EdWorkingPaper No. 21-388

Inequality in Public School Spending Across Space and Time

Christopher Biolsi
Western Kentucky University

Steven G. Craig
University of Houston

Amrita Dhar
University of Mary Washington

Bent E. Sorensen
University of Houston

This paper takes a novel time series perspective on K-12 school spending. About half of school spending is financed by state government aid to local districts. Because state aid is generally income conditioned, with low-income districts receiving more aid, state aid acts as a mechanism for risk sharing between school districts. We show that temporal inequality, due to state and local business cycles, is prevalent across the income distribution. We estimate a model of local revenue and state aid, and its allocation across districts, and use the parameters to simulate impulse response functions. We find that state aid provides risk sharing for local shocks, although slow speed of adjustment results in temporal inequality. There is little risk sharing for statewide income shocks, and the risk from such shocks to school spending is more severe in low income districts because of their greater reliance on state aid.

VERSION: April 2021

Suggested citation: Biolsi, Christopher, Steven G. Craig, Amrita Dhar, and Bent Sorensen. (2021). Inequality in Public School Spending Across Space and Time. (EdWorkingPaper: 21-388). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/6fsz-pp28

Inequality in Public School Spending across Space and Time

Christopher Biolsi[†]

Steven G. Craig[‡]

Amrita Dhar[§]

Bent E. Sørensen[¶]

March 31, 2021

Abstract

This paper takes a novel time series perspective on K-12 school spending. About half of school spending is financed by state government aid to local districts. Because state aid is generally income conditioned, with low-income districts receiving more aid, state aid acts as a mechanism for risk sharing between school districts. We show that temporal inequality, due to state and local business cycles, is prevalent across the income distribution. We estimate a model of local revenue and state aid, and its allocation across districts, and use the parameters to simulate impulse response functions. We find that state aid provides risk sharing for local shocks, although slow speed of adjustment results in temporal inequality. There is little risk sharing for statewide income shocks, and the risk from such shocks to school spending is more severe in low income districts because of their greater reliance on state aid.

JEL: I22, H72, H77

[*]This paper has benefitted from excellent comments from the Editor and two excellent referees. We also benefitted from comments at the meetings of the Allied Social Science Association, the European Economic Association, the Oxford Education Research Symposium, the Public Choice Society, the Regional Science Association, Texas Camp Econometrics, the Econometric Society (North American Meetings), the Institute for Public Policy and Economic Analysis Network (IPPEAN), the Kentucky Economic Association, the Midwest Macro group, the Urban Economics Association, and the Western Regional Science Association. Seminar participants at the University of Houston provided useful feedback.

[†]Western Kentucky University; christopher.biolsi@wku.edu

[‡]University of Houston; scraig@uh.edu

[§]University of Mary Washington; adhar@umw.edu

[¶]University of Houston and CEPR; besorensen@uh.edu

1 Introduction

Over the last forty years, U.S. state governments have attempted to reduce spending disparities between school districts in K-12 education financing. While the initial impetus for these attempts arose from the courts, starting with the *Serrano v. Priest* decision in California in 1976, most states—even those that have avoided court decisions—now use some form of income-conditioned grants. A substantial economic literature has studied inequality in school spending, but it has been less appreciated that school spending varies over time. Our goal is to empirically model the variation in school spending over time and its impact on inequality between cohorts of students. Being income-conditioned, state aid partly offsets the impact of purely local income shocks on local school taxes ("local revenue") and serves as a mechanism for risk sharing across school districts, especially at longer horizons. State aid, however, is positively correlated with state-level income shocks which affect all districts, leaving school spending vulnerable to such shocks.

To characterize the dynamics of school system finances, we use data from 8,676 independent school districts in the United States from 1992 to 2014, focusing on intertemporal fluctuations in school spending caused by income fluctuations. The dynamic patterns in school spending and their dependence on state-level and local income shocks have not been studied in detail before. Local income shocks are found to be as likely to be negative (or positive) in relatively wealthy school districts as in relatively poor school districts, so a study of risk sharing between districts is quite separate from a study of redistribution between rich and poor districts. As districts change their position in the income distribution, the allocation of aid will change and have dynamic implications.

School spending is mainly financed by local revenue and state aid, and we construct a model of state and local government behavior with an objective function for each level of government.[1] For the state, we model the choice between school spending and lower taxes while allowing for habit formation, and we model preferences for equality in spending across school districts. For the local school district, we model the choice between school spending and lower taxes while allowing for habit formation, and we model the preferences for offsetting state aid. We do not attempt to identify "natural experiments" and we do not model the many constraints that school districts operate under, so we do not consider this a structural model of state and local agents. We interpret the results as showing reactions to exogenous income shocks and, in particular at the local level, the estimates may be biased due to migration of wealthier families to school districts with increases in school spending. The model is designed to capture salient patterns in school spending over the business cycle and interprets the patterns in terms of declining marginal utility of state aid and local school revenue as well as habit persistence, which captures the gradual adjustment of spending found in the data. Decisions are made by politicians, courts, voters who replace state representatives and school boards, etc., rather than by a single agent, but we still find it meaningful to study if this decision process prioritizes school spending more when it is low (captured as concave utility of "the government"), and if it leads to slow adjustment

[1] Federal aid is comparatively small, and we ignore it in the present analysis. The federal government indirectly smooths school spending as federal taxes and transfers smooth state-level income shocks to gross state product as documented by Asdrubali, Sørensen, and Yosha (1996), but in this paper we take state income as exogenous to school aid.

("habit formation"), and if poorer districts gets more funds ("utility from equalization"). As politicians and judges and school boards serve for limited amounts of time, we find it unattractive to couch decisions in term of intertemporal preferences and we assume myopic decision making.

The first-order conditions from the model deliver three equations that we take to the data, obtaining highly statistically significant parameter estimates. We display results from pooled regressions and our findings are thus showing average patterns for the U.S. states, although we also show results for pre- and post-schooling reforms. We simulate the model using the empirical parameter estimates and assuming exogenous income shocks. The steady state distributions are similar to the empirical distributions which indicates that estimation bias is not severe.[2]

Using simulated data, we provide a detailed picture of how local revenue and state aid interact dynamically following income shocks. First, we simulate impulse response functions, which show how state aid and local revenue react to local and statewide income shocks while accounting for how state aid and local revenue depend on each other. Second, we highlight that there is significant variation in school spending between cohorts within the same school district. Third, we find the incidence of district-level income shocks on after-tax local income, school spending, and state aid (which, via taxes, are transfers from other districts) in the short and long run. Fourth, we analyze recent changes in school finance systems and find that efforts to equalize school spending may exacerbate intertemporal disparities.

In order to provide intuition for our results, we present two examples which illustrate what we try to capture with our model. Youngstown, Ohio, had substantially lower income growth over 1995–1998 than Ohio as a whole (7.1 percent versus 11.0 percent). As a result, local revenue declined by 5.0 percent (of initial school spending in 1995), which was more than compensated for by state aid increasing by 8.6 percent. State aid is ultimately financed by taxes on all districts in Ohio, so other school districts in the state shared the idiosyncratic income shock to Youngstown. In the case of statewide shocks, school districts cannot share the aggregate risk. Consider the South San Antonio Independent School District in Bexar County, Texas. State income per capita fell by 1.1 percent in 2013, though it barely changed in Bexar County and, as a result, state aid per student fell by close to 1.6 percent of 2012 school spending. Local revenue increased by 0.3 percent (of initial school spending) to partly offset this loss of aid, but it was not sufficient to prevent a substantial drop in school spending even if local income changed little.

Dupor and Mehkari (2015) develop a model in which school districts behave as optimizing consumers. They focus on school districts and treat revenue as exogenous, while we model school spending and the interactions between school districts and state governments as endogenous. Our paper also relates to the work of Fernández and Rogerson (1996) and Fernández and Rogerson (1998) in that it examines the distribution of school spending across the income distribution. These authors consider the long-run dynamic effects of schooling on migration and the future income of students—issues we do not touch upon.

The paper proceeds as follows. Section 2 describes our data. Section 3 develops the model and the resulting estimating equations for total state aid, for its distribution across

[2]We also show results from Granger causality tests, which indicates that reverse causality exists but is minor.

districts, and for local revenue. Section 4 reports our empirical estimates, while Section 5 shows the steady-state allocations, impulse response functions, and dynamic incidence of income shocks. Section 6 performs the analysis splitting the sample into the periods before and after school finance reforms. Section 7 concludes.

2 Data

Education in the United States is the responsibility of state governments, which decide on the organization of local education. 45 states partially or completely devolve responsibility to single purpose independent school districts. These school districts, with separately elected boards, act within constraints imposed by state governments, but in general choose the level of property tax rates, debt, and the distribution of funds to individual schools. For virtually all school districts in the United States, the local tax base is the value of property, which it could be argued created the environment resulting in education resource disparities. The other school district organizational form, with the exception of the statewide school district in Hawaii, is one where education is undertaken as part of the responsibility of general purpose local government, typically a city (Fischel, 2009). For simplicity, and consistent with their dominance in the United States, we use only the independent school districts for our analysis.[3] We collect data on revenue by source, enrollment, and current expenditure for independent school districts for the years 1992 to 2014, using the U.S. Census Bureau's Annual Survey of School System Finances.

We delete districts with less than 100 students and a small number of school districts for which the county indicator in the Census data changes at some point over the sample, which is possible if a school district spills over county lines. To obtain a balanced panel, we exclude districts that are not present in the data for the entire sample. Because the Census Bureau's School System Finance data provides less coverage for the fiscal years 1993 and 1994, this entails removing a number of district-year observations that would otherwise meet our criteria.[4]

These exclusions leave us with a panel of 8,676 independent school districts observed at the annual frequency over 23 years in 45 states, resulting in 199,548 district-year observations—see Appendix Section A for details by state.[5] On average, our sample includes 67 percent of the district-year observations available in the raw data, ranging from 64.5 percent of those appearing in the 1992 file to 77.4 percent of those in the 1994 file. Our final sample also contains 72.9 percent of total enrollment across all districts and years, and the share of enrollment by year ranges from 72.4 percent in 2000 to 76.7 percent in 1994.

Independent school districts come in four types by purpose. Most are unified, meaning

[3]We use the indicator for independence that is encoded in the district identification variable for each school district by the Census Bureau. Our focus on states that at least partially use independent school districts implies that we exclude all school districts from Alaska, Hawaii, Maryland, Virginia, North Carolina, and the District of Columbia.

[4]There are a small number of school districts where local revenue or state aid had a value of zero in at least one year. We assign these observations a nominal \$1000, but the results are robust to dropping them as shown in Appendix Table **??**.

[5]There is a wide variety in the number of school districts across states, with 3 in Rhode Island and over 900 in Texas.

that they comprise both elementary and secondary schools, while others may be elementary or secondary only. 86.6 percent of the district-year observations are unified, while 10.0 percent are elementary-only, and 3.1 percent are secondary-only. The final 0.3 percent are vocational school districts.

We model both state and local education expenditure as depending on income. Using income has the advantage that it is being uniformly measured across the country and it is measured at both state and school district levels. Collected property taxes are endogenous as school districts choose the tax rate, while measurement of the property tax base is inconsistent across school districts because it varies significantly with how appraisals are conducted, and this issue is particularly problematic for commercial property. State governments usually do not use property taxes but rely on sales and income taxes.[6] The simulation of the model is much simplified by letting both local school revenue and state aid depend on income, rather than, say, modeling property taxes and adding separate shocks (correlated with income) to the property tax base in order to generate local revenue fluctuations. For completeness, we include regressions of local school spending on growth in house prices; see Appendix Table D2. For those regressions, we use standardized coefficients where the regressors are normalized by their standard deviation and we report our main specification using county-level income with standardized coefficients as well. The coefficients can then be compared across the two specifications in terms of their impact on the fluctuations in the dependents variables. The estimated coefficients found using house prices are similar to those found using income, so the general patterns found regarding school spending over the business cycle seem robust.

Table 1 provides statistics on personal income at the school district and state levels. We assign each school district the per capita personal income of the county in which it is predominantly located, which we refer to as "district income." County-level personal income from the Bureau of Economic Analysis is available for the entire time period of our analysis. The Census Bureau's American Community Survey (ACS) makes income available by school district, but these data are only available from 2009 and on, implying that the sample is without any recessions. For completeness, we report a full set of results using district income, rather than country income, in Appendix G. The results are quite similar, except that with this income variable local revenue is somewhat less sensitive to local income.

Table 1 also gives summary statistics for the other key variables in our analysis. Our measure of "school spending" is what the Census terms "Current Expenditure" (i.e., we do not include capital spending). Table 1 shows that school spending is roughly equal to the sum of state aid and local revenue. In the model that we develop in Section 3, we will explicitly define school spending as the sum of these two variables. School spending is financed roughly half by local taxes and half by state aid, and we ignore federal aid because it is a small fraction of total school revenue and it is almost exclusively directed towards specialized functions such as school breakfast and lunch.[7] On average, state governments provide 47.6 percent of total revenue as aid, local governments provide 45.6 percent of total

[6]Hoxby (1998) shows that per capita income predicts school spending even after controlling for property valuations in a linear regression and that income in some decades is the more significant predictor.

