as well as other proxies for public spending preferences) across U.S. municipalities and counties over the past century, despite plummeting mobility costs that in theory should have facilitated *greater* Tiebout sorting. Perhaps the most striking of their findings relates to income—they show that within-county income inequality has remained roughly constant since 1949 (declining over the 1949-1979 period, and then rising thereafter), while between-county inequality declined over the 1949-1979 period (but rose modestly during the 1980s). This result parallels a similar finding for counties within the Boston metropolitan area over the same years. The authors interpret these results as evidence of little, if any, increase in sorting by income across U.S. counties over time.[7]

Other authors have pointed out patterns or trends in demographics that appear on the surface to be inconsistent with perfect Tiebout sorting. Pack and Pack (1978) in a frequently cited paper find sufficiently large variation in income and house prices within communities in Pennsylvania MSAs to rule out perfect Tiebout sorting. Cutler, Glaeser and Vigdor (1999)—while not intended as a test of the Tiebout hypothesis per se—find evidence of a persistent increase in racial integration within census tracts in metropolitan areas, and particularly in suburban tracts, since 1970.[8]

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[7] The sharp decline in the number of local jurisdictions over this period of falling mobility costs would also appear to support this conclusion.

[8] It should be pointed out that race and ethnicity continue to be important correlates with preferences over local policies, independent of income. A recent article in *The Washington Post* about opinions in Prince George's County, Maryland—a county described in the article as "a symbol of black affluence"—is illustrative: "A stark divide exists in the way blacks and whites view a broad spectrum of institutions and conditions in Prince George's County, from the police and public schools … Blacks were twice as likely to be satisfied with the public schools and to view the police force as being overly aggressive … Half of blacks said African Americans do not hold enough political power, [and] half of the whites said it would be better if more whites moved to Prince George's." ["Prince George's Split Along Race Lines, Poll Shows," August 25, 2002].

The question of how much heterogeneity is sufficient to refute the Tiebout hypothesis persists, and none of these findings should be taken as prima facie evidence against Tiebout sorting. Indeed, a score of capitalization studies, beginning with Oates (1969), have demonstrated that homebuyers almost certainly take local policies into account when making their housing investments. They do, however, suggest that forces other than Tiebout sorting have been important enough to prevent perfect stratification of households across communities along demographic characteristics—a condition that is key to our analysis that follows.

B. A Median Voter Model of School Expenditure

Absent the ability (or desire) to sort into perfectly homogeneous jurisdictions, conflicting household demands for public goods must instead be resolved through the political process.[9] When public decisions are made through non-market processes, it becomes necessary to consider the mechanism through which household preferences are aggregated into a collective choice. In the public finance literature, the median voter model remains a simple yet powerful tool for modeling the demand for public goods in heterogeneous communities. Under certain conditions (among other things, preferences that are single-peaked), the median voter model predicts that voting by majority rule over a single-dimensional public good will result in the provision of the median voter's desired level of public services.

Suppose there are H households in a school district, each containing one school aged student, and one voter. Household income y_h is exogenous and distributed according to $f(y_h)$, a non-symmetric income distribution. Preferences over public schooling and private consumption are identical across households, and are given by the following utility function for household h:

(1) $u(g, c_h)$

where $g = G/H$ is per pupil expenditure (the same for all households), G is the total school budget, H is the number of households and c_h is private consumption (the price of both g and c_h is assumed to be one).

School district residents determine by majority vote the size of the district budget G, as well as a constant proportional tax rate on income t.[10] The individual household and government budget constraints are given by (2) and (3), respectively:

(2) $y_h = c + ty_h$

(3) $$G = tH\int_h y_h f(y_h) = tH\mu_y$$

It is illustrative to combine (2) and (3), noting that $t\mu_y = g$ (that is, that per-pupil expenditure G/H must equal the expected income tax per household), and re-write the household's budget constraint as:

(4) $$y_h = c + \left(\frac{y_h}{\mu_y}\right)g$$

In this expression, the term in brackets represents the "tax price" of an additional unit of per-pupil expenditure to household h. Solving the household's optimization problem is

[9] Drazen (2000) points out that even when preferences for public goods are identical within a community, voters often have the incentive to disagree over the incidence of taxation (he refers to this as *ex-post* heterogeneity in the electorate).

[10] Most school districts in the United States finance local school expenditures via property taxes, not income taxes—the average unified school district in 2000-01 received 65 percent of its local revenues from property taxes, and less than 1 percent from income taxes (see U.S. Bureau of the Census (2001)). Our interest in this paper, however, is the effect of income inequality on school spending. While income and housing values are highly correlated, we acknowledge the limitations of this model. [Need to more fully explore the different implications of income and property tax financing].

straightforward, and results in the following first order condition which characterizes the preferred level of per-pupil spending for household *h*:

$$(5) \qquad \frac{u_g}{u_c} = \left(\frac{y_h}{\mu_y} \right)$$

If $u(\cdot)$ is quasi-concave, preferences will be single-peaked and the median voter theorem will apply — the majority voting outcome will be that level of g demanded by the household with the median income (y_m). In this simple case, the level of per-pupil spending observed in each school district will be a function of both the median income in the district and the tax price to the median household (which differs from one whenever the distribution of income is skewed, and in particular will be less than one whenever $y_h < \mu_y$). As the median voter's tax share falls—as when, for example, the mean income in the district grows relative to the median—the price of an additional unit of school spending to the median voter falls, and the median voter will optimally choose a higher level of per-pupil expenditure.[11] In this scenario, an increase in income inequality that raises the mean district income relative to the median income should be expected to *increase* per-pupil spending.[12]

Demand for g may not, however, be monotonic in income.[13] If both low- and high-income households prefer lower levels of per-pupil expenditure, per-pupil expenditure may have no clear systematic relationship with median income (the household with the median income will no longer be the decisive voter), and any increase in income inequality that results in higher

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[11] Whether or not the median voter outcome is socially efficient is another question (it will not be, in general)—see Rubinfeld (1987).

[12] Extending this model to allow for the disincentive effects of taxation do not qualitatively change this result—see Meltzer and Richard (1981).

[13] See Stiglitz (1974).

concentrations of households in the tails of the income distribution is likely to result in *lower* levels of per-pupil spending. Thus, even the most basic theory of public expenditure is ambiguous as to how income inequality will affect school spending. When demand is monotonic in income, greater income inequality will tend to increase expenditure (if greater income inequality represents a lower tax price for the median income household); it tends to lower expenditure when demand is not monotonic in income (a case of “the ends against the middle”).

The introduction of private schooling alternatives considerably complicates this theoretical analysis, as other authors, including Stiglitz (1974), Epple and Romano (1996), and Glomm and Ravikumar (1998) have pointed out. Both Glomm and Ravikumar (1998) and Epple and Romano (1996) prove the existence of a majority-voting equilibrium in the presence of private alternatives—in the former, the focus is on an equilibrium in which the voter with the median income is decisive, in the latter several possible equilibria are shown to exist. Epple and Romano argue that for public goods like education, the likely majority voting equilibrium will be one in which there are two opposing coalitions of voters—one comprised of high- and low-income households who prefer a low level of expenditure on public education (with high-income households opting for private schooling alternatives), and another made up of middle-income households who prefer a high level of public expenditure on education. Thus, where private schooling alternatives exist, greater income inequality may increase the likelihood of an “ends against the middle” outcome, with lower spending on education and higher rates of private schooling.

While the model presented in this section provides few clear predictions about the impact of income inequality and population heterogeneity on support for public education, it does illustrate some of the ways in which diversity in the local population might affect school financing and overall participation in the public schools. It remains an empirical question as to how these forms of heterogeneity actually do affect public support for education in practice. Before introducing our own empirical model in Section III, we briefly review in the following section the results from a recent empirical literature that has begun to explore the relationship between local population heterogeneity and local support for public schools.

C. Related Literature: Heterogeneity and Support for Public Schooling

A small but growing literature has begun to study the impact of heterogeneity on local support for public education. Like the work mentioned in the introduction, much of this literature finds a negative relationship between heterogeneity and the support for education. For example, Poterba (1997), Murray and Ladd (2000), and Harris, Evans, and Schwab (2001) show that per-pupil education spending within school districts declines with the elderly share, an observation consistent with an elderly preference to vote down public programs that they themselves do not benefit from.[14]

In a study of the growth of secondary schooling the United States during the early part of the 20th century, Goldin and Katz (1997) find that localities that supported the expansion of secondary schools were more likely to have relatively equal income distributions, as well as populations that were homogeneous in religious or ethnic background. Hoxby (1998) points out that the time pattern of spending inequality across school districts closely follows that of national income inequality—i.e. "the two decades in which spending inequality rose the most (the 1930's

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[14] Both Harris et al and Murray and Ladd find that this effect is less pronounced at the local level, where elderly homeowners are likely to benefit indirectly from education spending via property values.

and the 1970's) were also decades of rising income inequality. The decade in which spending inequality fell the most (the 1940's) was a decade of falling income inequality" (p. 310).

[Look for additional and more recent work on this subject].

A smaller literature has looked at the impact of local population heterogeneity on private school enrollment. Betts and Fairlie (2003) use household-level Census data from 1980 and 1990 to test whether a rising foreign-born population is associated with higher enrollment of (native-born) white students in private schools. While they find no relationship between immigration and enrollment in private elementary schools, they do find a statistically significant impact of immigration on enrollment in private secondary schools (they attribute this effect primarily to differences in the native languages of school-aged children). Clotfelter (1997) finds that private school enrollment is positively affected by income inequality and the presence of nonwhites in the public schools. [Review this paper again]. Hoxby (2000) includes measures of income inequality and racial and ethnic heterogeneity in district- and MSA-level regressions in a paper assessing the impact of school district competition on private school enrollment, school expenditure, and student achievement, but—because her paper focuses on the effects of competition between school districts and not heterogeneity per se—does not discuss her empirical findings on these measures. In a study of the impact of school finance equalization programs on private school enrollment, Hoxby (2001) find not statistically significant relationship between income inequality and private schooling shares.

Finally, in a separate context some authors have treated income inequality or other measures of within-district heterogeneity as endogenous variables; many of these papers might be characterized as tests of the Tiebout sorting hypothesis within metropolitan areas. Urquiola (2000), for example, examines how competition between school districts within metropolitan areas affects the level of ethnic heterogeneity and income inequality within school districts. He finds that greater competition within MSAs tends to result in greater homogeneity in income and race within school districts located in those MSAs. Aaronson (1999) finds that the school finance reforms of the 1970s and 1980s (which effectively reduced the level of between-district competition in affected states) reduced sorting by income across school districts (which he measures using within-district measures of income inequality).[15]

Through our empirical model introduced in the next section, we hope to contribute to this literature by examining the relationship between changes in within-school district income inequality over time (and two other dimensions of population heterogeneity—race and schooling fractionalization) and support for public education, as measured through per-pupil spending, and private school enrollment.