[7]The primary concern with the omission of federal aid is Title I aid for low-income districts. Title I aid is small enough that our results are not sensitive to its inclusion and school food aid is not generally fungible with other school expenditures.

revenue, and the rest is provided by the federal government. Capital outlays are about 10 percent of total revenue. Table 1 also demonstrates the significance of balanced budget constraints as school districts typically spend all of their revenue. The average (across districts) standard deviation across time is substantial at a magnitude of about half of the average (over time) standard deviation across districts for most variables, including school spending. The bottom panels of Table 1 report growth rates, and it is apparent that district-level income is much more variable than state-level income as one would expect from the Law of Large Numbers if idiosyncratic district income shocks are not highly correlated.

Figure 1 shows the (average) relation between our central variables and district level income. The figure plots time-averaged real outcomes per student as a function of time-averaged district income per capita using all of the independent school districts in our sample across the 45 states after subtracting state-specific averages and adding back the overall average.[8] Panel (a) shows an almost linear relation between local income and local revenue, while Panel (b) shows a declining convex relation between local income and state aid. Panel (c) shows the resulting level of school spending by income and reveals for an average state a convex shape with wide differences in spending across school districts; however, most differences are to be found for middle- or high-income districts. For low-income districts, school spending increases only weakly, if at all, with income due primarily to state aid being aimed at low-income districts.

Table 2 reports the sources of fluctuations in total school revenue and it is apparent that variation in state aid is as important as variation in local revenue for the dynamics of school spending.[9] As we will show, state aid may fluctuate to offset idiosyncratic local income shocks or because of state-level income shocks.

State aid to a district changes partly because the income distribution across districts changes. Table 3 shows the transition matrix for quintiles using the five-year moving average of per capita district income from 1992 to 2014, and it is clear that districts can experience substantial changes in their position in the income distribution within the state. Mobility of districts between quintiles is largest for the middle three; for example, of the districts in the middle-income quintile at the beginning of our sample, only 35 percent are still in the middle quintile by the end of our sample. But even for districts in the top or bottom quintiles, there is significant mobility.

We evaluate the level of school spending by cohort assuming students do not change school districts. That is, we sum the spending of the school district over 13 years of K-12 education and assume a student is exposed to the average level of spending each year. We perform this calculation for all complete cohorts, consisting of students that begin school in the years between 1992 and 2002 and summarize the results in Table 4, which reports

[8]Because the number of school districts is very large, we compress the information and use binned scatter graphs, where we plot the outcomes against income which is sorted and collected into 100 quantiles on the x-axis. The corresponding value on the y-axis is averaged over the observations with income in that quantile.

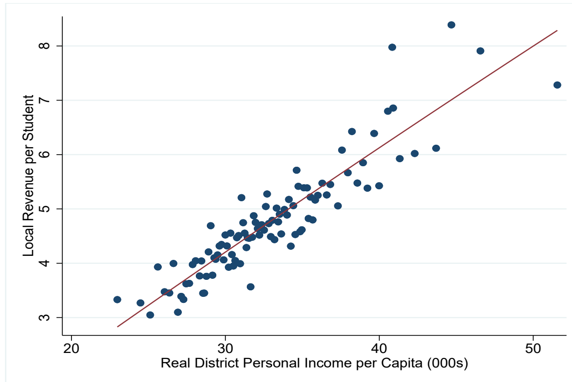
[9]Because Total Revenue= State Aid+Local Revenue+Federal Aid, the variance of total revenue is the sum of the covariances of total revenue with state aid, local revenue, and federal aid, which implies that OLS coefficients of regressions of each of these three components on total revenue sum to unity. The OLS coefficients have the interpretation of the fraction of variance explained (in a non-causal sense) by the relevant variable and provide measures of relative importance in explaining fluctuations in total revenue. See Asdrubali, Sørensen, and Yosha (1996) for further details.

Table 1: Summary Statistics for Key Variables: Total Sample

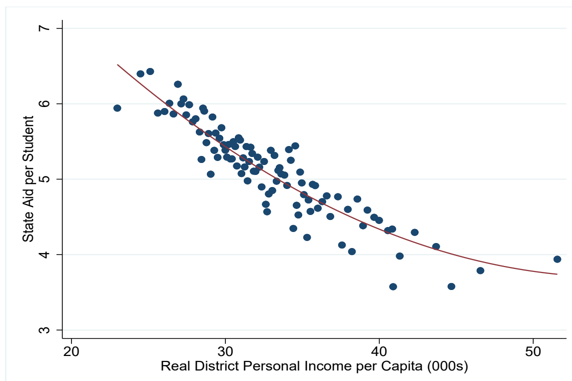
Variable	Mean	Std Dev 1 (across districts within years)	Std Dev 2 (across years within districts)
Per-Student Values (000s of 2009 dollars)			
Total Revenue	10.74	3.80	2.08
State Aid (District-Level)	5.11	2.38	1.24
Local Revenue	4.90	3.86	1.17
School Spending (District-Level)	9.02	2.78	1.56
Revenue from Federal Govt	0.74	0.85	0.35
Capital Outlay	1.05	1.89	1.44
Per-Capita Values (000s of 2009 dollars)			
County Personal Income	30.55	7.33	7.88
District Personal Income	61.41	21.40	2.51
State Personal Income	35.60	5.49	4.38
Percentage Point Growth in Per-Student Values			
Total Revenue	2.13	8.71	9.93
State Aid	2.88	15.89	21.01
Local Revenue	1.49	14.73	18.62
School Spending	2.02	6.06	6.94
Percentage Point Growth in Per-Capita Values			
County Personal Income	1.85	4.93	5.11
District Personal Income	-0.13	4.65	3.86
State Personal Income	1.74	1.60	2.44
As Share of Income			
Total School Spending	4.3%	1.9%	1.6%
Total State Aid	1.8%	0.9%	0.2%

Notes: The table reports summary statistics of the different types of revenue and income for the sample of 8,676 independent school districts in the United States for the period 1992 to 2014 (199,548 district-year observations). Values for levels are expressed in thousands of 2009 dollars per student (for the education variables) or 2009 dollars per capita (for the income variables). "Std Dev 1" is defined as the average across years of $[(1/D)\sum_d (X_{d,t} - \bar{X}_t)^2]^{1/2}$. "Std Dev 2" is defined as the cross sectional average of $[(1/T)\sum_t (X_{d,t} - \bar{X}_d)^2]^{1/2}$. For education variables, the denominator for each variable is the number of students in district d in year t. For income variables, the denominator for each variable is the total population in county c or state s in year t or total households in district d. The correlation coefficient between log real county income per capita and log real district income per household net of state and year effects is 0.78.

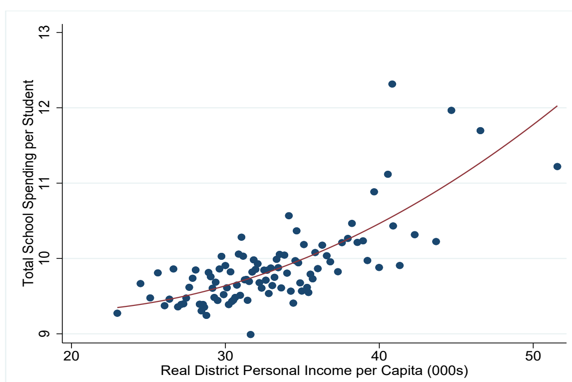
Figure 1: Average School Spending, Local Revenue, and State Aid by Income



(a) Local Revenue per Student



(b) State Aid per Student



(c) School Spending per Student

Notes: The figure plots the average of each district's local revenue, state aid, and school spending (all in per student terms) over the sample period (1992–2014) against the average of its per capita income over the sample period, along with a fitted quadratic regression line controlling for average state effects. The figures are binned plots where income is sorted and averaged into 100 quantiles and the data on the y-axes are averaged over the observations with income in the relevant bin. The figure excludes 413 districts where income per person averaged more than $51.5 thousand or less than $19.2 thousand, as well as those districts (51) spending $20 thousand more than the state average.

Table 2: Variance Decomposition of Total Revenue of School Districts (Percent)

Revenue Source	(1)	(2)	(3)
State Aid	42.5	42.4	42.8
	(3.7)	(3.7)	(3.8)
Local Revenue	43.4	43.7	42.9
	(2.6)	(2.6)	(2.6)
Federal Aid	14.1	13.9	14.3
	(4.8)	(4.9)	(4.8)
Year Fixed Effects	No	Yes	No
District Fixed Effects	No	No	Yes

Notes: The table reports coefficients estimated from regressions of $\Delta Y_{d,t} = \alpha + \beta \Delta Total\ Revenue_{d,t} + \epsilon_{d,t}$, where $Y_{d,t}$ denotes, sequentially, real state aid per student in district d in year t, real local revenue per student in district d in year t, and real federal revenue per student in district d in year t. Each coefficient represents the share of overall variation in total revenue of district d in year t accounted for by each source of total revenue. Standard errors are clustered at the district level and are reported in parentheses.

Table 3: Transition of School-District Income Between State-Specific Income Quintiles

	2010–2014				
1992-1996	Q1	Q2	Q3	Q4	Q5
Q1	0.77	0.18	0.02	0.02	0.01
Q2	0.09	0.52	0.30	0.07	0.02
Q3	0.07	0.23	0.35	0.27	0.08
Q4	0.03	0.09	0.21	0.48	0.20
Q5	0.01	0.03	0.07	0.17	0.71

Notes: Each cell of the table reports the percentage of school districts in the state income quintile given by the row header averaged over 1992 to 1996 that is in the state income quintile indicated by the column header averaged over 2010 to 2014.

that the average spending per student is about $118 thousand in real 2009 dollars. The cohort calculation allows for smoothing over the 13 years if lean years are compensated by abundant years but despite that, the within-district cohort standard deviation is more than 28 percent of the annual average cross-sectional standard deviation. In more than three percent of the cohorts, students are subject to lower spending than their peers starting the prior year. Further, despite the fact that the average growth in per-student spending of 2.02 percent is greater than average income growth, in over a quarter of the cohorts, students are educated in school districts where school spending grew more slowly than income.

Table 4: Summary Statistics of School Spending per K-12 Cohort

Total District-Cohort Observations	95,436
Average Spending by School Districts over Primary/Secondary School Career	$118,199.40
Average Across-District Standard Deviation	$33,553.15
Average Within-District Standard Deviation	$9,510.82
District-Cohort Observations Exposed to Less Spending than Previous Cohort	3,188 (3.7% of total)
District-Cohort Observations Exposed to Less Spending than Cohort 5 Years Prior	556 (1.1% of total)
District-Cohort Observations in which Spending Grows more Slowly than Income over 1 Year	27,403 (31.6% of total)
District-Cohort Observations in which Spending Grows more Slowly than Income over 5 Years	13,464 (25.9% of total)

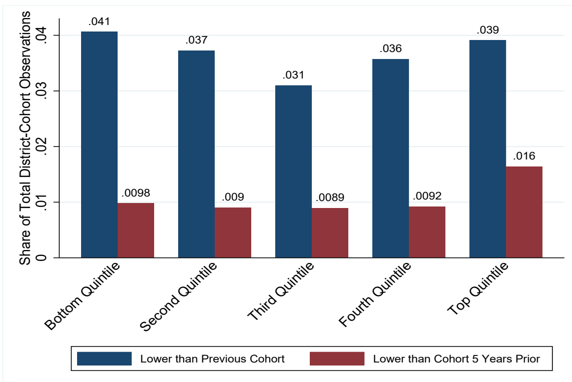
Notes: The table reports summary statistics for school spending (measured in 2009 dollars per student) that students would be exposed to over the course of their entire K-12 education career. The table includes only complete cohorts, covering students entering kindergarten between 1992 and 2002. The calculations assume that a student stays in the same school district for 13 years. The last four rows of the table show the number of district-cohort observations who, relative to older cohorts (one year and five years older), received lower spending or had spending growth slower than income growth. The percentages in parentheses are calculated using the appropriate comparison cohorts.

2.1 School Spending by Cohort is Unrelated to Average District Income

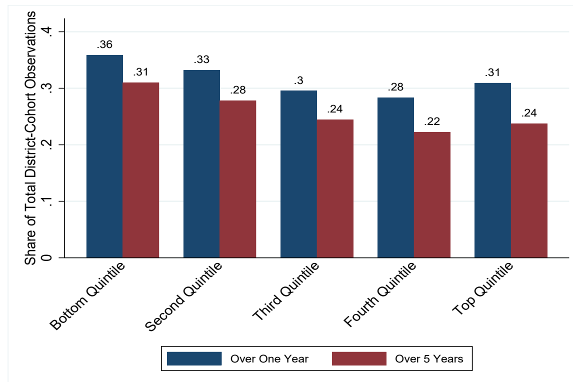
Figure 2 reveals that the time series disparities are roughly orthogonal to the cross-sectional disparities that have motivated the school finance literature. The top row of Figure 2 depicts the share of student cohorts which have experienced lower spending than earlier cohorts in the same school district. The school districts are organized by their state-specific income quintiles in 1992. In Panel (a), we see that 4.1 percent of the district-cohort observations in the bottom quintile experienced lower spending than the previous cohort. For the top income quintile of school districts, however, 3.9 percent of cohorts experience lower spending than the immediately previous cohort. The middle-income quintile school districts experienced the lowest rate of reductions, with 3.1 percent of the cohorts experiencing spending reductions. Panel (b) shows a similar pattern with low-spending-growth years being evenly distributed across income levels.