III. Empirical Model and Data

A. Econometric Strategy

The goal of this paper is to examine how rising within-district income inequality has affected the support for public education. The stylized model and subsequent discussion in Section II suggested several ways that increased heterogeneity might affect this support. First, when demand is monotone in income, increased income inequality may represent a reduction in the tax price to the voter with the median income, yielding an increase in the overall level of spending. Second, even if demand is monotone with income, heterogeneity in preferences over the nature of school spending may result in reduced support for public education if households find themselves unable to agree over the allocation of school funds. Interpersonal preferences

[15] See also Eberts and Gronberg (1981), Grubb (1982), and Schmidt (1992), for other empirical studies that treat within-district income inequality as an endogenous variable.

that reflect households' willingness to support members of other racial or socioeconomic groups may also be important in this context. Third, where private schooling alternatives exist, rising income inequality may result in a coalition of the "ends against the middle," where low- and high-income households reduce their support for public education (and the high-income households enroll in private schools). Finally, to the extent that mobility is an option, some households may respond to greater within-district heterogeneity through exit.

In this section, we present an empirical model designed to explore how changes in within-district heterogeneity over time are associated with changes in local support for public education. We estimate this model with a balanced panel of roughly 8,700 school districts in the United States over a 30-year period.[16] The panel structure of our data allows us to control for certain unobserved characteristics correlated with tastes for education spending and private schooling that a cross-sectional analysis would not, a feature we describe in further detail below.

Our basic empirical model is as follows:

$$(6) \qquad y_{ijt} = X_{ijt}\beta + H_{ijt}\gamma + \delta_{ij} + S_{jt} + \varepsilon_{ijt}\,.$$

Our endogenous variable y_{ijt} is, alternately, local per-pupil education revenues in district *i* in state *j* in year *t*, and the fraction of students within district *i*'s boundaries enrolled in private school in year *t*.[17] X_{ijt} is a vector of (exogenous) demographic and socioeconomic characteristics in district *i* in year *t* thought to be correlated with tastes for school expenditure and private schooling, while H_{ijt} is a vector of within-district heterogeneity. Specifically, we include in X_{ijt} measures of the racial composition of the district, median family income, the fraction of households in poverty, the share of housing units in the district that are owner-occupied, and the educational attainment

[16] This data is described in more detail in Corcoran (2003), and in the data appendix to this paper.

of district residents.[18] H_{ijt} includes measures of within-district income inequality, and race and schooling fractionalization. The error term ε_{ijt} is assumed to have a zero mean and constant variance.

Because much of the variation in local revenues and private school enrollment shares is between districts—not within districts over time—we include district fixed effects (δ_{ij}) in each model. While much of the between-district variation in spending and private school enrollment can be explained through observed district characteristics, one might be concerned that there are unobserved characteristics (e.g., a stronger preference for education) that are correlated with our right-hand-side variables of interest (e.g., income). Our district fixed-effects will capture any of these unobserved characteristics that are permanent within districts over time.

Likewise, some of the variation in school revenues and private schooling shares may be due to state-specific trends in or shocks to these variables that are also correlated with our right-hand side variables. For example, a statewide economic downturn may affect both local revenues for education and income inequality. We include year-specific state effects S_{jt} in each of our models to capture any such trends.[19]

Taken together, our empirical model estimates how local per-pupil revenues and private school enrollment shares change as population demographics and within-district income

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[17] Per-pupil revenues and per-pupil expenditures are nearly identical measures (revenue data excludes capital expenditures), so we will use these terms interchangeably.

[18] The inclusion of these variables follows a long tradition of empirical estimation of demand functions for local public goods. See Bergstrom and Goodman (1973) for the seminal empirical work on the demand for local public goods. Lovell (1978), Brown and Saks (1985), Brazer and McCarty (1987), Rubinfeld and Shapiro (1989), Santerre (1989), Magna and Lee (1990), and Sass (1991) all provide examples of empirical estimates of demand functions for school spending. Most models typically include a "tax price" as a right-hand-side variable. We do not, however as discussed in Section 3.2, our measure of income inequality may proxy for the tax price to the median voter.

heterogeneity change over time, absent any trends in these variables within a state. Our use of district fixed-effects implies that we are using a within-group estimator, which means that we will use within-district variation in population heterogeneity and spending over time to identify our parameter of interest (γ).

One might be concerned that some of the changes over time in within-district income heterogeneity are in response to the policies or performance of local school districts (in particular, to the spending policies of the district). Work by Urquiola (2000), Aaronson (1999), and others discussed in the previous section suggested that income inequality within school districts might in part be a function of the competitiveness of the local market for education. Where households have a greater ability to Tiebout-sort into neighboring districts, dissatisfaction with local school spending may result in out-migration and a subsequent change in the local income distribution. To the extent this sorting occurs, our heterogeneity measures H_{ijt} will be endogenous and ordinary least squares estimates of γ will be biased and inconsistent.

We deal with the potential endogeneity of H_{ijt} in several ways. First, we estimate (6) using subsamples of low-mobility districts (as measured by the percent of residents who lived in a different county five years earlier) and districts located outside of metropolitan areas, where Tiebout sorting would seem less likely to be an important force. Next, we estimate an instrumental variables model, where we instrument for within-district income inequality using a measure of income inequality from a nearby district outside a specified distance. The idea here is to identify the effect of local income inequality only with that portion of within-district income inequality that is attributable to regional labor market conditions, not to inter-district sorting.

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[19] We will also be estimating this model on a sample of school districts within metropolitan areas. In those specifications, we include year-specific MSA effects, rather than state-year effects.

B. *Data Sources*

The empirical strategy outlined above requires a dataset that contains school-district level demographic and financial data, together with detailed measures of within-district population heterogeneity and income inequality. There is no readily available data source that meets all of these criteria—however, we constructed such a data set by merging eight national school district data sources: the *1970 Census of Population and Housing Special Fifth-Count Tallies,* the *1980 Census of Population and Housing Summary Tape File 3F,* the *1990 Census School District Special Tabulation,* the *2000 Census of Population and Housing School District Tabulation (STP2),* the *1972, 1982, and 1992 Census of Governments: School Districts,* and the *2000-01 F-33 School System Finance File.*[20] The first four of these data sets provide detailed information about the demographic characteristics of the population living within each U.S. school district, while the latter represent the primary historical source of school finance data in the United States. By merging these eight data sources, we were able to construct a national panel of the socioeconomic, demographic, and financial characteristics of unified public school districts for 1970, 1980, 1990, and 2000. Detailed information about the construction and contents of this panel can be found in Appendix A of Corcoran (2003).[21]

School districts in the United States are typically organized as unified (K-12), elementary-only, or secondary-only districts. Because the organization and cost structure varies across these different types of school districts, we chose to restrict our analysis to unified

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[20] Caroline Hoxby (1996 and 2001) was the first to merge these datasets (at least through 1992) to create a national panel of public school districts.

[21] An earlier version of this panel was used in Harris, Evans, and Schwab (2001). For information about the construction of the original panel, see Harris (1999), at http://www.bsos.umd.edu/econ/evans/wkpap.htm (access date August 9, 2003).

districts. This decision was not overly restrictive—despite having only 62 percent of all U.S. districts in our panel (as measured in 2000-01), the included districts represent over 80 percent of all publicly enrolled K-12 students in the nation.[22] [Think about this decision again].

In our analysis in Section IV, we make use of three different samples of school districts. The first is our full sample of unified public school districts, a balanced panel of 8,699 school districts in 1970, 1980, 1990, and 2000 (a total of 34,796 observations). The other two are subsets of the full panel—one a sample of districts located in metropolitan areas (MSAs), with 3,292 districts (13,168 observations), and the other the remaining sample of districts located outside of MSAs, with 5,407 districts (21,628 observations).[23] Within-district variation in income inequality tends to be greater and more prevalent in urban areas; private schooling also tends to be more important in urban areas where private schools are more plentiful than in rural or sparsely populated districts. Thus, we present most results for both the full sample of districts and our subset of districts in MSAs. On the other hand, our estimates from the MSA subsample are most likely to suffer from the endogeneity bias discussed in the previous section. Therefore, we supplement our results with estimates from the non-MSA subsample, where appropriate.

Our two endogenous variables are local school district revenues per pupil, and the fraction of school age children enrolled in private school. Data on local revenues per pupil comes from the Census of Governments data files. This variable represents all revenues raised

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[22] Total public Pre-K-12 enrollment in 2000-2001 was 47 million, according to the 2001 Digest of Education Statistics (see http://nces.ed.gov/pubs2001/digest/dt003.asp, access date August 10, 2003). Our panel represents a total of 37.7 million K-12 students in 2000. About a third of all unified districts in 2000 are missing from our panel—this is due primarily to the aggregation of small districts in the 1970 Census data, or the consolidation of districts over the sample period.

[23] Districts were included in the MSA subsample if they reside in a county that was considered part of a metropolitan area according to the U.S. Census 1973 standards (see http://www.census.gov/population/estimates/metro-city/73mfips.txt (access date August 9, 2003) for a complete list of 1973 metropolitan areas).

locally for education, via property taxes, income taxes, sales taxes, special fees, or any other local revenue source. Of course, more than half of the typical school district's budget comes from outside the district, from state or federal sources. However, we focus on local revenues because we feel this measure best reflects local commitment to public education. [Need to consider the effects of state equalization programs on local funding decisions—Hoxby (2001)]. Private school enrollment shares (at least in 1970, 1980, and 1990) are calculated using enrollment data from the special school district tabulations of the decennial Census. Unfortunately, the Census did not provide private school enrollment counts in 2000. To obtain these counts, we used GIS 'shapefiles' to match census tracts to school districts and aggregate private school enrollment counts to the school district level. [Note Figure 1].

While the Census frequently reports Gini coefficients of income inequality at the state and national level, they do not report these coefficients for smaller geographic areas like counties or school districts. Fortunately, our Census data does contain some information about the distribution of income in each school district, in the form of counts of families who fall into certain income ranges in each year. As we explain in the data appendix to this paper, if one assumes a flexible functional form for the CDF of income within a district, the counts of families in each income group can be used in a maximum likelihood procedure to estimate the parameters of this distribution. Given these parameters, the Gini coefficient can then (for some distributions) be directly calculated. We assume that family income in each school district follows a three-parameter Dagum (1977, 1980) distribution—a re-parameterization of the Burr Type III distribution—and compute Gini coefficients of income inequality for each district in our panel. In addition to these school district Ginis, we use the Dagum parameters to compute three other measures of within-district income inequality—the log of the ratio of the 95th centile of income to the median income (the log(95/50) ratio), the log of the ratio of the median income to the 5th centile of income (the log(50/5) ratio), and the log of the ratio of the 95th centile of income to the 5th centilie of income (the log(95/5) ratio).

Summary statistics for our full sample and MSA subsample are provided in Tables 1 and 2. In these tables—as with all of our regression models—school district observations are weighted by the number of publicly enrolled students in the district, and all monetary variables are in constant (1992) dollars. Through weighting, we are estimating the impact of population heterogeneity or income inequality on a randomly selected public school student from the population.[24]

The rise in within-district income inequality alluded to in our introduction is observable in both our full sample and MSA subsample regardless of how income inequality is measured. In the full sample, we find that the average Gini coefficient has risen almost 15 percent, from 0.34 to 0.39. The growth in within-district heterogeneity was even more striking in MSAs, with income inequality in the average district rising 19 percent, from 0.33 to 0.39. Inequality in the lower half of the income distribution (as measured by the log(50/5) ratio) also rose over the 1970-1990 period in both samples, but fell slightly from 1990 to 2000.