The bottom row of Figure 2 illustrates the same point using selected individual school districts. Panel (c) shows the five slowest growing school districts measured by expenditures

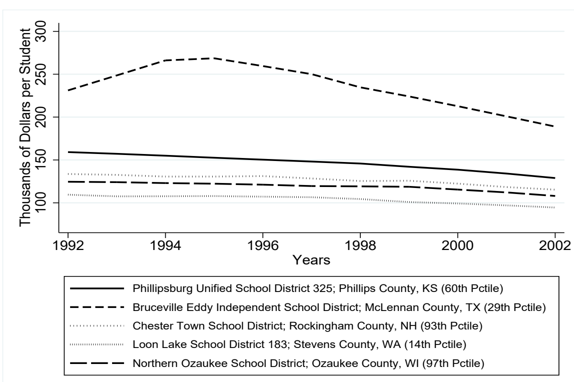
Figure 2: Changes in School Spending Per Cohort by Income Quintile
(Based on 1992 Income Quintiles)



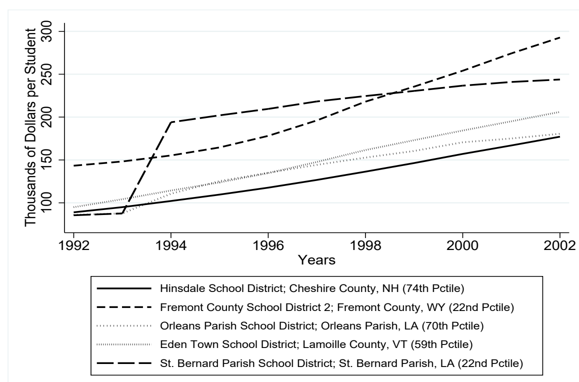
(a) Share of Cohorts Receiving Less Spending than Previous Cohort



(b) Share of Cohorts for Which Spending Grows More Slowly than Income



(c) Slowest Growth in Spending



(d) Fastest Growth in Spending

Notes: The top two panels in the figure report summary statistics for school spending per student in a cohort, covering all primary and secondary education, according to the income quintile at the beginning of the sample (1992). The bottom two panels report total spending per cohort in the five school districts with the slowest growth in school spending, and in the five districts with the fastest growth in school spending. The sample includes the complete cohorts entering kindergarten in the years 1992 through 2002.

per student. We see that districts with both high and low income at the start of the sample period have experienced reductions in school spending for cohorts over time. Similarly, Panel (d) shows the fastest growing districts in spending per student, and these districts likewise originated at very different points in the income spectrum. This evidence suggests that school spending disparities over time is a problem distinct from disparities at a single point in time.

In Figure 3, the top panels show the annual share of cohorts experiencing spending reductions relative to previous cohorts in the same school district. We again separate cohorts according to income quintile. The Great Recession is associated with spending reductions in many districts, and these reductions were almost equally likely to be experienced by cohorts in the top income quintile districts as by those in the bottom quintile. Further, it is clear that even before the Great Recession, there were a nontrivial number of cohorts experiencing spending reductions, with high-income cohorts starting in the early 1990s relatively more likely to suffer spending declines than lower-income cohorts starting school at the same time. The bottom panels show the same basic pattern for cohorts experiencing spending growth slower than income growth.[10]

3 A Preference Model for K-12 Education Finance

Our goal is to interpret the dynamics of school spending in terms of standard utility functions.[11] We model the behavior of a state government and of a local school district which we will estimate using mainly pooled regressions. States choose the total level of state education aid as a function of state-level income and then decide on the distribution of aid across districts as a function of local revenue. School districts choose local taxes as a function of state aid and local income.[12] The model allows for trade-offs between school spending and other uses of income, while dynamics are introduced by allowing for habit persistence. The habit persistence feature is capturing the slow adjustment to changes which is clearly visible in the empirical data (see Appendix Figure E3). This specification allows us to derive impulse response functions in a simple manner without attempting to model in detail the complex political process of governmental choice that underlies the outcomes. We present the sub-models for state and local behavior with first-order conditions used for empirical estimation while details of derivations are presented in Appendix Section B.

3.1 State Government Behavior

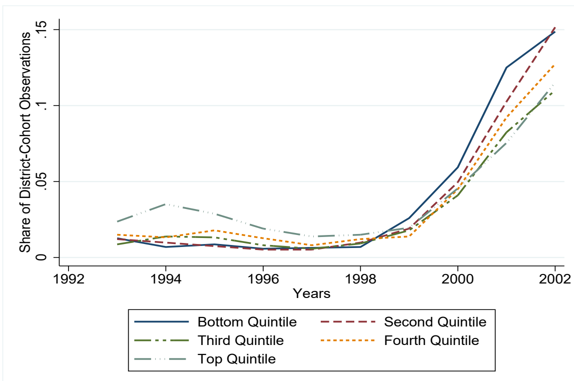
The state government is assumed to have preferences for the level of total state aid to local districts, for the distribution of aid, and for income net of state aid. We do not model whether income not spent on school aid is taxed or left to taxpayers, nor do we model if taxpayers spend or save their after-tax income—our goal is to capture that taxes have opportunity

[10]Panel (d) is the only one in the eight panels of the two figures that suggests a correlation with income.

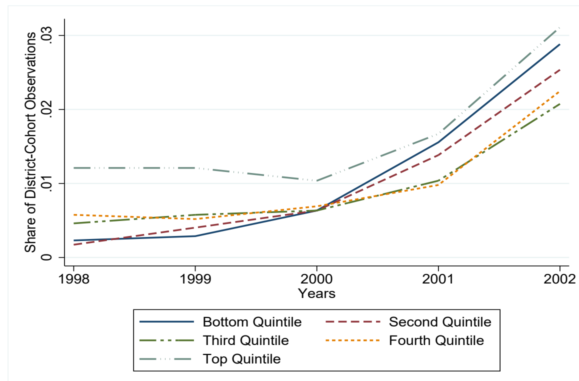
[11]Most previous research has focused on the changes in educational outcomes that may result from shocks to school spending, but this is not our concern here. See, for example Jackson, Johnson, and Persico (2016) or Lafortune, Rothstein, and Schanzenbach (2018).

[12]Our specification is consistent with assuming a Nash equilibrium in repeated static games.

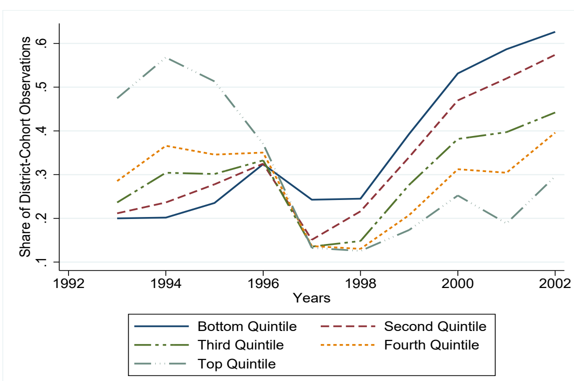
Figure 3: Evolution Over Time of Changes in Spending by Cohort by Income Quintile (Based on 1992 Income Quintiles)



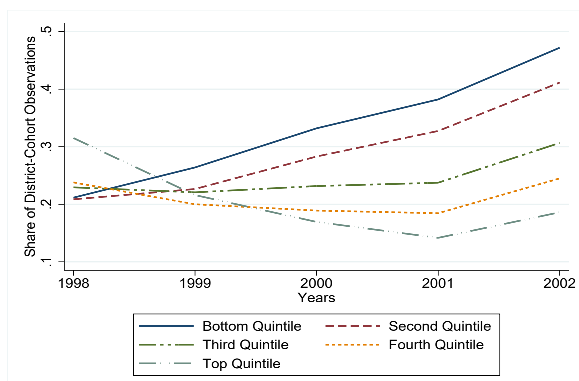
(a) Share of Cohorts Receiving Less Spending than Previous Cohort



(b) Share of Cohorts Receiving Less Spending than Cohort 5 Years Prior



(c) Share of Cohorts for which Spending Grows More Slowly than Income over 1 year



(d) Share of Cohorts for Which Spending Grows More Slowly than Income over 5 years

Notes: Each panel in the figure reports the share of cohorts with reduced total cohort school spending in a different comparison- either to the previous cohort, the five years' prior cohort, or more slowly than income over one or five years. Cohorts are sorted according to the income quintile of the school district at the beginning of the sample period (1992). The calculations assume that a student stays in the same school district for 13 years for the cohorts starting between 1992 and 2002.

costs which are increasing in taxation. Local revenue and state aid do not instantly adjust to income shocks, which the model captures by allowing for habit persistence. The preference function is specified as:

$$\max_{\{R^S_{d,t}\}_{d=1}^D} \Sigma_d \,(R^L_{d,t})^\omega \,\frac{1}{1-\eta}\left[(\frac{R^S_{d,t}}{R^S_t})/(\widetilde{\frac{R^S_{d,t}}{R^S_t}})\right]^{1-\eta} + \frac{1}{1-\gamma}\left(\frac{R^S_t}{\tilde{R}^S_t}\right)^{1-\gamma} + \frac{1}{1-\kappa}(Y^S_t - R^S_t)^{1-\kappa}\,,$$

where $R^S_{d,t}$ is state aid to school district d (at time t), $R^L_{d,t}$ is local revenue in district d, and $R^S_t = \Sigma_{d\in D} R^S_{d,t}$ is total state expenditure on school aid. Y^S_t is income in state s and the state myopically solves its optimization problem in each period t. We assume balanced budgets so that total school aid equals taxes (which fall evenly per capita on all districts).

A negative value of ω indicates that states weight aid more highly for districts with lower local revenue per student—the case with a non-zero value of ω is referred to as unequal concern. η describes the degree of inequality aversion with respect to state aid: if η is larger than 1, states have aversion to unequal state aid across districts.[13] Preferences over inequality in state aid are specified relative to a reference level, $\widetilde{\frac{R^S_{d,t}}{R^S_t}}$.

The second term in the equation reflects the utility derived from total state aid relative to a reference level, with concavity captured by the parameter γ. The third term in the equation captures the utility of personal income minus total state aid per capita, which is all other public and private uses of income outside of state education aid. κ reflects the degree of concavity for this term. We specify the reference levels for total state aid as functions of past levels:

$$\log \tilde{R}^S_t = \varrho^S + \log R^S_{t-1}\,,$$

and

$$\log\left(\widetilde{\frac{R^S_{d,t}}{R^S_t}}\right) = \varrho^d + \log\left(\frac{R^S_{d,t-1}}{R^S_{t-1}}\right)\,,$$

which is a simple way of modeling habit persistence.[14]

Estimating equations are derived assuming that the states decide first how much to spend in total on education without regards to its distribution. The first order condition, after adding a noise term to create an estimation function, takes the form:

$$\log R^S_{s,t} = \mu_s + \zeta_t + \frac{\gamma-1}{\gamma}\log R^S_{s,t-1} + \frac{\kappa}{\gamma}\log(Y^S_{s,t} - R^S_{s,t}) + \varepsilon_{1,s,t}\,. \tag{1}$$

From Equation 1, the reaction of state aid to state-level economic shocks is shaped by the ratio of κ to γ; i.e., from the relative curvature of utility from non-taxed income to the curvature of the utility from aid. For interpretation, consider the case of a fixed value of

[13] The CES-specification of inequality aversion is similar to that of Behrman and Craig (1987).

[14] In models of habit persistence with forward-looking agents, the future loss of utility from higher current consumption will make current consumption overall less attractive and tilt the consumption profile relative to the myopic case. State governments may or may not be forward looking but they are subject to a number of institutional constraints that imply slow adjustment. Also, politicians face elections which may lead to compressed time horizons or strategic behavior, but detailed modeling of this belongs in a more specialized paper on government decision making. Overall, we find the assumption of non-forward-looking behavior more suitable here.

κ and $\gamma > 1$: as γ gets larger, the state government alters education aid less for any given shock. In the extreme, as $\gamma \to \infty$, the level of state aid becomes constant. In the case where both κ and γ become very large, the process approaches a random walk.

The solution (assuming atomistic districts) for the allocation of aid across districts, with state-year fixed effects, $\mu_{s,t}$, for state-level terms and with a noise term added, takes the form:

$$\log R^S_{d,t} = \mu_{s,t} + \frac{\omega}{\eta} \log R^L_{d,t} + \frac{\eta - 1}{\eta} \log R^S_{d,t-1} + \varepsilon_{2,d,t} \ . \tag{2}$$

This second estimating equation shows that state aid to district d depends on local revenue and on the level of aid to the district in the previous year.[15] ω and η interact to describe the state response to local revenue $R^L_{d,t}$—a numerically larger negative value of ω implies that higher local revenue results in lower state aid, holding η constant.

3.2 Local School District Model

Our model of the representative school district captures that school spending has an opportunity cost and that local school revenue responds to state aid. The preference function for local districts is similar to that of the state. District d chooses revenue $R^L_{d,t}$ (which equals local taxes) to maximize the following preference function:

$$\max_{R^L_{d,t}} (R^S_{d,t})^{\phi} \frac{1}{1-\xi} (\frac{R^L_{d,t}}{\tilde{R}^L_{d,t}})^{1-\xi} + \frac{1}{1-\theta} (Y^L_{d,t} - R^L_{d,t})^{1-\theta} \ ,$$

where $Y^L_{d,t}$ is personal income for district d. The local district behaves myopically with respect to the reference spending level, $\tilde{R}^L_{d,t}$, which is specified as follows

$$\log \tilde{R}^L_{d,t} = \pi_0 + \log R^L_{d,t-1} \ .$$

Solving for the first-order conditions and adding an error term and fixed effects for years and states provides a third estimating equation:

$$\log R^L_{d,t} = \mu_s + \zeta_t + \frac{\xi - 1}{\xi} \log R^L_{d,t-1} + \frac{\phi}{\xi} \log R^S_{d,t} + \frac{\theta}{\xi} \log(Y^L_{d,t} - R^L_{d,t}) + \varepsilon_{3,d,t} \ . \tag{3}$$

The parameter ϕ determines the extent to which school districts offset state aid with local tax reductions. For example, $\phi = 0$ would imply that the school district does not take state aid into account when choosing local revenue, a finding of a complete flypaper effect. Finding that $\phi < 0$ would imply that school districts reduce local school taxes following increases in state aid, indicating that state aid would not result in increases in spending on education dollar for dollar.