Tables 1 and 2 also show a steady rise in real local per-pupil revenues over our sample period. While the average district in our full sample raised $1,861 in revenues per pupil in 1970 (in 1992 dollars), by 2000 this sum had risen to $2,736. At the same time, local school districts were contributing a smaller and smaller share of their total per-pupil budget—we see that the local share of total per-pupil revenues has steadily fallen, from over half in 1970 to just above 40

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[24] In our regressions where the private school enrollment share is our left hand side variable, we weight using the total school age population in each district, rather than public school enrollment. We have

percent in 2000. Most of this decline is attributable to large increases in state support for education over this period—on average, state contributions to district per-pupil spending rose more than 127 percent from 1970 to 2000.[25]

There was no discernible trend in private school enrollment shares over this time period in the full sample—mean district enrollment in private schools in our sample remained roughly constant at 10 percent. Not surprisingly, the private school enrollment share was higher in metropolitan areas—on average, about 12 percent of school age children were enrolled in private schools in our MSA sample; only 6 percent of K-12 children outside of MSAs were enrolled in private schools over our sample period (although there is a distinct upward trend in private school enrollment in non-MSA districts—the share in private schools was about 4.9 percent in 1970, and 7.0 percent in 2000).[26]

One might be concerned that these observed increases in mean within-district heterogeneity and income inequality are driven by our use of enrollment weights—in other words, that income inequality or race fractionalization was only important in a few select heavily populated districts. Table 3 shows this not to be the case. In this table, we provide greater detail about the distribution (both weighted and unweighted) of within-district changes in income

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experimented with several other weights, including an average of public school enrollment over the 1970-2000 period. Our results are generally insensitive to our choice of weights.

[25] See Corcoran, et al (2003) for a recent survey.

[26] We also noticed a downward trend in private school enrollment shares in some of the largest U.S. urban school districts over this period, particularly between 1990 and 2000. Our finding that private school enrollment shares rose significantly outside of MSAs may be due to measurement error in our 2000 private school enrollment share variable, which was constructed by matching census tracts to school districts (rural districts were most likely to suffer from measurement error under this method). See Corcoran (2003).

inequality. Just under 75 percent of the school districts in our full sample experienced a rise in income inequality between 1970 and 2000.[27]

IV. RESULTS

A. Local Revenues per Pupil

We begin by estimating our empirical model in equation (6), using local revenues per pupil as our endogenous variable. Again, we include district fixed effects and year-specific state effects in all specifications, and all observations are weighted by total district public school enrollment. The results are shown in Table 4.

Our baseline specification in column (1) includes a detailed set of demographic and economic controls, as well as a within-district Gini coefficient of income inequality. In columns (2) – (4) we add our two other heterogeneity measures (race and schooling fractionalization), and in column (5) two additional controls (the percent of district households with children, and the fraction of the district population residing in an urbanized area).

Our estimated coefficient on the Gini coefficient is positive, sizable, and statistically significant. Given that the mean Gini coefficient in our sample is about 0.36 (with a standard deviation of 0.06), this result suggests that a two standard deviation increase in income inequality within a district in the full sample is associated with a \$363 to \$428 increase in per-pupil spending. This estimate is quite large—roughly equivalent in magnitude to a \$8,500 increase in real median district family income.

The estimated coefficients on our demographic and economic characteristics are generally of the expected sign, and qualitatively similar to those found in other empirical

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[27] The shape of this distribution was virtually identical for districts outside of MSAs. Roughly 75 percent

estimates of local demand functions for education. Real local per-pupil revenues are positively related to median family income, with a $1,000 increase in real median family income associated with a $43 to $53 increase in per-pupil spending (implying an approximate income elasticity of demand for per pupil spending of 0.7 to 0.9 at the mean, quite in line with other estimates, see Rubinfeld (1987)). Per-pupil revenues tend to be lower, all else equal, in districts with higher poverty rates and in districts where a greater proportion of residents are nonwhite; per-pupil revenues are higher in districts with a greater fraction of college graduates and a greater share of residents who are 65 and older.[28] We also find the typical "renter effect" found in other empirical estimates of local demand functions for public goods—a one standard deviation increase in the fraction of homeowners is associated with roughly a $170 to $300 decrease in per-pupil spending.[29]

At a first pass, the results in columns (1) and (2) are consistent with the basic median voter model: changes in the income distribution affect the tax price to the median voter, and the level of educational expenditure demanded. We explore this idea further in columns (6) – (10).

In columns (6) through (10) of Table 4, we replace our Gini coefficient measure of income inequality with two other measures—the logged ratio of the 95th centile of income to the median (log(95/50)), and the logged ratio of the median income to the 5th centile (log(50/5)). The former can be considered a measure of income inequality in the top half of the distribution,

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of districts saw an increase in income inequality.

[28] Our estimated coefficient on the elderly share would seem to contradict the conclusion of Harris, Evans and Schwab (2001) that a larger elderly population share reduces public spending on education. However, in their paper they find that the impact of the elderly is much less pronounced at the local level, where older voters may feel that greater spending on education is capitalized into property values. Their model also uses the log of total revenues or local revenues as left hand side variables, which seems to have some effect on their result.

[29] See Oates (1998) for a survey of the "renter effect" literature.

while the latter measures income inequality in the bottom. Given our stylized model in Section III, increases in income inequality that increase the mean income relative to the median should lower the tax price to the voter with median income, and increase per-pupil spending; increases that reduce the mean income relative to the median should reduce per-pupil spending. We find exactly this pattern in columns (6) through (10)—as the 95th centile of income rises relative to the median within a district, we observe increases in per-pupil spending; as the 5th centile of income falls relative to the median, we observe decreases. Specifically, a one percentage point increase in the 95th centile of income relative to the median is associated with (all else equal) an \$8.20 increase in real per-pupil revenues; a one percentage point increase in the median income relative to the 5th centile of income is associated with a \$1.81 decline in per-pupil revenues. Given that the standard deviations of these variables in our full sample are 0.18 and 0.32, respectively, a two standard deviation increase in the log(95/50) ratio would increase spending per-pupil by \$294; a two standard deviation increase in the log(50/5) ratio would decrease spending by \$116. Our estimates of the coefficients on race and schooling fractionalization in these columns are nearly identical to those in columns (1) through (5).

Clearly, a 0.01 increase in the log(95/50) ratio will not have an equivalent effect on the tax price to the median voter as a 0.01 fall in the log(50/5) ratio. Because households at the top of the income distribution comprise a disproportionate share of total income, an increase in the log(95/50) ratio will add more to mean income than an equivalent decline in the log(50/5). Therefore, to compare the magnitudes of our coefficient estimates on these inequality measures, we performed the following exercise: using the estimated parameters for the income distribution in each district, we computed the fraction of total district income coming from the bottom quartile ($\ell(0.25)$, where $\ell(p)$ is the Lorenz curve for an individual district) and the fraction of total district income comprised by the top quintile (1-ℓ(0.75)). Averaged across all districts, the upper quartile makes up roughly 47 percent of total income; the bottom quartile makes up about 8 percent of total income. Thus, for the mean district, a hypothetical rise in income of 10 percent among the top quartile of the distribution (with an accompanying rise in the 95/50 ratio of 10 percent) will increase mean income by 4.7 percent. A rise in income of 10 percent among the bottom quartile of the distribution (with an accompanying fall in the 50/5 ratio of 10 percent) will increase mean income by 0.8 percent. In other words, a 10 percent rise in income at the top of the distribution (for the mean district) will have an effect on total income that is roughly 5.8 times that of 10 percent rise in income at the bottom of the distribution. This ratio is similar in magnitude to the ratio of our two regression coefficients on the log(95/50) and the log(50/5): the coefficient on the log(95/50) is 4.5 times that on the log(50/5) ratio, suggesting that our coefficient estimates—in relative terms—are quite reasonable.

Table 5 presents the results of the same ten specifications in Table 4, estimated on our subsample of districts located in MSAs.[30] Our coefficient estimates for the effect of income inequality on school spending are quite similar to those in Table 4. Based on this sample of districts in MSAs, we estimate that a two standard deviation increase in the Gini coefficient corresponds to a \$442 to \$564 increase in per-pupil spending, about the same size effect when considered as a percentage of mean local revenues per pupil (mean per-pupil revenues in our sample of MSA districts is higher than that for our full sample). Increases in the log(95/50), log(50/5), and schooling fractionalization index all have similar effects in the MSA subsample as in the full sample. The primary difference between our estimates using the full sample and our estimates from the MSA subsample is our coefficient estimate for race fractionalization—in contrast to the full sample results, our point estimate for this coefficient is positive, and statistically significant in all specifications except column (5).

In summary, our results so far find a consistent positive relationship between income inequality and local per-pupil revenues, whether income inequality is measured using a Gini coefficient, or through the log(95/50) and log(50/5) ratios. This result holds for our full sample of districts, as well as our subsamples of districts in MSAs. The same is true for heterogeneity in schooling—we find a sizeable negative relationship between fractionalization in educational attainment and per-pupil spending across all samples. We find some evidence that race fractionalization decreases per-pupil revenues in our full sample; the opposite result arises in our subsample of MSAs. In the next section, we consider another possibility—whether heterogeneity in population characteristics or income result in an increase in a change in the fraction of children enrolled in private schools.

B. Private School Enrollment Share

Table 6 presents our coefficient estimates from model (8), where our dependent variable is now the fraction of school age children within a district enrolled in private schools. The order of model specifications is exactly the same as that in Table 5, and we continue to include district fixed effects and year-specific state effects in all models. In these regressions, we weight all observations by total K-12 enrollment (i.e. both public and private) in the district.[31]

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[30] In these regressions we use time-specific MSA effects (which subsume state level trends), rather than state effects. The results are not significantly changed when state effects are used.

[31] This weight (public plus private enrollment) is more appropriate in this context than total public enrollment. Rather than weighting to estimate the impact of population heterogeneity on the average student (appropriate in our school spending regressions), we weight here to account for heteroskedasticity in our error term (the fraction of students enrolled in private schools is an estimate from the Census 1-in-6 longform data, an estimate that is likely to be more precise in more populated school districts). We have experimented with other weights with these specifications (public enrollment, average total enrollment over the sample period, etc), and the choice of weights has little effect on our results.

We find that in the full sample, the Gini coefficient of income inequality has a negative, statistically significant relationship with the fraction of students enrolled in private school. Our point estimates range from –0.041 to –0.051, with a standard error of 0.011 in all cases. Given that the standard deviation of income inequality in our sample across all years is 0.06, these estimates suggest that a two standard deviation increase in income inequality within a school district is associated with a 0.2 to 0.3 percentage point reduction in the share of school aged children enrolled in private schools. With a mean private school enrollment share of 10 percent, this effect represents about a two to three percent rise in the private school enrollment share over the mean, a small but not insignificant effect.[32]

Our estimated coefficients on our demographic and economic controls are mostly as expected. Private schooling shares tend to be lower in districts where a greater share of the population is nonwhite, in poverty, or are homeowners; private schooling shares rise with the fraction elderly and with real median family income (we find that a $1,000 increase in real median family income is associated with about a 0.2 percentage point increase in private schooling).