In Equation 3, the parameter ξ for the curvature of the utility of local revenue interacts with both the ϕ parameter and the θ parameter. θ captures the curvature of the utility from local after-school-tax income. θ/ξ is the (approximate) elasticity of local revenue with respect to local income.

[15]We assume the number of school districts in the state are fixed at D.

4 Empirical Estimation

We estimate the three equations derived above; namely, the state choice over the level of state aid (Equation 1), the distribution of state aid to school districts (Equation 2), and local choice of revenue (Equation 3). The model is exactly identified from the linear reduced form regressions presented in Appendix Section C. Each of the reduced-form equations identifies the same number of parameters in the linear estimation as the number of parameters in the non-linear structural equation and we estimate the linear equations and solve non-linearly for the structural parameters, estimating standard errors via the delta method.

Two of the estimating equations have as independent variables income minus taxes, for example, $\log(Y^S_{s,t} - R^S_{s,t})$, which is a function of the dependent variable and therefore correlated with the residual. School aid is a small fraction of state income so the estimates are similar if we simply regress on $\log Y^S_{s,t}$, but we here use IV estimation because state aid and local revenue are simultaneously determined. We use the contemporaneous value and four lags of log real state income per capita as instruments which we assume are not a function of local revenue.

In Equation 2, we use the contemporaneous value and four lags of log school district personal income per capita as instruments for $R^L_{d,t}$, and in Equation 3, we use the contemporaneous value and four lags of log school district personal income per capita as instruments for $\log(Y^L_{d,t} - R^L_{d,t})$ and $\log R^L_{d,t-1}$, while the contemporaneous value and four lags of log state personal income per capita serve as instruments for $\log R^S_{d,t}$.[16]

Income may be endogenous to school spending to the extent that school quality affects migration patterns. In particular, wealthier families are likely to move to better school districts and to the extent that higher school spending improves the reputation of the school district, this will create an endogeneity bias when the results are interpreted as the impact of an exogenous change in income as is the case in our model simulations. In our estimations that pool many states, it is very hard to find instruments for this and we do not attempt to do so. We believe this bias is minor: we show that the steady state outcomes of the simulated model are similar to the empirical patterns as are the simulated impulse response functions. In Appendix Table D3, we show regressions of per-household district-level income growth on lagged school spending display small (but significant) effects, while the same holds less strongly at the county level. Nonetheless, the results should be interpreted with some caution and are not intended as alternatives to natural experiment-type studies of, say, school spending on learning outcomes.

Our pooled parameter estimates can be seen as weighted averages of state-level regressions. This is a mechanical result which holds in a linear pooled panel regression with cross-sectional fixed effects as pointed out (for the symmetric case of a time fixed effect) in Asdrubali, Sørensen, and Yosha (1996).[17]

[16]For all three estimating equations, the estimation results are not qualitatively sensitive to the number of lags used as instruments. Further, the results are similar if we specify reference utility as being a weighted average of the previous two periods. Column 2 of Appendix Table D1 reports OLS estimates corresponding to our main results. While some coefficients change magnitude somewhat, none of the qualitative results are affected.

[17]The result is easily demonstrated, but for notational simplicity, we first demonstrate the results for simpler case. A typical pooled coefficient $\hat{\beta}$ of a cross-sectional fixed effect regression of a generic variable

4.1 Estimation Results

The estimated parameters are highly statistically significant and, for brevity, we will not comment further on their statistical significance. We present the estimates of the just identified preference parameters in Table 5.

Overall state education aid. The preference parameters estimated from Equation 1 capture how states choose total education aid versus all other uses of income, public and private. We estimate γ, the curvature of the utility from total state aid, to be 3.029 and κ, the curvature of the utility of income after school taxes, to be 1.669. These parameters imply that state governments have a stronger preference for limiting fluctuations in school spending than for limiting fluctuations in after-tax income. The value of the γ parameter implies an autoregressive parameter for total state aid of 0.67.[18]

Allocation of state education aid across school districts. The parameters η and ω are estimated from Equation 2, which expresses states' preferences over the allocation of state aid across districts. The unequal caring parameter ω, which weights local revenue in the objective function, is estimated to be -0.59 implying that states distribute more aid to school districts with lower local revenue. This finding is consistent with the equalization push for aid since *Serrano*. From the reduced form coefficient in Appendix Table C1, we see that states are estimated to reduce aid to a district with a negative elasticity of 0.108 with respect to local revenue. The parameter η is estimated to be 5.480 which suggests a relatively steep curvature, implying that state governments have a low willingness to change aid levels relative to past values. Together with the corresponding term for overall state spending, the implication is that state governments have considerable "stickiness" in aid levels.

Local school district spending. The responses of local school districts to local income and state aid are captured by Equation 3. The parameter ξ, identified from a reduced-form coefficient to lagged local revenue of 0.738, is estimated at 3.82, which implies that school districts have a fairly high degree of aversion to fluctuations in local school revenue. The concavity in the utility of other uses of local income, captured by θ, is estimated to be 0.77 which, together with the value of ξ implies a low elasticity in the reduced form of 0.202 for school spending with respect to local income. Overall, these results imply that local districts tend to limit fluctuations in school spending.

The parameter ϕ captures how local revenue responds to state aid, with the reduced form elasticity in Appendix Table C1 taking a low value of –0.148, implying that local

---

y on a generic variable x (which can be a second stage variable in an IV regression) is $\hat{\beta}_y = \Sigma_i \Sigma_t (x_{it} - \overline{x}_i) y_{it} / \Sigma_i \Sigma_t x_{it}^2$, where $\overline{x}_i$ is average across years for cross-sectional unit i. In a time-series regression for i, estimating the i-specific parameter $\hat{\beta}_i$, we have $\hat{\beta}_i = \Sigma_t (x_{it} - \overline{x}_i) y_{it} / \Sigma_t (x_{it} - \overline{x}_i)^2$. Thus, $\hat{\beta}$ is a weighted average of the $\hat{\beta}_i$ coefficients with weights $\Sigma_t (x_{it} - \overline{x}_i)^2 / \Sigma_t \Sigma_i (x_{it} - \overline{x}_i)^2$. The Least Squares estimator gives higher weight to cross-sectional units with larger time-series variation in the regressor since they are more informative about risk sharing. This derivations simply uses partial summation and the fact that the fixed effect is the average in the cross-sectional regression. In our case, by similar math, our pooled panel regressions with state fixed effects are also mechanically a weighted average of coefficients from state-level regressions pooled over school districts. This follows from splitting the summation over districts into a summation of districts within each state followed by a summation over states.

[18] The combination of the κ and γ parameters result in an elasticity with respect to income of 0.551 in the reduced form, see Table C1 in the appendix. Literally, the coefficient on $\log(Y_t^S - R_t^S)$ is 0.551, but because school spending is a small fraction of state-level income, we interpret the coefficient as an elasticity with respect to state income.

Table 5: Model Estimation Results: Preference Parameters

	Based on County Income	Based on District Income
	Total State School Aid	
Utility Function Parameters:		
κ (Curvature of After Tax Inc.)	1.669^{***}	1.669^{***}
	(0.394)	(0.394)
γ (Curvature of Total School Aid)	3.029^{***}	3.029^{***}
	(0.692)	(0.692)
State-Year Observations	855	855
	State Aid to Districts	
η (Curvature of Inequality Aversion)	5.480^{***}	5.121^{***}
	(0.338)	(0.737)
ω (Curvature of Local Offset)	-0.593^{***}	-0.742^{***}
	(0.014)	(0.023)
District-Year Observations	164,844	37,900
	Local Revenue	
ξ (Curvature of Local Revenue)	3.818^{***}	2.891^{***}
	(0.443)	(0.516)
θ (Curvature of After Tax Inc.)	0.773^{***}	0.492^{**}
	(0.023)	(0.197)
ϕ (Curvature of State Offset)	-0.568^{***}	-0.583^{**}
	(0.028)	(0.283)
District-Year Observations	164,844	37,900

Notes: The table reports the parameters from estimating the equations $\log R_t^S = \mu_s + \zeta_t + \frac{\gamma-1}{\gamma} \log R_{t-1}^S + \frac{\kappa}{\gamma} \log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (total state aid), $\log R_{d,t}^S = \mu_{s,t} + \frac{\omega}{\eta} \log R_{d,t}^L + \frac{\eta-1}{\eta} \log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), and $\log R_{d,t}^L = \mu_s + \zeta_t + \frac{\xi-1}{\xi} R_{d,t-1}^L + \frac{\phi}{\xi} \log R_{d,t}^S + \frac{\theta}{\xi} \log(Y_{d,t}^L - R_{d,t}^L) \ + \epsilon_{3,d,t}$ (local revenue). All parameters are derived from the estimates reported in Appendix A. $R_{d,t}^S$ is state aid to school district d at time t in real per student dollars, $R_{d,t}^L$ is local revenue of school district d in year t in real per student dollars, Y_t^S is the real per capita personal income of state S in year t, and $Y_{d,t}^L$ is real per capita income of school district d in year t. Estimation includes year fixed effects and state dummies or state-year dummies as appropriate. The first column reports results with county income proxying for district income. The second column uses directly measured district income from the American Community Survey (ACS). ***,**,* represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Delta method standard errors (in parentheses) are clustered by state for results in the top panel and clustered by school district for results in the bottom two panels.

school revenue falls to a limited degree when the state government increases aid. The low coefficient also illustrates the flypaper effect of state aid as fluctuations are only partly offset by local revenue adjustments.

Robustness. In Appendix Section D, we report the results of numerous robustness checks to demonstrate that our broad findings are not sensitive to our estimation sample or our choice of instruments. For example, we show that OLS estimates bring no qualitative differences, and that we get similar results from a specification that drops all observations from any school district with a zero for either state aid or local revenue. An important alternative specification exploits the recent school district income data from the ACS. To obtain a longer sample, we backcast the ACS income data using changes in county income. Results from this alternative specification of local income are little changed relative to the benchmark. As an alternative to the income instruments, we estimate the model using higher-order moments as instruments (as in Lewbel, 2012), which produces similar estimates. Finally, we limit the sample only to school districts that were unified elementary and secondary districts for every year in our data set. We also estimate several models substituting the log of house prices at the county level (obtained from Zillow and available for the period from 1996 to 2014) for local income in the local revenue equation (Equation 3), using both OLS and instrumental variables specifications. Our results are robust to all of these alternative specifications, with the quantitative implications of various different specifications similar to those presented. Thus, we are assured that the results are not an artifact of the chosen estimation strategy.

5 Steady State and Dynamic Implications of Model

5.1 Steady State Behavioral Implications

Using the estimated preference parameters, we perform simulations and show the dynamic adjustment, steady states, and patterns of risk sharing. Our simulations are constructed for a synthetic state with 200 small school districts within the state, each equally sized with one student per household. At the state level, the logarithm of personal income per capita is constructed as $\log y^S = \log(\frac{1}{D}\sum_{d=1}^{D} y_d^L)$. The stationary distribution is log-normal with mean 3.45 and standard deviation 0.18, which is the average empirical mean and standard deviation of log school district income. The model assumes that the budget is balanced, so that school spending equals total revenue, which is the sum of local revenue and state education aid.[19]

The intercepts in the model are calibrated to match two important features of the data. First, we impose that in the steady state, per-student state spending on education as a share of per-capita income matches the sample mean.[20] The second target is for state aid to make up 54 percent of the sum of state aid and local revenue on average as in the data.[21]

Figure 4 shows the model-implied steady state distributions of the three main variables

[19]As throughout, we ignore federal aid and capital expenditures.

[20]This is equivalent to about 2 percent of income being devoted to education as students comprise about 14 percent of the population.

[21]Calibrating the model to these moments determines the model values of χ^S and π, which are absorbed by fixed effects in the empirical estimation.

in the analysis, namely, local revenue per student, state aid per student, and the implied school spending, $S_{d,t}$, per student:

$$S_{d,t} = R^L_{d,t} + R^S_{d,t}\,.$$

The figure is the simulated data analogue of Figure 1, which is constructed from the actual data. Each panel plots an outcome variable against school districts' steady state income. Panel (a) simulates local revenue per student and, unsurprisingly, the relationship between steady state income and local revenue is upward sloping and nearly linear in spite of caps on local revenue in some states. Panel (b) shows how state aid per student varies with per capita school district income. Given state preferences for equalization, it is not surprising that it is downward sloping. What is interesting is that the relationship is convex, implying that state aid to local districts rises at an increasing rate as local per capita income falls.

Panel (c) of Figure 4 depicts arguably the most important of the relationships, which is how school spending per student varies with the per capita income of school districts. This panel represents the net sum of the relationships in Panels (a) and (b). The figure shows that the lowest income school districts do not have the lowest school spending, but rather the relationship has a U-shape with minimum spending at about the 14th percentile of income. The figure also illustrates that K-12 school spending climbs with per capita income for districts with income above the 14th percentile. A comparison of Figure 1 with the corresponding simulated Figure 4 shows that the model captures the data well; in particular, the model matches the convex shape of school spending as a function of income.

5.2 Impulse Response Functions

To illustrate the impact of income shocks on the level and distribution of school spending, we focus on districts with median per-capita income. We find that local per-capita income is well described by an autocorrelated process with normal errors and an AR coefficient of 0.98.[22]

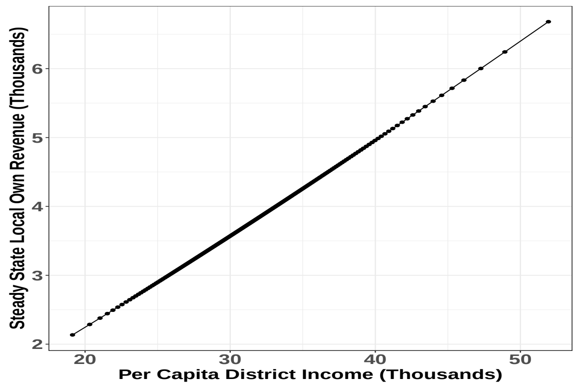
Panel (a) of Figure G2 depicts the effects of an idiosyncratic negative shock of 10 percent of steady state income to a single local district at the median of the income distribution, while Panel (b) illustrates the impact of a negative 10 percent statewide income shock.[23] From Panel (a), local revenue falls by more than 8 percent at the trough 10 to 15 years after the shock. As local revenue falls, state aid rises, but the state only slowly changes aid from the levels of prior years. Hence, the response to the local resource decline is slow, with the rise in state aid being less steep than the decline in local revenue. The result is that, for many years following the local income loss, expenditures per student lie below the district's steady state level. The trough in expenditure occurs within 5 years and is around 2 percent lower than steady state spending. In the long run, as local revenue recovers along with income, school spending returns to its steady state value.

Panel (b) of Figure G2 shows the effects of a negative 10 percent state-level shock which hits all districts. State aid falls considerably, by close to 15 percent at the trough, which

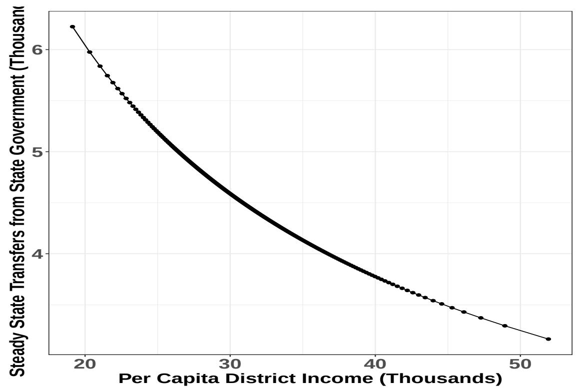
[22] Using the Im, Pesaran, and Shin (2003) panel unit root test, we reject a unit root in the income process at the school district level.

[23] In a "statewide" shock, all 200 districts in a state are hit with a 10 percent decline in income.

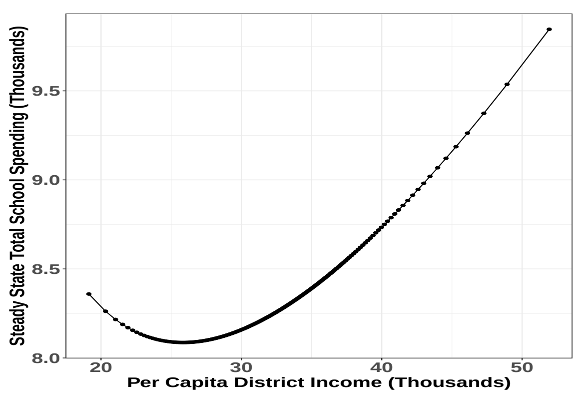
Figure 4: Model-Implied Steady State Distributions



(a) LocalRevenue per Student



(b) State Aid per Student

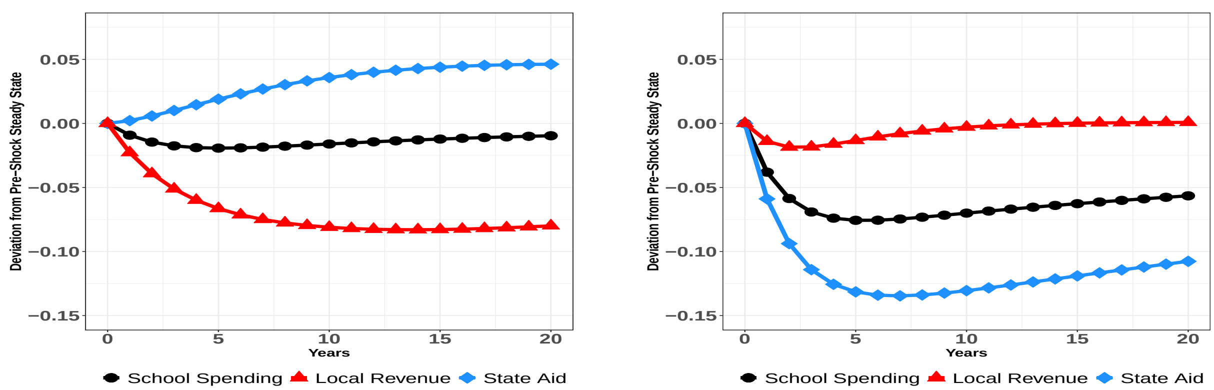


(c) School Spending per Student

Notes: The figure shows the steady state distribution implied by the theoretical model for local revenue, state aid, and school spending (all in per student terms), conditional on an income distribution with mean and standard deviation taken from the pooled data. Model parameters are based on the estimated preferences using the pooled sample, reported in Table 5.

is about 8 years after the shock occurs. Local revenue falls in the near term, though by less, as the local tax effort increases. Despite increased local efforts, the effect on total expenditures per student is quite large: 5 years after the statewide income shock, spending in the middle-income district is about 7.5 percent lower than it was before the shock, and school spending only recovers very slowly. Overall, students carry substantial risk in the short and intermediate run because of the slow adjustment of aid.[24] The slow mean reversion following income shocks is partly due to the shocks themselves being highly persistent. In Appendix Section E, we show impulse responses for counterfactual i.i.d. shocks: school spending is about back to the initial level after 5 years for such shocks.[25]

Figure 5: School Finance Variables: Impulse-Response Functions



(a) Middle-Income District: Idiosyncratic Shock

(b) Middle-Income District: State-Level Shock

Notes: The figure shows, in terms of log deviations from steady state, the model-implied responses of local revenue, state aid, and school spending (all in per student terms) to a negative income shock of 10 percent of steady state income. Panel (a) shows responses to an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and Panel (b) shows responses of the median district to a statewide income shock.

Table 6 summarizes the responses for districts with different levels of income following a 10 percent local income shock. It illustrates how the impact of income shocks depends on the initial level of local incomes. We consider high- and low-income school districts in addition to the middle-income school district discussed above. The percentage point responses of state aid and local revenue are similar for different income levels, so we focus on the spending responses. At all horizons following the shock, and for all three districts reported, spending

[24]Students in poorer districts are more sensitive to state-level shocks, which accords with findings in Jackson, Wigger, and Xiong (2018) and Evans, Schwab, and Wagner (2019), who show that school districts that were more dependent on state aid suffered bigger cuts to school spending. This result is not surprising and we do not tabulate the details.

[25]Figure E3 is based on the data, and the similarity between the estimated empirical responses and the model-generated impulse response functions of Figure G2 further shows the model is capturing movements in the data well (albeit the shock in the text is negative and the impulse responses in the Appendix are with respect to a positive shock).

declines, but it falls the least in the relatively poor school district, and it falls the most in the relatively well-off school district. This is because state aid makes up a greater share of the poor district's school spending than it does for the richer districts, so a similar amount of state aid results in a larger percent increase in school spending for the poor district. Similarly, the decline in local revenue, while proportionally the same as in other districts, is smaller in terms of dollars in the poor districts. Eight years after the negative income shock on the order of 10 percent of steady state income, spending on education in the poor district has fallen by less than 1 percent. In contrast, in the rich district, it has fallen by more than 2.5 percent or three times as much as in the poor district.

Table 6: School District Responses to 10% Local Income Shock. Components of School Revenue

			School Spending		
Pctile:	Steady State	Impact	1 year after	3 years after	8 years after
Rich (85th)	\$8576	−\$97 (−1.1%)	−\$157 (−1.8%)	−\$214 (−2.5%)	−\$224 (−2.6%)
Middle (50th)	\$8210	−\$75 (−0.9%)	−\$119 (−1.4%)	−\$154 (−1.9%)	−\$138 (−1.7%)
Poor (15th)	\$8087	−\$57 (−0.7%)	−\$87 (−1.1%)	−\$102 (−1.3%)	−\$62 (−0.8%)
			State Aid		
	Steady State	Impact	1 year after	3 years after	8 years after
Rich (85th)	\$3919	+\$8 (+0.2%)	+\$23 (+0.6%)	+\$57 (+1.5%)	+\$132 (+3.4%)
Middle (50th)	\$4448	+\$10 (+0.2%)	+\$26 (+0.6%)	+\$65 (+1.5%)	+\$150 (+3.4%)
Poor (15th)	\$5049	+\$11 (+0.2%)	+\$30 (+0.6%)	+\$74 (+1.5%)	+\$171 (+3.4%)
			Local Revenue		
	Steady State	Impact	1 year after	3 years after	8 years after
Rich (85th)	\$4657	−\$105 (−2.3%)	−\$179 (−3.9%)	−\$271 (−5.8%)	−\$357 (−7.7%)
Middle (50th)	\$3762	−\$85 (−2.3%)	−\$144 (−3.8%)	−\$219 (−5.8%)	−\$288 (−7.7%)
Poor (15th)	\$3038	−\$68 (−2.2%)	−\$117 (−3.8%)	−\$177 (−5.8%)	−\$232 (−7.7%)

Notes: The table reports the model-implied steady state values of total expenditure, state aid, and local revenue for a "rich" district (85th percentile of the distribution), "middle-income" district (50th percentile of the distribution), and "poor" district (15th percentile of the distribution), as well as the changes in each variable in dollar and percentage point terms on impact, and one, three, and eight years after the shock. The changes are in response to an idiosyncratic 10 percent negative shock to local income, assuming that each district's income process is characterized by an AR(1) model with an autoregressive parameter of 0.98.

5.3 Cohort Effects

.

Irrespective of a school district's income, the lag in income insurance causes substantial intertemporal disparities as students exposed to a shock and its aftermath experience different levels of school spending compared with students who avoid the episode. Figure G3 illustrates this phenomenon assuming 10 percent negative shocks. As in Figure G2, the local idiosyncratic shock and responses to it are illustrated in Panel (a), and the state-level negative income shock is illustrated in Panel (b). The horizontal axis in Figure G3 measures the number of years after the negative income shock that a given student starts kindergarten.[26] For example,"0" means that a student starts kindergarten in the same year that the income shock occurs. A value of "1" means that the cohort started kindergarten a year after the shock, and "-1" indicates the cohort started a year before the shock. The figure reveals that students starting school up to 12 years before the negative income shock and for many years after are exposed to lower school spending over their entire career than a student whose years in school are entirely unaffected by the shock. A student starting in the year of the shock experiences the most dramatic decline in overall spending of around 2 percent over the 13 years in school relative to her peers unaffected by the shock. Part of this disparity occurs because of the delay in state aid in offsetting the local revenue drop.

We repeat our cohort analysis for the statewide shock in Panel (b) of Figure G3. This figure demonstrates that a student starting school in the year a statewide economic downturn begins is exposed to reduced school spending of around 7 percent during their tenure in elementary and secondary school, compared with a student not exposed to the shock. Again, this is because of the sharp fall in state aid provided to the district and an insufficient response of local revenue. Cohorts starting school several years after a negative state shock also have to contend with reduced school spending relative to those not attending school in any year affected by the state-level shock.

5.4 Incidence of Income Shocks

Income-conditioned state aid implies risk sharing between school districts, but some remaining risk is carried by students. In the case of state-level shocks, no risk sharing across districts is possible on average, but risk is shared between taxpayers and students.[27]

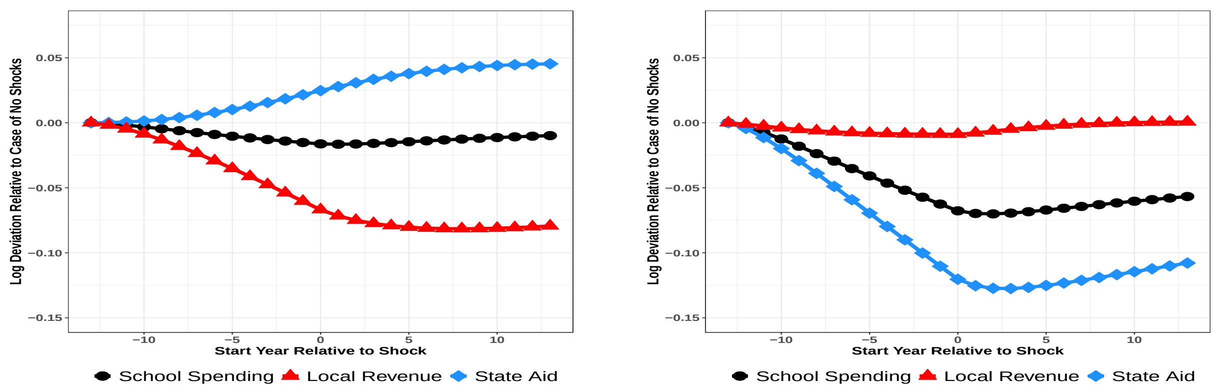
We calculate the short- and long-run impacts of income shocks on local taxpayers and students in a district and on taxpayers in other districts. When there is an idiosyncratic income shock to local taxpayers, local school revenue (taxes) increases or decreases, triggering offsetting flows of state aid, which again affects school revenue, etc., which in connection with slow adjustment implies that the longer-run impacts are quite different from the initial impacts.[28] If the shock is statewide, schools and taxpayers of a representative district will

[26]We assume throughout that each student remains in the same school district for the entirety of their primary and secondary education career.