Our results for race and schooling fractionalization are somewhat contradictory. While we find that increased racial fractionalization has a positive, statistically significant relationship with private schooling, we find the opposite is true with fractionalization in schooling. According to Table 6, a one standard deviation increase in race fractionalization within districts (0.20 in the full sample) is associated with a 0.36 to 0.38 percentage point increase in the fraction of students enrolled in private schools; a one standard deviation increase in schooling

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[32] This finding is dependent on our use of weights. In the unweighted version of these regressions, we find a positive and statistically significant effect of income inequality on private schooling (in the

fractionalization (0.07), on the other hand, corresponds with a 0.27 to 0.37 percentage point reduction in the private schooling share.

Table 7 presents the same five specifications, estimated using the subsample of districts in MSAs. Here, we find generally the same pattern—increases in within-district income inequality are associated with reductions in the share of students enrolled in private schools, while increases in racial fractionalization increase the private school enrollment share. However, in this case, our estimate for the coefficient on income inequality is imprecise—in no column in Table 7 is the negative coefficient on income inequality statistically significant.

C. A Robustness Check: Low Mobility Districts and Districts Outside of MSAs

In this section, we repeat our analysis from Sections IV.B and IV.C, but with two additional subsamples—the first, a sample of "low mobility" districts, with a relatively low proportion of new residents and the second a sample of districts that lie outside of metropolitan areas. To construct our "low mobility" sample, we selected all of those districts that were in the lowest three quintiles of household migration—that is, with the lowest proportion of households that lived in a different county five years prior to the 1980, 1990 and 2000 censuses.[33] 3,955 districts met our criteria for inclusion in this subsample.[34] These low mobility districts were not strictly rural, unpopulated districts—in fact, over 40 percent of the districts in our low mobility sample were located in MSAs.

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unweighted version of column (4), we estimate this coefficient to be 0.019, with a standard error of 0.009).

[33] Specifically, we placed each district into a quintile of migration (the fraction of households who lived in a different county five years before) for 1980, 1990, and 2000 (migration information was not available in the 1970 census tabulation). If a district was in the lowest three quintiles of this distribution *in all three census years*, we included them in our subsample.

[34] The mean fraction of households who lived in a different county, by quintile in 2000 were 9 percent, 12.7 percent, 15.7 percent, 19 percent, and 26.9 percent.

Our findings are summarized in Table 9. Coefficient estimates on income inequality, race, and schooling fractionalization are qualitatively similar to those found for the full sample and MSA sample in earlier sections. A two standard deviation increase in income inequality is associated with a $308 increase in per-pupil spending in our low mobility sample (about 13.8 percent of the sample mean in low mobility districts, a slightly smaller effect in percentage terms than the full sample result), and a $180 increase in per-pupil spending in our non-MSA sample (about 9.3 percent of the non-MSA sample mean). As in our MSA sample, there is no statistically significant impact of income inequality on the private schooling share in either our low mobility sample or our non-MSA sample. Schooling fractionalization continues to have a negative relationship with the private school enrollment share, while fractionalization in race continues to have a positive relationship with private schooling (although this coefficient is statistically insignificant in our non-MSA subsample).

It appears that our general findings from earlier sections are robust to varying definitions of our underlying school district sample—with few exceptions, we find the same pattern of results across these subsamples.

D. Instrumental Variables Results

Finally, in this section, we estimate our per-pupil spending regression in (8) using an instrumental variables model in which we instrument for within-district income inequality with a measure of inequality from another nearby school district. As we discussed in Section III, our OLS estimates of the impact of income inequality on local per-pupil revenues may be biased and inconsistent if households sort into districts based on the level of per-pupil revenues—it may be that changes in income inequality over time within a school district are due in part to the in- and out-migration of families who are responding to changes in local school finance policies.

We address this possibility by estimating three instrumental variables models, where our instruments for within-district income inequality are the Gini coefficient for the closest school district, the Gini coefficient for the closest district in another county, and the Gini coefficient for the closest district in another state.[35] To the extent that changes in income inequality within a school district over time are due to (exogenous) regional labor market conditions, we would expect that the level of income inequality in a district and that of its neighboring districts to be highly correlated. It is this portion of variation in within-district income inequality that we would like to use to identify the impact of income inequality on local per-pupil revenues—not the variation in inequality that is a mechanical response to inter-district sorting. Of course, the problem is identifying districts that are close enough to be subject to the same economic conditions, but far enough away to preclude any sorting effects.

In Figure 1, we illustrate the spatial distribution of within-district income inequality across school districts in the United States.[36] Each block within this figure is a unified, elementary or secondary school district; shading within each block indicates the school district's quartile in the nationwide distribution of within-district income inequality, where darker shading represents a higher degree of income inequality. This figure suggests that the level of within-district income inequality is in many parts of the United States a regional phenomenon, with the level of income inequality highly correlated across neighboring districts. Much of the South, Appalachia, the Northeast corridor, Texas and California is characterized by smooth patterns of regional within-district inequality—not the checkerboard pattern that one might see if there were

[35] More information about the construction of these instrumental variables can be found in Corcoran (2003).

[36] All school districts (unified, elementary, and secondary) and included in this Figure. Some districts (but not all) without shading are missing income inequality data.

high degrees of sorting occurring between districts (the Upper Midwest is an exception to this rule—while some of this pattern in the Upper Midwest can be explained by missing data, the degree of spatial correlation in these districts is certainly lower).

The results of our first-stage regressions shown in column (1) of Table 10 confirm this pattern. The estimated coefficients on our three instruments are precisely estimated and have the correct sign—within-district income inequality is highly correlated with income inequality in the nearest district, nearest district in another county, and nearest district in another state, and the first-stage coefficient falls monotonically with distance.[37] Column (2) reports our instrumental variables estimate of the coefficient on income inequality from specification (4) in Table 4. With our first two instruments, our IV estimates of the coefficient on income inequality ($2,980 and $2,837) are only slightly less than our original point estimate from column (4) in Table 4 ($3,512), and well within a 95 percent confidence interval around our original estimate. Our third instrument (income inequality within the nearest district in another state) produces an IV estimate that is less than half that produced by the first two instruments ($1,167).

V. Summary and Conclusion

In this paper, we have used a panel of unified school districts to estimate the effects of local population heterogeneity and income inequality on the support for public schools. We measured support for schools using two variables—local per-pupil education revenues and the fraction of district students enrolled in private schools. Our results suggest that rising income inequality within a district may actually increase per-pupil revenues, a result consistent with a median voter model in which rising income inequality lowers the tax price to the voter with the median income (which occurs when the mean income rises relative to the median income). The estimated impact of income inequality on per-pupil revenues is sizable—about a $200 (or 8 percent) per-pupil rise in local expenditure for a one standard deviation increase in income inequality—and robust across a number of specifications. We also find that, all else equal, increased fractionalization in race tends to reduce local per-pupil expenditure on education, and increase the fraction of school aged children in private school. Fractionalization in schooling also tends to reduce educational spending; it also tends to be associated with lower private school enrollment rates—a result that clearly deserves further study.

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[37] Note *t*-statistics are reported in this table rather than standard errors. Our first- and second-stage regressions both incorporate observation weights.

DATA APPENDIX

A. Private School Enrollment Shares, 2000

Computing private school enrollment counts for 2000 was one of the more challenging tasks of this dataset compilation. Because the *2000 Census of Population and Housing School District Tabulation (STP2)* failed to include a table reporting public and private school enrollments by grade, we instead used the following procedure to estimate private school enrollment for 2000.[41]

First, we obtained public and private K-12 enrollment for every census tract in the United States, from the *2000 Census Summary File 3.* These tracts were then mapped into school districts using census tract and unified school district cartographic boundary files provided by the Census Bureau.[42] Using ArcInfo GIS software, these boundary files were overlaid and merged, creating thousands of tract-district intersections (see Figure 2 for an illustration using census tracts and school districts in the Lawrence, Kansas area).

While census tracts are almost always smaller than school districts, they are not necessarily contained entirely within the boundaries of one school district. In cases where census tracts crossed school district boundaries, we allocated total public and private school enrollment to school districts based on the fraction of the census tract land area residing in each district (in Figure 2, for example, Census tract 0014 lies in at least five different school districts).

Of course, this method has some obvious problems. To provide a simple example, suppose that 10 percent of a large census tract lies in District A, while 90 percent of the same tract lies in District B. Allocating enrollment by land area would place 10 percent of the total enrollment in A and 90 percent in B. This method only works well when the population is uniformly distributed over the census tract. If, say, the 10 percent region were a densely populated urban area, and the 90 percent region were a rural or mountainous area, we would clearly be understating enrollment in A and overstating enrollment in B. Without the help of smaller geographic units—like census block group—this problem seems to be unavoidable.[43]

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[41] The 2000 School District Tabulation does include one table (PCT23) that reports school enrollment for males and females age three and older, by various age categories: 3-4, 5-9, 10-14, 15-17, 18-19, etc., with no public-private distinction. Together with the total K-12 public enrollment counts taken from the *Common Core*, it would be possible to use the residual (census enrollment – CCD public enrollment) as an estimate of the number of children enrolled in private school. This would, however, require the use of two different data sources in the construction of one variable, as well as critical assumptions about the fraction of five-year olds in kindergarten and the fraction of 15-17 and 18-19 year olds in secondary school.

[42] These boundary files can be downloaded from http://www.census.gov/geo/www/cob/ bdy_files.html (access date August 9, 2003).

[43] Census data and cartographic boundary files are indeed available at the block group level. We have not yet attempted to map block groups to tracts—however, the use of tracts seems to work reasonably well for the vast majority of school districts.

Fortunately, the most densely populated census tracts are located in urban areas, are quite small in land area, and typically are contained in one and only one district; tracts that traverse boundaries are more frequently located in large, sparsely populated rural areas. The measurement error in our private school variable, then, is likely to be highest in those districts with the smallest populations. The use of enrollment weights in most of our regressions should thus ameliorate at least some of the effects of this measurement error, where it exists. We also benefit from the coterminous boundaries of school districts and counties in certain Mid-Atlantic and Southern states like Maryland, Virginia, and Georgia. In these cases, where school districts are typically operated by county governments, census tracts almost always lie within one and only one district.

B. Heterogeneity and Income Inequality Measures

Measures of population heterogeneity and income inequality within school districts are calculated using data from the 1970, 1980, 1990, and 2000 census. Our indices of race and schooling heterogeneity are simple fractionalization indices, i.e. one minus the sum of the squared shares of J different race or K different educational attainment categories (or, one minus a Herfindahl index based on these shares):

(1) $$racefrac_{it} = 1 - \sum_{j=1}^{J} s_{jit}^{\ 2}$$

(2) $$educfrac_{it} = 1 - \sum_{k=1}^{K} s_{kit}^{\ 2}$$

where s_{jit} and s_{kit} are the shares of race group j or education category k in school district i in census year t. Both of these indices can take on values from zero to one, with values closer to one representing greater heterogeneity (a value of zero would indicate perfect homogeneity).

There are no measures of income inequality reported by the Census at the school district level. As mentioned in Section III, the Census does report counts of families (or households) in various income categories in each district (inc_1 - inc_N above), as well as the median and total family (or household) income. Given aggregate income in each income *group*, one could compute an approximate Gini coefficient using simple procedures like those outlined in Gastwirth (1972), but these group aggregates are unfortunately not available. It is possible, however, to generate measures of within-district inequality by assuming a functional form for the distribution of income in each district, using the grouped income data to estimate the parameters of this distribution, and then using this distribution to compute common measures of income inequality. We use such a procedure—but it was necessary to first agree upon an appropriate income distribution.