[27]Asdrubali, Sørensen, and Yosha (1996) consider shocks to state-level GDP to be endowment shocks and show that interstate risk sharing results in state-level income being significantly less volatile than state-level GDP, so there is substantial risk sharing *across* states. We assume that state-level school aid depends on income, which we take as the endowment for the purpose of this study.

[28]Income shocks are very persistent; for example, a 10 percent income shock is predicted to lead to 8

Figure 6: Model-Implied Evolution of Total Spending over Educational Career by Cohort



(a) Middle-Income District: Idiosyncratic Shock

(b) Middle-Income District: State-Level Shock

Notes: The figure depicts, in terms of log deviation from steady state, the total school spending for a student cohort over their entire K-12 career, as it varies with when they start school in relation to a negative income shock of 10 percent. The x-axis measures the timing of the start of the cohort's educational career relative to the timing of the shock. Panel (a) offers model-implied responses to an idiosyncratic income shock, and Panel (b) offers model-implied responses conditional on a statewide income shock in the 50th income percentile, both for a district at the 50th percentile of the state income distribution.

not receive extra aid if all districts are equally affected. Using our model, we calculate the share of income shocks absorbed by school spending, the share absorbed by taxpayers in other districts through adjustments in state aid, and the share that falls on taxpayers in the affected district.

The decomposition uses the model impulse responses to calculate, for each future period, the expected dollar impact on after-school-tax district income.[29] Additionally, the impulse responses are used to determine changes in state aid (which is interpreted as the risk shared by taxpayers of all districts), and in school spending. In part, local revenue depends on state aid which depends on the statewide level of aid and on the fraction allocated to the district. Consider a negative shock: if state aid increases and the local district reduces taxes as a result, the local taxpayer will see after-school-tax income fall less than one-to-one with the income shock. Using the estimated process for local income, we predict $Y^L_{d,t}$ t periods out from the shock and use the model to predict the endogenous variables, such as $R^S_{d,t}$.

We consider the two separate cases of a local idiosyncratic shock to income and a statewide shock to income which hits all districts.[30] Consider the following decomposition.

percent lower income (compared with steady state) after 10 years and almost 7 percent lower income after 20 years.

[29]Impulse response functions are utilized by Asdrubali and Kim (2004) to evaluate risk sharing at different horizons.

[30]We assume each local district has a negligible impact on total state income.

The change in pre-tax household income in district d can be expressed as:

$$\Delta Y_{d,t}^{PRE-TAX} = \Delta R_{d,t}^{L} + \Delta \bar{R}_{t}^{S} + \Delta Y_{d,t}^{POST-TAX} ,$$

which shows that a pre-tax income shock ($\Delta Y_{d,t}^{PRE-TAX}$) is allocated to local revenue for the school district (R_{d}^{L}), school taxes paid to the state ($\bar{R}^{S}$) calculated as total state aid divided by the number of school districts (assuming that state school taxes fall evenly on all districts), and disposable (post-tax) income ($Y_{d}^{POST-TAX}$).

The change in spending on education in district d in our model is the change in local revenue plus the change in state aid, $\Delta S_{d,t} = \Delta R_{d,t}^{L} + \Delta R_{d,t}^{S}$, and subtracting the change in state aid from both sides and substituting for the change in local revenue in the income equation leads to the relation between the (pre-tax) local income shock and the after-school-tax income shock:

$$\Delta Y_{d,t}^{PRE-TAX} = \Delta S_{d,t} - \Delta R_{d,t}^{S} + \Delta \bar{R}_{t}^{S} + \Delta Y_{d,t}^{POST-TAX} .$$

Divide both sides by $\Delta Y_{d,t}^{PRE-TAX}$:

$$1 = \underbrace{\frac{\Delta S_{d,t}}{\Delta Y_{d,t}^{PRE-TAX}}}_{\text{Students}} + \underbrace{\frac{(\Delta \bar{R}_{t}^{S} - \Delta R_{d,t}^{S})}{\Delta Y_{d,t}^{PRE-TAX}}}_{\text{Other Districts}} + \underbrace{\frac{\Delta Y_{d,t}^{POST-TAX}}{\Delta Y_{d,t}^{PRE-TAX}}}_{\text{Local Taxpayers}} .$$

This provides a decomposition of income shocks into shares that fall on local students, other districts' taxpayers, and local taxpayers. Table 7 reports these shares for both local and statewide income shocks.

Consider an idiosyncratic shock for the case of a rich, poor, or middle-income district. From Table 7, about 97 percent of the income shock is borne by the local taxpayers on impact for each of the income categories. Over time, more of the shock is absorbed by changes in local school revenue, such that only about 88 to 89 percent of the shock feeds through to after-tax income eight years later. Spending on education changes the least in the low-income district as the incidence on low-income students of an idiosyncratic shock is only about 3 percent of the shock in the long run, compared with over 7 percent in the high-income district. However, taxpayers in low-income districts bear a slightly larger share of an income shock than their counterparts in the high-income district eight years after the shock occurs (88.9 percent compared with 88.3 percent). The remaining fraction falls on taxpayers in other districts in the state. This amount is negligible on impact, growing to 4.4 percent in the rich school district and 8.1 percent in the poor district.

Consider a state-level shock. We do not tabulate the dollar amounts but on impact the state reduces total state aid by an average of $256 across districts. Such a decrease is proportionally greater for a low-income district than for a high-income district. As a result, the right panel of Table 7 shows that the pass-through of the shock to after-tax income is greater for relatively high-income districts, at about 91 percent. For low-income districts, the pass-through is 88 percent. In the longer run, eight years after the shock, the difference is yet more stark, with after-tax income absorbing 81.3 percent of a shock in the high-income district and 73.3 percent in the low-income district. The relatively modest effect of

Table 7: Model-Implied District-Level Incidence of Income Shocks

	Idiosyncratic Shocks		Aggregate Shocks	
	Rich Districts		*Rich Districts*	
	Impact	8 years after	Impact	8 years after
Size of income shock	\$3603	\$3088	\$3603	\$3088
Incidence on Students	2.7%	7.3%	8.0%	16.4%
Incidence on Other Districts	0.3%	4.4%	0.9%	2.3%
Incidence on Taxpayers	97.0%	88.3%	91.1%	81.3%
	Middle Districts		*Middle Districts*	
	Impact	8 years after	Impact	8 years after
Size of income shock	\$2989	\$2561	\$2989	\$2561
Incidence on Students	2.5%	5.4%	10.3%	22.2%
Incidence on Other Districts	0.4%	6.0%	0.1%	0.1%
Incidence on Taxpayers	97.1%	88.6%	89.7%	77.7%
	Poor Districts		*Poor Districts*	
	Impact	8 years after	Impact	8 years after
Size of income shock	\$2479	\$2125	\$2479	\$2125
Incidence on Students	2.3%	2.9%	13.3%	30.1%
Incidence on Other Districts	0.5%	8.1%	−1.3%	−3.4%
Incidence on Taxpayers	97.2%	88.9%	88.0%	73.3%

Notes: The table reports the model-implied decompositions of income changes for a “rich” district (85th percentile of the distribution), “middle-income” district (50th percentile of the distribution), and “poor” district (15th percentile of the distribution) on impact and eight years after the shock. The top row of each panel reports the numerical pre-tax income change for a 10 percent income shock. The second row of each panel reports the change in local revenue for school districts owing to lower local income. The third row reports the change in state aid as a fraction of the income shocks. The fourth row reports the change in state taxes paid as a share of the income shocks (for state aid throughout the state), and the fifth row reports the changes in local income after accounting for the changes in local taxes. In the calculation, each district’s income process is modeled as an AR(1) process with an autoregressive parameter of 0.98.

an aggregate shock on after-tax incomes in those districts at the poorer end of the income distribution contrasts with school spending adjusting much more for a poor district than for a rich district. The incidence on school spending for the rich and poor district, respectively, is 8.0 percent and 13.3 percent on impact and 16.4 percent and 30.1 percent in the longer term. The fraction of the shock carried by the rest of the state for rich (poor) districts is 0.9 percent (–1.3 percent) on impact and 2.3 percent (−3.4 percent) after 8 years. The incidence of a statewide shock needs to be within-state, but it appears that state aid favors the rich districts in the face of statewide shocks. Overall, the current system of state aid leaves poor districts sensitive to shocks that affect the whole state.

6 Analysis of School Finance Reforms

In this section, we address that our presentation thus far has been about a "representative district in a representative state." In this section, we use our model to analyze school finance reform episodes used in the education literature. Irrespective of the impact of the reforms on education output, we re-estimate our model by splitting the sample into pre- and post-reform states and years. We illustrate that the estimated parameters on the two subsamples reflect the purported aims of the reforms. The estimates show the relevance for the impacts emphasized here, as we use the new estimates to examine how the reforms affect intertemporal disparities, a dimension that has previously been ignored in the literature.

Prominent papers that have used school finance reforms to examine the effect of school spending on student outcomes include, among others, Hoxby (2001), Card and Payne (2002), Jackson, Johnson, and Persico (2016), and Lafortune, Rothstein, and Schanzenbach (2018). This section uses the finance reforms identified in Lafortune, Rothstein, and Schanzenbach (2018) (building on Jackson, Johnson, and Persico, 2016) to examine whether the estimated parameters in our model change as a reflection of the new political equilibrium, and whether those changes are consistent with the presumed administrative content of the new education finance systems.

Table 8 reports parameter estimates pre- and post-reform. The rows in Table 8 correspond to those in Table 5 for the pooled model (with the pooled parameter estimates provided for comparison). The first set of rows are for Equation 1 (total state aid), the next set of rows are for Equation 2 (allocation of state aid to local districts), and the final set of rows are for Equation 3 (local school district revenue). In addition, the p-values to the right of the parameter estimates report the result of a test for equality of the parameters pre-and post-reform, while the p-values under the rows report pooling tests for the equality of all the coefficients in the equation.

We find that the parameters describing the overall level of state aid are not significantly different before and after reforms, while the allocation of state aid changes after reform with the curvature of the local offset increasing in numerical magnitude. This implies that state aid gets channeled more intensively to the poorer districts which provide less local revenue. From the local revenue equation, we find very significant differences before and after reform: the curvature of the utility function for local revenue and after-tax income decline implying less aversion to fluctuations in local revenue. There is a small borderline significant (at the 5 percent level) numerical increase in the offset to state aid. These changes in parameter

Table 8: Preference Parameters: Pre- and Post-School Finance Reform

	Benchmark	Pre	Post	P-Value
	Total State School Spending (Equation 1)			
Utility Function Parameters:				
κ (Curvature of After Tax Income)	1.669***	1.464**	2.904***	0.27
	(0.394)	(0.715)	(1.092)	
γ (Curvature of Total School Spending)	3.029***	4.378	2.596***	0.52
	(0.692)	(2.732)	(0.492)	
Joint P-Value		0.30		
State-Year Observations	855	538	317	
# of States	45	33	19	
	State Aid to Districts (Equation 2)			
η (Curvature of Inequality Aversion)	5.480***	6.533***	4.809***	0.07
	(0.338)	(0.931)	(0.273)	
ω (Curvature of Local Offset)	−0.593***	−0.532***	−0.657***	< 0.01
	(0.014)	(0.021)	(0.023)	
Joint P-Value		< 0.01		
District-Year Observations	164,844	95,914	68,930	
# of States	45	33	19	
	Local Revenue (Equation 3)			
ξ (Curvature of Local Revenue)	3.818***	13.197***	2.573***	< 0.01
	(0.443)	(3.495)	(0.380)	
θ (Curvature of After Tax Income)	0.773***	0.877***	0.660***	< 0.01
	(0.023)	(0.061)	(0.043)	
ϕ (Curvature of State Offset)	−0.568***	−0.423***	−0.642***	0.04
	(0.028)	(0.093)	(0.049)	
Joint P-Value		< 0.01		
District-Year Obs.	164,844	95,914	68,930	
# of States	45	33	19	

Notes: The table reports the parameters from estimating Equation 1: $\log R_t^S = \mu_s + \zeta_t + \frac{\gamma-1}{\gamma}\log R_{t-1}^S + \frac{\kappa}{\gamma}\log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (total state aid), Equation 2: $\log R_{d,t}^S = \mu_{s,t} + \frac{\omega}{\eta}\log R_{d,t}^L + \frac{\eta-1}{\eta}\log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), and Equation 3: $\log R_{d,t}^L = \mu_s + \zeta_t + \frac{\xi-1}{\xi}R_{d,t-1}^L + \frac{\phi}{\xi}\log R_{d,t}^S + \frac{\theta}{\xi}\log(Y_{d,t}^L - R_{d,t}^L) + \epsilon_{3,d,t}$ (local revenue). $R_{d,t}^S$ is state aid to school district d at time t in real per student dollars, $R_{d,t}^L$ is local revenue of school district d at time t in real per student dollars, Y_t^S is the real per capita personal income of state S in year t, and $Y_{d,t}^L$ is real per capita income of school district d during t. "Pre" and "Post" refer to state-year observations before and after school finance reforms listed in Lafortune, Rothstein, and Schanzenbach (2018). The "Joint P-Value" reported is for the joint null that each parameter in each block of coefficients is the same before and after the reforms. The combined number of states across pre- and post-reform specifications exceeds 45 (the total number in the sample), because of some states having both pre- and post-reform observation years. Estimation includes year fixed effects and state dummies or state-year dummies as appropriate. ***,**,* represent statistical significance from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively. Delta method standard errors (in parentheses) are clustered by state for results in the top panel and clustered by school district for results in the bottom two panels.

values are likely less driven by "basic" local preferences, but rather by state-level legislation which may provide incentives for wealthier districts to shoulder a relatively large share of the educational burden.

Panels (a), (b), and (c) of Figure 7 illustrate the steady state values of the three main variables for pre- and post-reform parameterizations. These panels clearly show the changes from the school finance reform. Panel (a) shows that reliance on local revenue is lower post-reform. Panel (b) demonstrates that the state aid curve is rotated such that low-income districts receive more aid from the state at the expense of aid to higher-income districts. This implies more equality in school spending, but mainly as a result of "leveling down" in the language of Hoxby (2001). The steady state distributions from our model illustrate these results clearly.

The impulse response functions with respect to a negative local income shock are illustrated in the second row consisting of Panels (d), (e), and (f) of Figure 7. When a single district faces a decline in income, panel (d) shows that local revenue falls faster and farther than pre-reform. This pattern is consistent with local tax rates being more constrained by the state government, so local districts have reduced scope for increasing their own tax effort. Panel (e) shows that state aid rises post reform more and slightly earlier than would have occurred pre-reform. What is interesting in terms of the risk sharing response is shown in Panel (f), where school spending is lower immediately following the reform than would have occurred before, but after about seven years school spending is higher. Thus we see that, for an idiosyncratic shock, the school finance reforms, which are designed to reduce inequality, make school spending more sensitive to income shocks in the first seven years following a shock, relative to pre-reform.

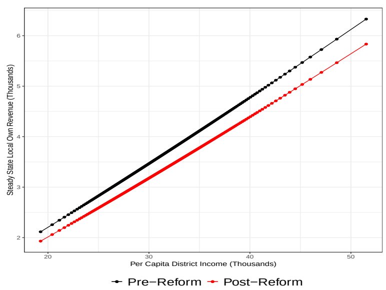
The last row of panels illustrates the impact on school spending when the entire state suffers an economic decline. The key factor in this analysis is that overall reliance on state aid has increased for middle-income school districts, making them more vulnerable to decreases in state school aid. Panel (g), for example, shows that post-reform local revenue rises in the face of the income drop. Panel (h) explains why: state aid plummets post-reform by over 20 percent in five years. Panel (i) shows that despite the local revenue increases, middle-income school district spending is considerably more sensitive to income shocks than pre-reform until about ten years after a shock.

Overall, school spending is more sensitive to economic shocks after the school finance reforms which may be an unintended consequence of making school finance more dependent on state-level aid, consistent with the evidence presented in Jackson, Wigger, and Xiong (2018). These findings raise questions about which details of schooling reforms have contributed to these unintended effects, but such a study belongs in a more micro-founded analysis of the incentive effects of policy details.

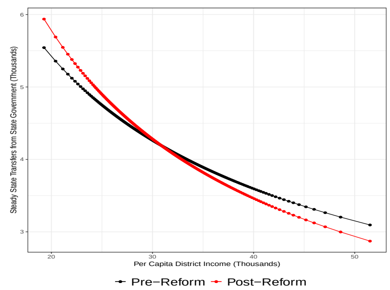
7 Conclusion

This paper broadens the traditional view of education inequities by considering the dynamic impact of economic fluctuations in state and local income. In particular, by relaxing the implicit assumption in much of the school finance literature that inequities are static, we are able to fill a gap in the education finance literature by exploring the dynamic aspects

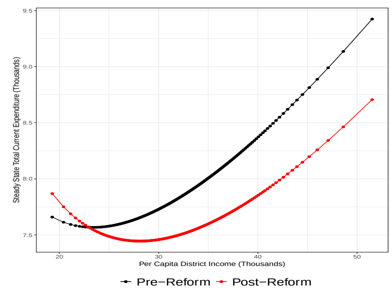
Figure 7: Model-Implied Steady State Distributions and Impulse Responses, Pre- and Post-Schooling Reforms



(a) Local Revenue

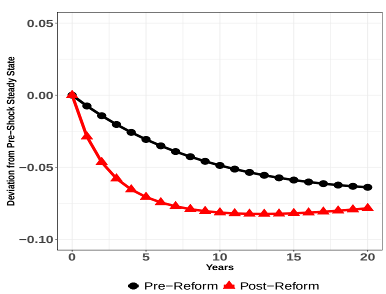


(b) State Aid

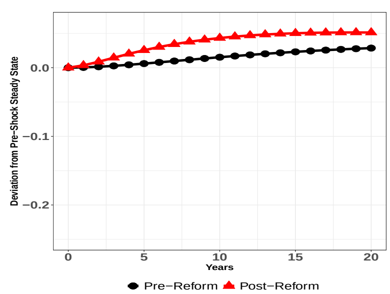


(c) School Spending

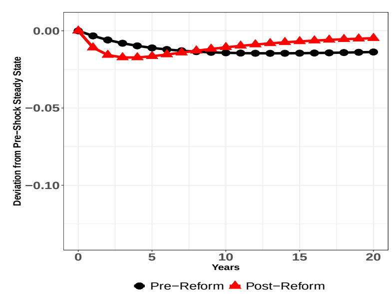
Impulse Response, Idiosyncratic Shock



(d) Local Revenue

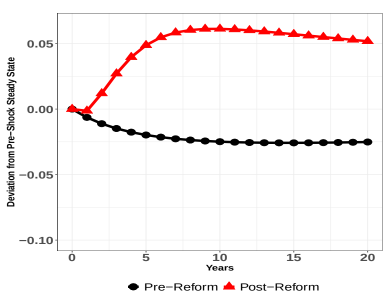


(e) State Aid

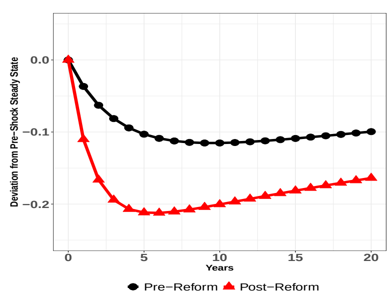


(f) School Spending

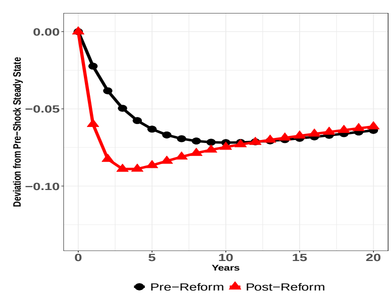
Impulse Response, State-Level Shock



(g) Local Revenue



(h) State Aid



(i) School Spending

Notes: The figure shows the steady state distributions and impulse responses implied by the theoretical model for local revenue, state aid, and school spending (all in log per student terms), conditional on an income distribution with mean and standard deviation taken from the pooled data. Model parameters are based on the estimated preferences using the pre-reform and post-reform samples, based on the reform lists in Lafortune, Rothstein, and Schanzenbach (2018).

of education finance systems. We are able to accomplish this because our model, which characterizes state aid as a function of state-level income shocks and local revenue, and local revenue as a function of local income and state aid, successfully captures dynamic features of the data. The results suggest that more policy attention to intertemporal fluctuations is needed.

Specifically, our paper suggests consideration of policies that would allow for better smoothing of school spending over time even if balanced budget restrictions work against this need (Poterba, 1994). Our research provides evidence on dynamic patterns in school spending along three dimensions. First, there is a potential need for further intertemporal smoothing. That is, because of income fluctuations, there are disparities in school spending for children that attend school at different points in the business cycle. Second, income-conditioned state aid provides a mechanism that smooths idiosyncratic local shocks, albeit with a lag. Third, school spending is significantly impacted by state-level income fluctuations.

We believe an explicit insurance mechanism similar to the federally operated unemployment system might provide risk sharing between states' school systems. In the unemployment-insurance scheme, states pay an earmarked tax paid into the UI trust fund operated by the treasury. The states can then withdraw funds to cover unemployment benefits. This system is administratively separate from states' general fund spending and if states accept objective rules (such as withdrawals linked to state personal income growth) moral hazard could be kept very low. In the unemployment system, states can borrow in bad times, but this is discouraged and rarely used (partly because of federal aid in severe recessions); see Craig, Hemissi, Mukherjee, and Sørensen, 2016. We believe a similar federal framework might work well for school finance. One could imagine a more comprehensive system insuring state government spending, but moral hazard issues would likely make this politically infeasible, while a school-finance insurance system may be palatable, as is the unemployment-insurance system.

References

Asdrubali, P., and S. Kim (2004): "Dynamic risksharing in the United States and Europe," *Journal of Monetary Economics*, 51(4), 809–836.

Asdrubali, P., B. E. Sørensen, and O. Yosha (1996): "Channels of Interstate Risk Sharing: United States 1963-1990," *Quarterly Journal of Economics*, 111 (4), 1081–1110.

Behrman, J. R., and S. G. Craig (1987): "The Distribution of Public Services: An Exploration of Local Governmental Preferences," *The American Economic Review*, 77(1), 37–49.

Card, D., and A. A. Payne (2002): "School Finance Reform, the Distribution of School Spending, and the Distribution of Student Test Scores," *Journal of Public Economics*, 83(1), 49–82.

Craig, S. G., W. Hemissi, S. Mukherjee, and B. Sørensen (2016): "How Do Politicians Save? Buffer Stock Management of Unemployment Insurance Finance," *Journal of Urban Economics*, 93(1), 18–29.

Dupor, B., and M. S. Mehkari (2015): "Schools and Stimulus," Federal Reserve Bank of St. Louis Working Paper 2015-004A.

Evans, W. N., R. M. Schwab, and K. L. Wagner (2019): "The Great Recession and Public Education," *Education Finance and Policy*, 14(2), 298–326.

Fernández, R., and R. Rogerson (1996): "Income Distribution, Communities, and the Quality of Public Education," *The Quarterly Journal of Economics*, 111(1), 135–164.

——— (1998): "Public Education and Income Distribution: A Dynamic Quantitative Evaluation of Education-Finance Reform," *The American Economic Review*, 88(4), 813–833.

Fischel, W. A. (2009): *Making the Grade: The Economic Evolution of American School Districts*. University of Chicago Press, Chicago, IL.

Hoxby, C. M. (1998): "How Much Does School Spending Depend on Family Income? The Historical Origins of the Current School Finance Dilemma," *American Economic Review*, 88(2), 309–314.

Hoxby, C. M. (2001): "All School Finance Equalizations are not Created Equal," *The Quarterly Journal of Economics*, 116(4), 1189–1231.

Im, K. S., M. H. Pesaran, and Y. Shin (2003): "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics*, 115(1), 53–74.

Jackson, C. K., R. C. Johnson, and C. Persico (2016): "The Effects of School Spending on Educational and Economic Outcomes: Evidence from School Finance Reforms," *The Quarterly Journal of Economics*, 131(1), 157–218.

Jackson, C. K., C. Wigger, and H. Xiong (2018): "Do School Spending Cuts Matter? Evidence from the Great Recession," NBER Working Paper 24203.

Lafortune, J., J. Rothstein, and D. W. Schanzenbach (2018): "School Finance Reform and the Distribution of Student Achievement," *American Economic Journal: Applied Economics*, 10(2), 1–26.

Lewbel, A. (2012): "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models," *Journal of Business and Economic Statistics*, 30(1), 67–80.

Poterba, J. M. (1994): "State Responses to Fiscal Crises: The Effects of Budgetary Institutions and Politics," *Journal of Political Economy*, 102(4), 799–821.