Economists have experimented with literally dozens of distribution functions for income. The lognormal distribution, for example, is commonly thought to closely approximate the shape of the income distribution in the United States. In an article in *Econometrica,* McDonald (1984) examined a large number of one to four parameter distributions in order to assess their ability to fit the U.S. income distribution. Among these he included the popular lognormal, gamma, beta, and Pareto distributions—many of which were shown to be special cases of "generalized beta" distributions. As might be expected, the four-parameter generalized beta distribution provided a better fit than almost all other distributions, but its lack of a closed-form representation for its moments makes it quite difficult to estimate in practice. Among the three-parameter models, McDonald concluded that the Dagum (1977, 1980) distribution—a re-parameterization of the Burr Type III distribution—outperformed all other three-parameter models (and even some four-parameter models), at least for U.S. family income in 1970-1980. These results suggest that the Dagum distribution would be a good candidate for our estimation procedure, and we implement it as described below.

For a random variable *z*, the cumulative distribution function for the three-parameter Dagum distribution is as follows, for $z \geq 0$ and $(a, b, p) > 0$:

$$(3) \qquad F(z) = \left[1 + \left(\frac{b}{z}\right)^{a}\right]^{-p}$$

The r^{th} moments of this distribution are defined as:

$$(4) \qquad E[z^{r}] = pb^{r}\beta\left(1 - \left(\frac{r}{a}\right), p + \left(\frac{r}{a}\right)\right),$$

(where $\beta(*)$ is the complete beta function).

Given this distribution, $K+1$ income groups, and N_{K+1} families in each group, the probability that a family falls in group *k* is Pr(k; *a, b, p*). For the lowest income group this can be written (with y_1 as the upper limit on the first income category):

$$(5) \qquad \Pr(1; a, b, p) = \Pr(y \leq y_1) = \left[1 + \left(\frac{b}{y_1}\right)^{a}\right]^{-p},$$

and for the next $K-1$ income groups (where y_{k-1} and y_k are the lower and upper bounds of the *kth* income category ($k=2 \ldots K-1$)):

$$(6) \qquad \Pr(k; a, b, p) = \Pr(y_{k-1} \leq y \leq y_k) = \left[1 + \left(\frac{b}{y_k}\right)^{a}\right]^{-p} - \left[1 + \left(\frac{b}{y_{k-1}}\right)^{a}\right]^{-p},$$

and for the highest income group:

$$(7) \qquad \Pr(K+1; a, b, p) = \Pr(y > y_K) = 1 - \left[1 + \left(\frac{b}{y_K}\right)^{a}\right]^{-p}.$$

To estimate the parameters *a, b,* and *p*, we write the log-likelihood function as:

$$(8) \qquad \ln L(a, b, p) = \sum_{k=1}^{K+1} N_k \ln\left[\Pr\left(k; a, b, p\right)\right]$$

and estimate values for *a, b,* and *p* using maximum likelihood. According to McDonald (1984), "the estimators obtained by maximizing the multinomial likelihood function will be asymptotically efficient relative to other estimators based on grouped data; however, they will be less efficient than maximum likelihood estimators based on individual observations." With parameter estimates for *a, b,* and *p,* Dagum (1980) showed that the Gini coefficient can be calculated simply as:

(9) $$Gini = -1 + \frac{\beta(p,p)}{\beta\left(p, p + \left(1/a\right)\right)}.$$

We estimated the parameters *a, b,* and *p* for every school district in our panel, for 1970, 1980, 1990, and 2000. We then calculated gini coefficients for each district using (9). Various centiles of the income distribution were also estimated with these parameters, to generate several other measures of inequality in the income distribution (*log95_50, log50_5, log95_5,* and so on).

As one check of this procedure, we aggregated our counts of families in each school district income category to the state level for 1970, 1980, and 1990, estimated state-specific parameter values using our maximum likelihood procedure, and computed state-specific estimates of the Gini coefficient. We then compared our results to the actual Gini coefficients reported by the Census for each state (which they produce using individual family-level data from their one-in-six sample).[44] The results for 1970 and 1990 are plotted in Figure 3 (panels a and b, respectively). The maximum likelihood model seems to do remarkably well at the state level—the correlation coefficient between our estimated state Ginis and the actual Ginis in 1970, 1980 and 1990 are 0.998, 0.996, and 0.980, respectively.

Because school districts are much smaller than states, we were also interested in seeing how this procedure would perform in smaller geographic areas. Using the same maximum likelihood procedure, we estimated county-specific parameters of the Dagum distribution for 1970, 1980 and 1990. While the Census does not report Gini coefficients at the county level, they do report several other aggregate measures of the income distribution. For example, in 1990 the Census reports the fraction of families in each county earning $50,000 or more. We compared these fractions to the same fraction calculated with our estimated Dagum parameters (i.e. $1 - F(50{,}000; a,b,p)$)—again, the correlation between these values is quite high—0.996 for 1990. Analagously, we calculated average family income in each county using the moment generating function for the Dagum distribution, and compared these to the average family income reported by the Census—the correlation between the actual and predicted values in this case was 0.997. Overall, it appears our maximum likelihood procedure performs remarkably well.

[44] State Gini coefficients for 2000 had not been released as of this writing [September 2003].

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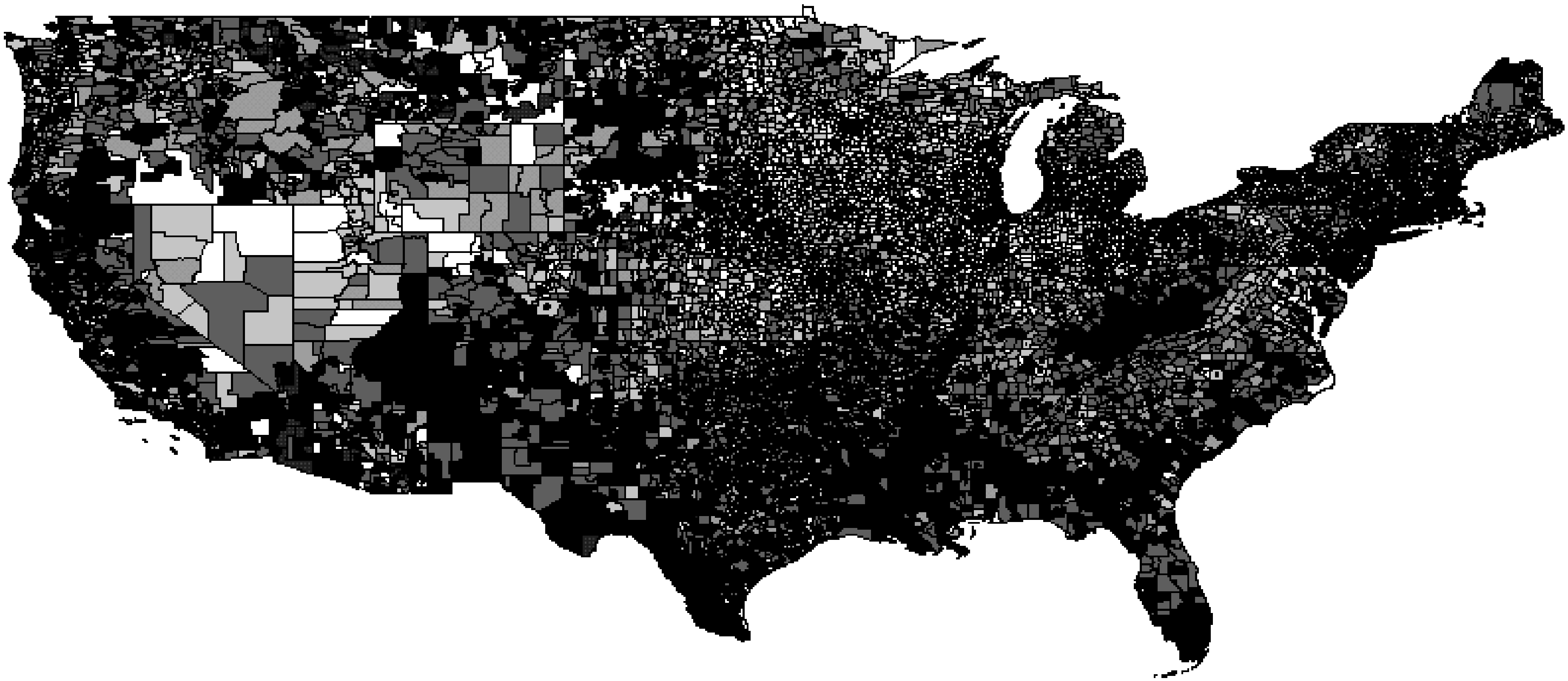
Figure 1: Spatial Distribution of 2000 Income Inequality—Elementary, Secondary and Unified School Districts



Source: 2000 Census of Population and Housing School District Tabulation (STP2)

Figure 2: Matching 2000 Census Tracts to School Districts—Example of Lawrence, Kansas Area School Districts

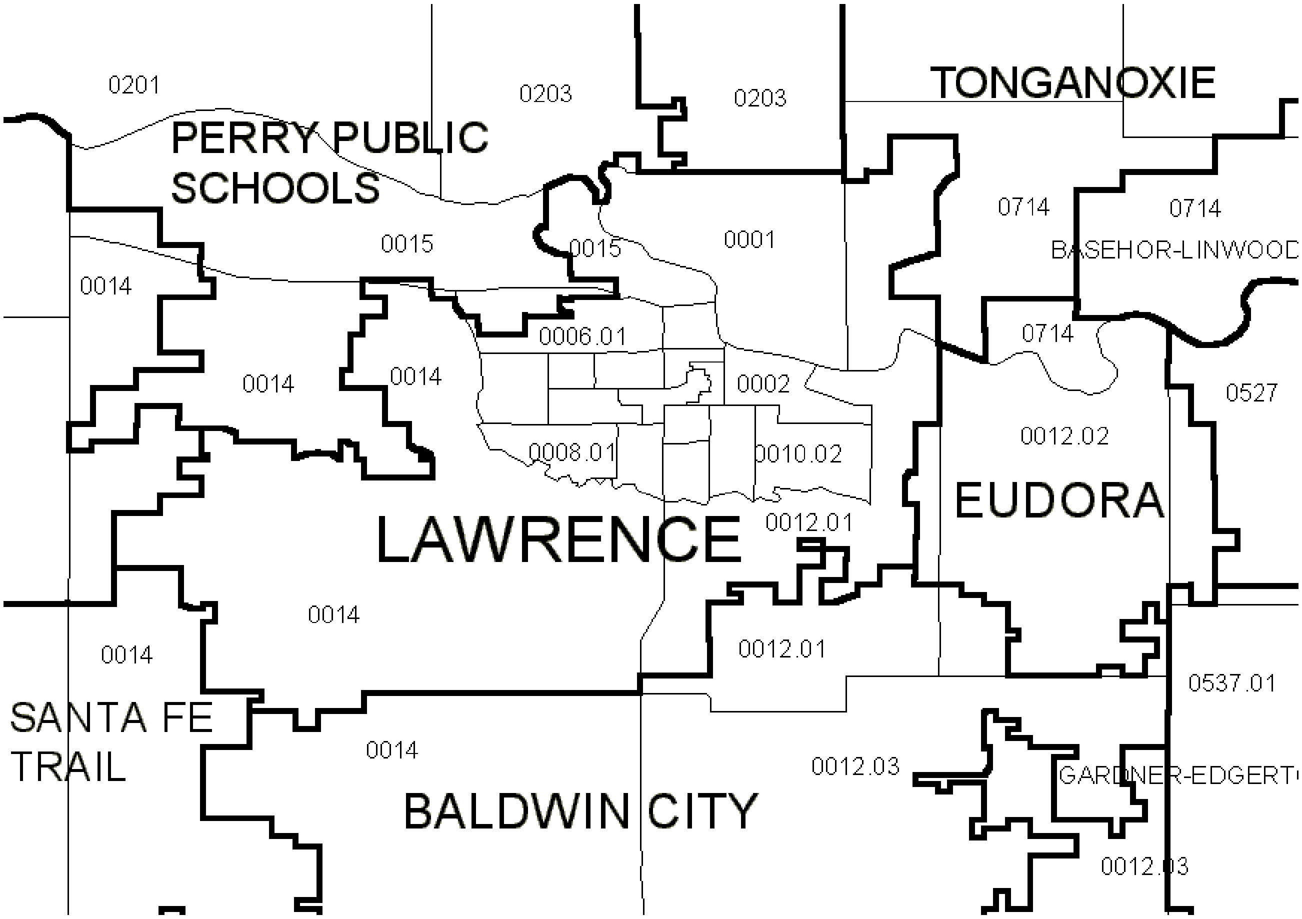


Figure 3a: Estimated Gini Coefficient vs. Actual Census Gini Coefficient Based on State Family Income (1969)

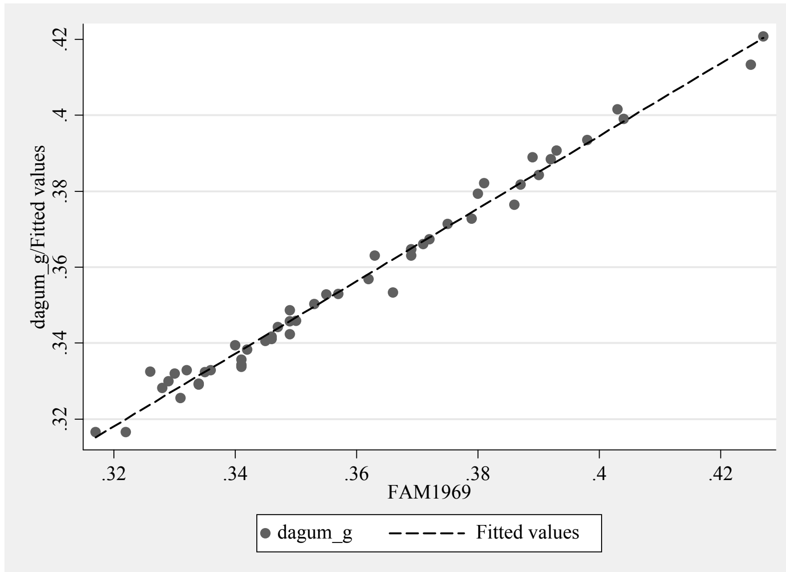


Figure 3b: Estimated Gini Coefficient vs. Actual Census Gini Coefficient Based on State Family Income (1989)

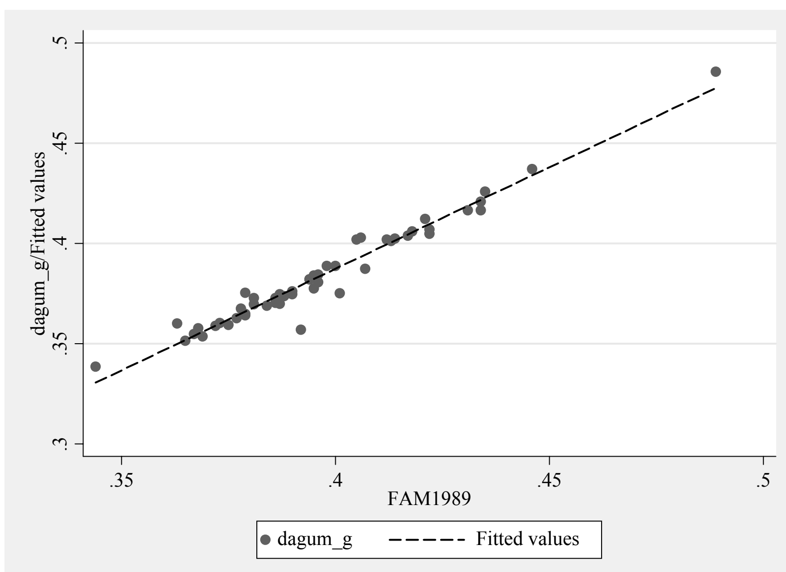


Table 1: Descriptive statistics, full sample

	All Years		1970		1980		1990		2000		1970-2000
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	%Change
Gini coefficient	0.36	0.06	0.34	0.05	0.35	0.05	0.38	0.05	0.39	0.06	14.6%
Schooling fractionalization	0.68	0.07	0.62	0.08	0.68	0.05	0.71	0.03	0.71	0.04	14.3%
Race fractionalization	0.25	0.20	0.17	0.17	0.22	0.19	0.26	0.20	0.33	0.20	90.0%
Ln(95/5) ratio											
Ln(95/50) ratio	0.97	0.18	0.88	0.16	0.92	0.15	1.00	0.17	1.06	0.18	20.5%
Ln(50/5) ratio	1.59	0.32	1.51	0.28	1.57	0.28	1.66	0.37	1.61	0.31	6.8%
Real local revenues per pupil	2239	1437	1861	1030	1847	1117	2520	1691	2736	1593	47.0%
Real state revenues per pupil	2306	1141	1377	578	2005	743	2737	1088	3135	1128	127.6%
Real federal revenues per pupil	144	242	79	185	23	67	23	84	422	265	430.9%
Real total revenues per pupil	4688	1757	3318	1091	3875	1049	5280	1528	6292	1453	89.6%
Local share of total revenues	0.47	0.19	0.54	0.18	0.46	0.19	0.45	0.20	0.42	0.18	-21.7%
Fraction enrolled in private school	0.10	0.07	0.10	0.08	0.10	0.07	0.10	0.07	0.10	0.06	-0.1%
Real median family income (thousands)	39.38	11.60	36.47	9.70	38.52	9.52	39.62	12.16	42.83	13.54	17.4%
Percent of households in poverty	0.13	0.08	0.14	0.09	0.13	0.07	0.13	0.08	0.12	0.07	-15.6%
Percent high school dropouts	0.32	0.16	0.48	0.13	0.34	0.13	0.26	0.11	0.20	0.10	-57.9%
Percent high school grads only	0.31	0.08	0.31	0.07	0.35	0.07	0.31	0.08	0.29	0.08	-7.0%
Percent with some college	0.19	0.09	0.10	0.04	0.15	0.05	0.24	0.06	0.27	0.06	161.3%
Percent college grads or higher	0.17	0.11	0.10	0.07	0.15	0.08	0.19	0.10	0.23	0.12	124.3%
Percent nonwhite	0.23	0.22	0.16	0.17	0.20	0.20	0.24	0.23	0.30	0.25	89.2%
Percent black	0.12	0.15	0.11	0.14	0.12	0.15	0.12	0.16	0.12	0.15	12.8%
Percent Hispanic	0.08	0.14	0.05	0.10	0.06	0.12	0.09	0.15	0.13	0.18	176.7%
Percent of housing units owner occupied	0.67	0.15	0.66	0.15	0.67	0.15	0.66	0.14	0.68	0.14	2.5%
Share of district population aged 65+	0.11	0.04	0.10	0.04	0.11	0.04	0.12	0.04	0.12	0.04	27.3%
Share of district population aged 0-19	0.33	0.06	0.39	0.05	0.33	0.04	0.29	0.04	0.29	0.04	-25.3%
Percent urban	0.72	0.35	0.70	0.36	0.70	0.36	0.71	0.35	0.77	0.31	9.6%
Share of households with children	0.41	0.10	0.43	0.10	0.48	0.08	0.39	0.07	0.35	0.07	-20.0%

The full sample consists of 8,699 districts for a total of 34,796 observations. All monetary values are in real 1992 dollars. Observations are weighted by district pubic enrollment.

Table 2: Descriptive statistics, MSA subsample

	All Years		1970		1980		1990		2000		1970-2000
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	%Change
Gini coefficient	0.36	0.06	0.33	0.05	0.35	0.05	0.37	0.06	0.39	0.06	19.0%
Schooling fractionalization	0.69	0.05	0.65	0.06	0.70	0.04	0.72	0.03	0.71	0.04	10.3%
Race fractionalization	0.27	0.20	0.18	0.17	0.24	0.19	0.30	0.20	0.36	0.20	102.6%
Ln(95/5) ratio											
Ln(95/50) ratio	0.96	0.19	0.86	0.14	0.90	0.15	1.00	0.18	1.08	0.20	25.7%
Ln(50/5) ratio	1.57	0.32	1.44	0.25	1.57	0.30	1.66	0.39	1.62	0.32	12.2%
Real local revenues per pupil	2,477	1,512	2,086	1,045	2,012	1,143	2,817	1,809	3,001	1,678	43.9%
Real state revenues per pupil	2,280	1,171	1,334	557	2,012	782	2,710	1,145	3,094	1,180	132.0%
Real federal revenues per pupil	144	237	90	203	22	47	21	61	408	256	351.7%
Real total revenues per pupil	4,901	1,805	3,510	1,134	4,046	1,046	5,548	1,589	6,503	1,513	85.3%
Local share of total revenues	0.50	0.19	0.58	0.16	0.48	0.18	0.48	0.21	0.45	0.18	-22.0%
Fraction enrolled in private school	0.12	0.07	0.13	0.08	0.12	0.07	0.12	0.07	0.12	0.05	-8.8%
Real median family income (thousands)	42.56	11.74	39.85	8.90	41.37	9.49	43.14	12.46	45.82	14.31	15.0%
Percent of households in poverty	0.11	0.07	0.11	0.07	0.11	0.07	0.12	0.08	0.11	0.07	-2.2%
Percent high school dropouts	0.30	0.15	0.45	0.12	0.31	0.11	0.23	0.10	0.19	0.10	-57.6%
Percent high school grads only	0.31	0.07	0.32	0.06	0.35	0.07	0.29	0.07	0.27	0.08	-17.2%
Percent with some college	0.20	0.08	0.11	0.04	0.17	0.04	0.26	0.06	0.28	0.05	147.6%
Percent college grads or higher	0.19	0.11	0.12	0.07	0.17	0.09	0.22	0.10	0.26	0.12	123.4%
Percent nonwhite	0.25	0.23	0.17	0.17	0.22	0.21	0.27	0.23	0.34	0.25	104.0%
Percent black	0.12	0.15	0.11	0.13	0.13	0.15	0.13	0.16	0.13	0.16	21.4%
Percent Hispanic	0.09	0.15	0.05	0.10	0.07	0.13	0.11	0.16	0.15	0.18	182.8%
Percent of housing units owner occupied	0.64	0.16	0.64	0.17	0.64	0.16	0.63	0.15	0.65	0.15	1.5%
Share of district population aged 65+	0.10	0.04	0.09	0.04	0.10	0.04	0.11	0.04	0.11	0.04	29.3%
Share of district population aged 0-19	0.32	0.06	0.39	0.05	0.32	0.04	0.29	0.04	0.29	0.04	-24.6%
Percent urban	0.86	0.25	0.84	0.27	0.84	0.26	0.86	0.25	0.89	0.20	6.4%
Share of households with children	0.41	0.10	0.44	0.11	0.48	0.09	0.38	0.08	0.35	0.07	-20.0%

The MSA subsample consists of 3,292 districts for a total of 13,168 observations. Districts are included in this sample if they resided in a county that was located in a metropolitan area, according to 1973 standards. All dollar values are in real 1992 dollars. Observations are weighted by district public enrollment.

Table 3: Changes in income inequality and fractionalization, 1970—2000

	Percent Change in Gini Coefficient		Absolute Change in Race Fractionalizatoin		Absolute Change in Schooling Fractionalization	
	Full Sample	MSA Sample	Full Sample	MSA Sample	Full Sample	MSA Sample
Unweighted						
Mean	0.070		0.090		0.110	
5th centile	-0.161		-0.030		-0.023	
10th centile	-0.115		0.003		0.018	
25th centile	-0.032		0.023		0.058	
Median	0.065		0.053		0.098	
75th centile	0.166		0.126		0.160	
90th centile	0.259		0.253		0.242	
95th centile	0.314		0.340		0.286	
Weighted						
Mean	0.152		0.165		0.086	
5th centile	-0.075		-0.033		-0.068	
10th centile	-0.027		0.010		-0.015	
25th centile	0.059		0.047		0.036	
Median	0.153		0.133		0.079	
75th centile	0.245		0.271		0.132	
90th centile	0.327		0.383		0.207	
95th centile	0.352		0.442		0.262	

The full sample consists of 8,699 districts; the MSA subsample consists of 3,292 districts. In the bottom half of the table, observations have been weighted by district enrollment.

Table 4: OLS results, Real local revenues per pupil (full sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
gini coefficient	3027.949	3567.246	2972.546	3512.481	3166.224					
	(224.955)	(226.650)	(225.959)	(227.762)	(226.512)					
schooling fractionalization index		-2567.613		-2536.565	-2794.346				-2318.540	-2584.821
		(166.517)		(167.268)	(166.751)				(169.193)	(168.729)
race fractionalization index			-214.596	-181.801	-221.404				-130.935	-172.976
			(81.701)	(81.369)	(80.726)				(81.702)	(81.043)
log(95/50) ratio						817.549		817.551	901.052	821.097
						(60.366)		(60.329)	(60.933)	(60.559)
log(50/5) ratio							-181.953	-181.955	-96.071	-101.325
							(31.585)	(31.474)	(32.103)	(31.862)
%in poverty	-2482.635	-3264.822	-2531.773	-3299.914	-2988.629	-2130.684	-935.398	-1567.377	-2504.377	-2227.480
	(182.108)	(188.247)	(183.476)	(189.559)	(188.611)	(173.191)	(193.752)	(198.626)	(209.100)	(207.833)
real median family income	53.794	46.158	53.663	46.112	43.327	54.428	49.171	54.182	47.087	44.366
(in thousands)	(1.485)	(1.559)	(1.490)	(1.565)	(1.587)	(1.495)	(1.454)	(1.495)	(1.577)	(1.600)
%25+ with hs degree	-3033.690	-1223.948	-3095.914	-1299.337	-1055.264	-3014.752	-3067.578	-2945.000	-1390.950	-1139.183
	(134.275)	(177.881)	(135.458)	(179.507)	(178.676)	(134.354)	(134.979)	(134.811)	(179.273)	(178.441)
%25+ with some college	-3036.286	-1578.145	-3078.951	-1625.641	-1594.207	-3074.307	-3444.511	-3068.799	-1802.402	-1746.642
	(149.977)	(176.726)	(150.774)	(178.093)	(177.702)	(149.385)	(147.214)	(149.295)	(177.177)	(176.787)

Table 4, cont.

%25+ with college degree	541.574	1295.409	647.875	1397.811	1543.837	541.495	1170.399	650.531	1413.223	1560.989
or more	(188.450)	(193.862)	(189.597)	(195.130)	(193.803)	(188.395)	(185.941)	(189.220)	(195.737)	(194.360)
%nonwhite	-675.257	-417.098	-564.734	-326.214	-208.826	-627.699	-485.005	-537.525	-277.585	-162.267
	(80.052)	(81.429)	(98.048)	(98.874)	(98.356)	(79.797)	(81.451)	(81.258)	(99.363)	(98.806)
%owner-occupied housing	-2022.990	-1739.002	-2120.288	-1835.229	-1135.103	-2041.469	-1975.310	-2004.006	-1848.083	-1145.728
	(112.099)	(113.100)	(114.751)	(115.780)	(121.393)	(112.111)	(112.603)	(112.229)	(115.847)	(121.453)
%population 65+	3945.198	3890.683	3906.324	3848.956	988.935	4020.055	4228.813	4060.944	3950.442	1072.111
	(217.168)	(216.213)	(220.613)	(219.672)	(262.010)	(216.763)	(217.150)	(216.744)	(219.452)	(262.020)
%hh with kids					-2131.128					-2136.685
					(109.398)					(109.377)
%population in urban area					-315.219					-332.743
					(41.576)					(41.599)
Constant	1446.526	2226.333	1574.761	2331.974	3512.677	1676.509	2594.959	1802.047	2618.816	3778.438
	(147.113)	(154.932)	(149.273)	(156.778)	(165.600)	(138.901)	(128.189)	(140.502)	(151.397)	(160.015)
Observations	34,795	34,795	34,620	34,620	34,620	34,795	34,795	34,795	34,620	34,620
Adjusted R^2	0.8616	0.8629	0.8976	0.8637	0.8659	0.8616	0.8962	0.8618	0.8637	0.8659

The sample consists of a balanced panel of 8,699 unified public school districts located in 48 U.S. states, for the years 1970, 1980, 1990, and 2000. All specifications include district fixed effects and year-specific state effects. Observations have been weighted by district public enrollment. Standard errors are in parentheses.

Table 5: OLS results, Real local revenues per pupil (MSA subsample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
gini coefficient	3685.229	4531.783	3889.188	4706.562	4231.799					
	(435.097)	(438.988)	438.210	441.922	441.342					
schooling fractionalization		-3754.109		-3695.838	-3803.477				-3469.368	-3568.159
index		(340.090)		341.410	340.602				(343.427)	(342.617)
race fractionalization index			315.7557	292.3407	181.181				386.9414	271.3389
			139.292	138.424	137.916				(139.282)	(138.745)
log(95/50) ratio						984.854		1027.915	1304.26	1192.615
						(119.381)		(119.648)	(121.812)	(121.415)
log(50/5) ratio							-271.2465	-321.1577	-253.4194	-274.3108
							(72.053)	(72.001)	(72.721)	(72.377)
%in poverty	-5140.159	-5730.376	-5089.314	-5672.242	-4843.792	-4556.552	-2436.957	-3206.573	-3829.93	-3000.027
	(430.656)	(431.153)	(433.281)	(433.882)	(438.358)	(407.534)	(501.308)	(507.287)	(515.469)	(517.527)
real median family income	26.347	14.54663	26.25154	14.6048	14.29247	27.301	22.96902	27.62077	16.84638	16.80965
(in thousands)	(2.579)	(2.776)	(2.586)	(2.786)	(2.859)	(2.602)	(2.554)	(2.601)	(2.808)	(2.884)
%25+ with hs degree	-3724.542	-1131.218	-3642.823	-1096.829	-851.493	-3702.848	-3588.624	-3536.498	-1085.003	-841.3435
	(278.334)	(362.834)	(279.757)	(364.125)	(364.302)	(278.407)	(281.662)	(280.608)	(363.976)	(363.964)
%25+ with some college	-3888.257	-1052.375	-3782.982	-997.0155	-1129.456	-3941.223	-4436.519	-3872.899	-1166.55	-1257.938
	(283.336)	(381.088)	(284.524)	(382.311)	(383.321)	(282.307)	(275.802)	(282.430)	(380.191)	(381.271)

Table 5, cont.

%25+ with college degree	363.332	1511.418	404.1174	1534.511	1839.34	348.407	965.3603	510.0054	1548.377	1862.301
or more	(341.018)	(354.382)	(343.708)	(357.130)	(356.013)	(341.600)	(340.399)	(343.164)	(358.226)	(357.019)
%nonwhite	-1520.788	-1304.978	-1768.74	-1535.767	-1319.796	-1493.100	-1447.24	-1402.302	-1511.869	-1294.81
	(151.794)	(152.058)	(183.088)	(183.193)	(183.961)	(151.867)	(153.590)	(153.069)	(183.590)	(184.279)
%owner-occupied housing	-1582.617	-1246.164	-1604.787	-1274.594	-353.7409	-1639.867	-1653.105	-1636.604	-1348.155	-428.2555
	(206.170)	(207.070)	(212.249)	(213.094)	(236.213)	(206.041)	(206.642)	(205.829)	(212.650)	(235.924)
%population 65+	5290.021	5321.697	5192.584	5245.644	2527.209	5405.570	5588.27	5478.383	5388.6	2650.369
	(384.262)	(381.747)	(397.484)	(394.988)	(476.903)	(383.619)	(384.886)	(383.569)	(394.365)	(476.632)
%hh with kids					-1991.623					-1987.403
					(209.181)					(209.016)
%population in urban area					-429.4353					-469.2901
					(79.781)					(79.763)
Constant	2733.165	3853.622	2625.426	3736.48	4636.67	3026.195	4122.569	3182.752	4125.287	5006.741
	(271.269)	(287.968)	(275.063)	(291.950)	(301.776)	(255.865)	(234.592)	(257.999)	(281.183)	(290.215)
Observations	13,171	13,171	13,120	13,120	13,120	13,171	13,171	13,171	13,120	13,120
Adjusted R^2	0.8848	0.8863	0.8852	0.9218	0.8881	0.8847	0.884	0.8849	0.8867	0.8882

The sample consists of a balanced panel of 3,292 unified public school districts located in MSAs in 1973, for the years 1970, 1980, 1990, and 2000. All specifications include district fixed effects and year-specific MSA effects. Observations have been weighted by district public enrollment. Standard errors are in parentheses.

Table 6: OLS results, private school enrollment share

	(1)	(2)	(3)	(4)	(5)
gini coefficient	-0.051	-0.042	-0.049	-0.041	-0.050
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
schooling fractionalization index		-0.039		-0.040	-0.053
		(0.008)		(0.008)	(0.008)
race fractionalization index			0.018	0.019	0.018
			(0.004)	(0.004)	(0.004)
%in poverty	-0.005	-0.017	-0.005	-0.017	-0.010
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
real median family income (in thousands)	0.002	0.002	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
%25+ with hs degree	-0.079	-0.051	-0.077	-0.048	-0.036
	(0.007)	(0.009)	(0.007)	(0.009)	(0.009)
%25+ with some college	-0.018	0.005	-0.016	0.008	-0.004
	(0.007)	(0.009)	(0.007)	(0.009)	(0.009)
%25+ with college degree or more	-0.073	-0.061	-0.074	-0.062	-0.063
	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
%nonwhite	-0.053	-0.049	-0.064	-0.061	-0.054
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
%owner-occupied housing	-0.038	-0.033	-0.034	-0.030	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
%population 65+	0.126	0.125	0.121	0.120	0.020
	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)
%hh with kids					-0.077
					(0.005)
%population in urban area					0.017
					(0.002)
Constant	0.105	0.116	0.101	0.112	0.140
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Observations	34,793	34,793	34,618	34,618	34,618
Adjusted R^2	0.8763	0.8764	0.8762	0.8763	0.8776

The sample consists of a balanced panel of 8,699 unified public school districts located in 48 U.S. states, for the years 1970, 1980, 1990, and 2000. All specifications include district fixed effects and year-specific state effects. Observations have been weighted by total (public + private) enrollment in district. Standard errors are in parentheses.

Table 7: OLS results, private school enrollment share (MSA subsample)

	(1)	(2)	(3)	(4)	(5)
gini coefficient	-0.005	-0.002	-0.004	-0.001	-0.010
	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)
education fractionalization index		-0.013		-0.012	-0.028
				(0.016)	(0.016)
race fractionalization index			0.011	0.011	0.008
			(0.006)	(0.006)	(0.006)
%in poverty	-0.031	-0.033	-0.029	-0.031	0.002
	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)
real median family income (in thousands)	0.002	0.002	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
%25+ with hs degree	-0.133	-0.123	-0.132	-0.123	-0.100
	(0.013)	(0.017)	(0.013)	(0.017)	(0.017)
%25+ with some college	0.021	0.032	0.024	0.033	0.007
	(0.013)	(0.018)	(0.013)	(0.018)	(0.018)
%25+ with college degree or more	-0.079	-0.075	-0.082	-0.078	-0.067
	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)
%nonwhite	-0.031	-0.031	-0.039	-0.038	-0.024
	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)
%owner-occupied housing	0.000	0.001	0.004	0.005	0.057
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
%population 65+	0.206	0.206	0.203	0.203	0.086
	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)
%hh with kids					-0.098
					(0.010)
%population in urban area					0.020
					(0.004)
Constant	0.088	0.092	0.085	0.088	0.106
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Observations	13,171	13,171	13,120	13,120	13,120
Adjusted R^2	0.8963	0.8963	0.8963	0.8963	0.8977

The MSA subsample consists of 3,292 districts in 1970, 1980, 1990, and 2000 for a total of 13,168 observations. Districts are included in this subsample if they resided in a county that was located in a metropolitan area in 1973. All specifications include district fixed effects and year-specific state effects. Observations have been weighted by total (public + private) enrollment in each district. Standard errors are in parentheses.

Table 8: Interactions of gini coefficient and fractionalization measures with quintiles of school competition (MSA subsample)

(1)	dists10	dists25	dists50	frac10	frac25	frac50	enrlfrac	diststud
gini coefficient	3,448.782	7,948.584	7,699.180	4,709.360	5,154.200	6,161.835	1,153.928	5,068.279
	(797.721)	(718.294)	(733.192)	(607.692)	(639.985)	(737.329)	(819.161)	(570.521)
gini * 2nd quintile of competition	3,266.309	-4,829.156	-4,459.694	-1,535.712	-1,429.748	-2,134.445	-4,701.060	-5,019.806
	(851.355)	(1003.919)	(976.305)	(623.310)	(705.917)	(854.192)	(433.502)	(784.707)
gini * 3rd quintile of competition	262.025	-7,699.066	-2,794.989	747.541	-852.726	-3,066.431	26.742	-1,592.150
	(865.526)	(893.629)	(851.329)	(647.136)	(740.223)	(841.058)	(2.580)	(955.116)
gini * 4th quintile of competition	-2,146.291	-4,397.862	-2,540.098	-2,129.882	-2,966.919	-2,848.194	-3,655.120	-277.420
	(817.784)	(800.979)	(836.437)	(644.202)	(714.086)	(826.730)	(279.482)	(940.348)
gini * 5th quintile of competition	57.459	-5,233.352	-8,769.054	-2,640.082	-1,753.668	-3,178.816	-3,654.620	-23.987
	(794.163)	(808.620)	(931.431)	(601.074)	(645.583)	(767.766)	(284.692)	(1172.456)

(2)	dists10	dists25	dists50	frac10	frac25	frac50	enrlfrac	diststud
schooling fractionalization	-4186.589	-4211.917	-4789.185	-2575.528	-2266.518	-2187.080	-6607.061	-4440.995
	(450.066)	(467.083)	(454.013)	(439.854)	(475.753)	(509.463)	(521.260)	(382.833)
schooling fractionalization *	1774.865	742.898	2118.742	551.524	-99.941	745.831	2844.812	995.857
2nd quintile of competition measure	(484.869)	(586.074)	(578.104)	(453.943)	(502.304)	(548.127)	(567.785)	(470.913)
schooling fractionalization *	2111.798	1813.151	3163.463	13.029	-626.847	-687.801	1872.055	336.311
3rd quintile of competition measure	(503.314)	(577.602)	(558.717)	(485.973)	(505.815)	(533.379)	(566.018)	(480.557)
schooling fractionalization *	1466.830	521.629	2443.922	-1007.782	-1329.263	-960.685	5481.199	3575.544
4th quintile of competition measure	(481.998)	(506.847)	(529.146)	(439.316)	(485.027)	(501.094)	(597.724)	(522.354)

Table 8, cont.

schooling fractionalization *	35.305	638.055	120.720	-2917.969	-2363.871	-2482.182	4828.460	801.004
5th quintile of competition measure	(458.475)	(491.535)	(499.946)	(430.251)	(438.652)	(470.896)	(581.722)	(720.810)

(3)	dists10	dists25	dists50	frac10	frac25	frac50	enrlfrac	diststud
race fractionalization	161.871	324.472	172.014	623.658	1278.585	2357.504	-1461.411	235.740
	(229.793)	(245.801)	(253.978)	(192.596)	(220.317)	(293.509)	(318.244)	(177.847)
race fractionalization *	515.583	138.046	349.862	-391.352	-979.328	-1704.179	1997.004	-417.220
2nd quintile of competition measure	(271.202)	(349.492)	(350.120)	(197.396)	(220.983)	(317.949)	(349.003)	(251.774)
race fractionalization *	93.391	-803.671	-3.785	-187.345	-849.721	-2056.477	1348.209	-474.098
3rd quintile of competition measure	(236.039)	(289.424)	(289.494)	(212.403)	(240.219)	(292.880)	(345.515)	(298.805)
race fractionalization *	-511.008	-239.177	724.441	-689.580	-1267.762	-2138.053	1826.615	706.042
4th quintile of competition measure	(232.951)	(272.324)	(281.514)	(193.466)	(223.693)	(294.288)	(374.814)	(362.165)
race fractionalization *	366.098	45.640	-363.160	-951.671	-1328.140	-2417.723	2886.449	1902.613
5th quintile of competition measure	(237.441)	(267.854)	(316.530)	(194.441)	(208.485)	(280.618)	(357.700)	(364.604)

Standard errors in parentheses. Panel (1) displays the results of specification (1) in Table 6, allowing the coefficient on the within-district Gini coefficient to vary across quintiles of regional public school district competition. We use six different measures of district competition: dists10, dists25, and dists50 (indicating the number of districts within 10, 25, and 50 miles respectively), and frac10, frac25, and frac50 (indicating the fraction of public school students within 10, 25, and 50 miles that are enrolled in that particular district). In columns (1)-(3), higher quintiles of dists10, dists25, and dists50 represent districts in areas with greater competition; in column (4)-(6), higher quintiles of frac10, frac25, and frac50 represent districts in areas with less competition. Panel (2) and (3) display the results of specification (4) in Table 6, allowing the coefficient on within-district schooling and race fractionalization to both vary across quintiles of district competition (the gini coefficient enters linearly into these regressions).

Table 9: OLS results, low-mobility and non-MSA districts

Dependent variable	(1) Local Revenues per Pupil	(2) Local Revenues per Pupil	(3) Private School Enrollment Share	(4) Private School Enrollment Share
Sample	Low Mobility	non-MSA	Low Mobility	non-MSA
gini coefficient	2,969.142	1,952.237	-0.007	0.007
	(340.651)	(211.992)	(0.019)	(0.013)
schooling fractionalization index	-2,391.493	-1,126.774	-0.081	-0.024
	(256.286)	(172.169)	(0.014)	(0.011)
race fractionalization index	-1,113.340	-100.286	0.013	0.005
	(105.508)	(105.862)	(0.006)	(0.007)
%in poverty	-2,889.482	-301.055	-0.021	-0.062
	(272.831)	(164.387)	(0.015)	(0.010)
real median family income (in thousands)	50.059	46.562	0.002	0.001
	(2.463)	(2.143)	(0.000)	(0.000)
%25+ with hs degree	-2,152.233	-92.508	-0.031	-0.018
	(267.297)	(176.275)	(0.015)	(0.011)
%25+ with some college	1,630.735	-125.728	0.051	-0.011
	(309.263)	(238.982)	(0.017)	(0.011)
%25+ with college degree or more	2,302.358	2,485.727	-0.106	0.061
	(344.765)	(238.982)	(0.019)	(0.015)
%nonwhite	-458.831	84.124	-0.066	-0.057
	(131.883)	(111.346)	(0.007)	(0.007)
%owner-occupied housing	-1,538.289	-228.106	-0.016	0.005
	(202.771)	(131.891)	(0.011)	(0.008)
%population 65+	5,705.483	2,536.925	0.072	-0.095
	(337.716)	(250.076)	(0.019)	(0.015)
Constant	2,236.261	-278.943	0.140	0.079
	(244.492)	(177.653)	(0.014)	(0.011)

Observations	15,750	21,506	15,750	21,504
Adjusted R^2	0.8730	0.8377	0.921	0.841

The low mobility sample consists of 3,955 districts that were in the lowest three quintiles of mobility (the fraction of residents who lived in a different county five years prior to each population census). The non-MSA subsample consists of 5,407 districts that did not reside in a metropolitan area in 1973. Standard errors are in parentheses.

Table 10: IV estimates of local revenues per pupil model (full sample)

	(1) First Stage Gini Coefficient	(2) Second Stage Local Revenues per Pupil
Instrument:		
(a) Gini coefficient of closest district	0.110	2,980.2
	(27.5)	(2.29)
(b) Gini coefficient of closest district in another county	0.095	2,837.9
	(23.8)	(1.81)
(c) Gini coefficient of closest district in another state	0.054	1,167.6
	(13.5)	(0.43)

T-statistics are in parentheses. Coefficient estimates in (1) are the results of three separate regressions, where our Gini coefficient of income inequality is regressed on each of our three instrumental variables, along with district fixed-effects year-specific state effects, and all other exogenous variables included in column (4) of Table 4.