A Number of School Districts by State

Table A1: Sample of School Districts by State

State	Number of Independent School Districts in Sample	Share of District-Year Observations that are Independent
Alabama	126	100.0%
Arizona	159	97.6%
Arkansas	101	100.0%
California	210	95.7%
Colorado	49	100.0%
Connecticut	17	10.3%
Delaware	17	100.0%
Florida	67	100.0%
Georgia	65	100.0%
Idaho	98	100.0%
Illinois	747	100.0%
Indiana	283	99.9%
Iowa	311	100.0%
Kansas	257	100.0%
Kentucky	85	100.0%
Louisiana	65	99.5%
Maine	50	45.1%
Massachusetts	74	25.1%
Michigan	481	89.0%
Minnesota	246	100.0%
Mississippi	66	97.8%
Missouri	451	100.0%
Montana	171	100.0%
Nebraska	188	100.0%
Nevada	16	100.0%
New Hampshire	104	93.7%
New Jersey	108	91.5%
New Mexico	41	100.0%
New York	625	99.3%
North Dakota	102	100.0%
Ohio	583	100.0%
Oklahoma	61	100.0%
Oregon	151	100.0%
Pennsylvania	485	100.0%
Rhode Island	3	10.9%
South Carolina	77	100.0%
South Dakota	69	100.0%
Tennessee	14	10.3%
Texas	927	99.9%
Utah	40	100.0%
Vermont	144	100.0%
Washington	238	100.0%
West Virginia	55	100.0%
Wisconsin	403	> 99.9%
Wyoming	46	100.0%

Notes: The table lists the number of independent school districts in each state included in the analysis. We drop districts that have fewer than 100 students, that switch county assignments in the data, or that do not have an observation for each of the 23 years in the sample period. Alaska, Hawaii, Virginia, Maryland, North Carolina, and the District of Columbia are excluded from the analysis by these criteria.

B Detailed Derivations of Estimation Equations

B.1 State Government Behavior

The representative state government preference function is

$$\max_{\{R^S_{d,t}\}^D_{d=1}} \Sigma_d \, (R^L_{d,t})^{\omega} \, \frac{1}{1-\eta}\left[(\frac{R^S_{d,t}}{R^S_t})/(\widetilde{\frac{R^S_{d,t}}{R^S_t}})\right]^{1-\eta} + \frac{1}{1-\gamma}\left(\frac{R^S_t}{\tilde{R}^S_t}\right)^{1-\gamma} + \frac{1}{1-\kappa}(Y^S_t - R^S_t)^{1-\kappa} \ ,$$

where $R^S_{d,t}$ denotes state S government aid to school district d, $R^L_{d,t}$ denotes the local revenue in district d at time t, and $R^S_t = \Sigma_{d\in D} R^S_{d,t}$ denotes total state expenditure on school aid. The state myopically solves its optimization problem period by period and Y^S_t is income in state s at time t which, when education taxes are subtracted, equals all other uses of income.

Preferences over inequality in school aid are specified relative to a reference level, $\widetilde{\frac{R^S_{d,t}}{R^S_t}}$. The second term in the equation reflects the utility derived from total state aid with concavity captured by the parameter γ. Just as for the allocations to individual districts, we specify total aid relative to a reference level, $\tilde{R}^S_t$, which depends on overall aid levels in the previous year.

We specify the reference-level for, respectively, aggregate and district shares of state aid as

$$\log \tilde{R}^S_t = \varrho^S + \log R^S_{t-1} \, ,$$

and

$$\log\left(\widetilde{\frac{R^S_{d,t}}{R^S_t}}\right) = \varrho^d + \log\left(\frac{R^S_{d,t-1}}{R^S_{t-1}}\right) \, .$$

Estimating equations are derived assuming that the state government decides first how much to spend in total on education without regards to its distribution. Given overall funding, the state then decides how to allocate that funding across the various school districts. We find the optimal choice of total state aid by taking the derivative of the state's objective function with respect to R^S_t (holding the districts' shares constant):

$$(R^S_t)^{-\gamma}(\tilde{R}^S_t)^{\gamma-1} \quad = \quad (Y^S_t - R^S_t)^{-\kappa} \ ,$$

which can be solved for

$$\log R^S_t = \frac{\gamma-1}{\gamma}\log \tilde{R}^S_t + \frac{\kappa}{\gamma}\log(Y^S_t - R^S_t) \ .$$

Substituting the expression for the reference level, we arrive at:

$$\log R_t^S = \chi^S + \frac{\gamma - 1}{\gamma} \log R_{t-1}^S + \frac{\kappa}{\gamma} \log(Y_t^S - R_t^S) \,.$$

Here, χ^S is a constant term equal to $\frac{\gamma-1}{\gamma}\varrho^S$. With the addition of a random error term and fixed effects for states and years, we arrive at the first estimating equation, showing the logarithm of total state aid to be a function of state-level income and the reference spending level:

$$\log R_{s,t}^S = \mu_s + \zeta_t + \frac{\gamma - 1}{\gamma} \log R_{s,t-1}^S + \frac{\kappa}{\gamma} \log(Y_{s,t}^S - R_{s,t}^S) \ + \varepsilon_{1,s,t} \ ,$$

In order to estimate the preference parameters for redistribution, we take the derivative of the first segment of the preference function with respect to aid distribution, keeping total spending on education constant. We evaluate

$$\max_{\{R_{d,t}^S\}_{d=1}^D} \Sigma_d (R_{d,t}^L)^\omega \frac{1}{1-\eta} \left[(\frac{R_{d,t}^S}{R_t^S}) / (\frac{\widetilde{R_{d,t}^S}}{R_t^S}) \right]^{1-\eta} + \lambda_t^S (R_t^S - \Sigma_d R_{d,t}^S) \ .$$

Here λ_t^S is a Lagrange Multiplier measuring the shadow welfare value of an extra dollar of total state aid. The first order condition for aid to district d is

$$(R_{d,t}^L)^\omega (R_{d,t}^S)^{-\eta} (\frac{1}{R_t^S})^{1-\eta} \left(\frac{\widetilde{R_{d,t}^S}}{R_t^S} \right)^{\eta-1} = \lambda_t^S \,.$$

We take logarithms and use state-year fixed effects to absorb state-level terms into λ_t^S, obtaining

$$-\eta \log R_{d,t}^S + \omega \log R_{d,t}^L + (\eta - 1) \log \tilde{R}_{d,t}^S = \Lambda_t^S \,.$$

Using the expression for the reference aid level we obtain (after absorbing the additional state-level term into the state-year dummy)

$$\log R_{d,t}^S = \frac{\omega}{\eta} \log R_{d,t}^L + \frac{\eta - 1}{\eta} \log R_{d,t-1}^S + \Lambda_t^{S'} \ .$$

Using a set of state-year effects, $(\mu_{s,t})$ for $\Lambda_t^{S'}$ yields the second estimating equation:

$$\log R_{d,t}^S = \mu_{s,t} + \frac{\omega}{\eta} \log R_{d,t}^L + \frac{\eta - 1}{\eta} \log R_{d,t-1}^S + \varepsilon_{2,d,t} \ .$$

B.2 Local District Behavior

A local school district d chooses revenue $R^L_{d,t}$ to maximize the following preference function:

$$\max_{R^L_{d,t}} (R^S_{d,t})^{\phi} \frac{1}{1-\xi} \left(\frac{R^L_{d,t}}{\tilde{R}^L_{d,t}}\right)^{1-\xi} + \frac{1}{1-\theta} (Y^L_{d,t} - R^L_{d,t})^{1-\theta} \ .$$

As is the case for the state government, the local government behaves myopically with respect to the reference spending level, $\tilde{R}^L_d$, which is specified as follows

$$\log \tilde{R}^L_{d,t} = \pi_0 + \log R^L_{d,t-1} \ .$$

Maximizing the local objective function with respect to the choice of $R^L_{d,t}$ yields the first order condition:

$$\left(\frac{R^L_{d,t}}{\tilde{R}^L_{d,t}}\right)^{-\xi} \frac{1}{\tilde{R}^L_{d,t}} (R^S_{d,t})^{\phi} - (Y^L_{d,t} - R^L_{d,t})^{-\theta} = 0 \ ,$$

which, after taking logarithms and rearranging, is

$$-\xi \log R^L_{d,t} - (1-\xi) \log \tilde{R}^L_{d,t} + \phi \log R^S_{d,t} = -\theta \log(Y^L_{d,t} - R^L_{d,t}) \ ,$$

which, using the expression for the reference spending level, implies

$$-\xi \ \log R^L_{d,t} - (1-\xi)(\pi_0 + \log R^L_{d,t-1}) + \phi \log R^S_{d,t} = -\theta \log(Y^L_{d,t} - R^L_{d,t}) \ .$$

From this, we find

$$\log R^L_{d,t} = \pi + \frac{\xi - 1}{\xi} \log R^L_{d,t-1} + \frac{\phi}{\xi} \log R^S_{d,t} + \frac{\theta}{\xi} \log(Y^L_{d,t} - R^L_{d,t}) \ ,$$

and this, after adding an error term and fixed effects for years and states, provides a third estimating equation:

$$\log R^L_{d,t} = \mu_s + \zeta_t + \frac{\xi - 1}{\xi} \log R^L_{d,t-1} + \frac{\phi}{\xi} \log R^S_{d,t} + \frac{\theta}{\xi} \log(Y^L_{d,t} - R^L_{d,t}) + \varepsilon_{3,d,t} \ .$$

C Reduced Form Estimates

Table C1: Model Estimation Results: Reduced Form

	Benchmark	Benchmark (Standardized)	House Prices (Standardized)
		Total State Aid	
Lagged Total State Aid	0.670***		
	(0.075)		
State Income Net of School Aid	0.551***		
	(0.165)		
		State Aid to Districts	
Lagged State Aid to Districts	0.818***		
	(0.011)		
Local Revenue	−0.108***		
	(0.008)		
		Local Revenue	
Lagged Local Revenue	0.738***	0.884***	0.915***
	(0.030)	(0.021)	(0.003)
State Aid to Districts	−0.148***	−0.056***	−0.045***
	(0.020)	(0.010)	(0.005)
District Income Net of School Aid	0.202***	0.037***	0.019***
	(0.023)	(0.008)	(0.002)

Notes: The table reports estimates from the equations $\log R_t^S = \mu_s + \zeta_t + a_1 \log R_{t-1}^S + a_2 \log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (total state aid), $\log R_{d,t}^S = \mu_{s,t} + b_1 \log R_{d,t}^L + b_2 \log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), and $\log R_{d,t}^L = \mu_s + \zeta_t + c_1 \log R_{d,t-1}^L + c_2 \log R_{d,t}^S + c_3 \log(Y_{d,t}^L - R_{d,t}^L) + \epsilon_{3,d,t}$ (local revenue). The contemporaneous value and four lags of state personal income instrument for state-level variables, and the contemporaneous value and four lags of district personal income instrument for district-level variables. $R_{d,t}^S$ is state aid to school district d in real per student dollars, $R_{d,t}^L$ is locally raised revenue of school district d in real per student dollars, Y_t^S is the real per capita personal income of state S, and $Y_{d,t}^L$ is real per capita income of school district d. In the second two columns, variables are standardized by state. In the third column, the estimation method is ordinary least squares, and log average property values replace log per-capita income in the local revenue equation. Estimation includes year fixed effects and state or state-year dummies as appropriate. ***,**,* represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Standard errors (in parentheses) are clustered by state for results in the top panel and clustered by school district for results in the bottom two panels.

Table C2: Reduced Form Results: Average Property Values Regressed on Local Income

	County Income Growth	County Income Growth (Standardized)	District Income Growth	District Income Growth (Standardized)
t	0.22***	0.07***	0.27***	0.24***
	(0.03)	(0.02)	(0.05)	(0.03)
$t-1$	0.05**	0.03**	-0.01	0.02
	(0.02)	(0.01)	(0.03)	(0.02)
$t-2$	0.34***	0.19***	0.63***	0.28***
	(0.02)	(0.01)	(0.05)	(0.03)
$t-3$	0.03*	0.01		
	(0.02)	(0.01)		
$t-4$	0.91***	0.50***		
	(0.03)	(0.02)		

Notes: The dependent variables is the log of real average property values in county c in year t. In the first two columns, the independent variables are the contemporaneous value and four lags of log real per-capita county income. In the second two columns, the independent variables are the log of real per-household district income. In the second and fourth columns, all variables are standardized by state. Year fixed effects are included in all regressions, and state fixed effects are included when variables are not standardized. ***,**,* represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Standard errors (in parentheses) are clustered by state.

D Robustness of Estimates

Table D1: Model Estimation Results: Robustness Checks, Part I

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Total State Aid			
κ	1.669***	2.251***	2.495***	1.672***	1.670***	3.029***	−0.262
	(0.394)	(0.644)	(0.695)	(0.394)	(0.393)	(0.692)	(0.599)
γ	3.029***	5.135***	4.939***	3.033***	3.036***	1.669***	2.307***
	(0.692)	(0.868)	(0.803)	(0.694)	(0.697)	(0.394)	(0.869)
				State Aid to Districts			
η	5.480***	5.424***	5.424***	5.512***	6.446***	5.383***	6.058***
	(0.338)	(0.256)	(0.256)	(0.328)	(0.237)	(0.313)	(0.838)
ω	−0.593***	−0.424***	−0.424***	−0.590***	−0.591***	−0.596***	−0.636***
	(0.014)	(0.017)	(0.017)	(0.014)	(0.014)	(0.014)	(0.025)
				Local Revenue			
ξ	3.818***	9.168***	9.033***	3.870***	3.787***	3.601***	2.752***
	(0.443)	(0.305)	(0.295)	(0.451)	(0.434)	(0.388)	(0.422)
θ	0.773***	0.547***	0.623***	0.768***	0.769***	0.725***	0.961***
	(0.023)	(0.038)	(0.036)	(0.023)	(0.023)	(0.021)	(0.162)
ϕ	−0.568***	−0.695***	−0.681***	−0.577***	−0.574***	−0.628***	−0.336
	(0.028)	(0.039)	(0.039)	(0.027)	(0.027)	(0.024)	(0.221)

Notes: The table reports the parameters from estimating the equations $\log R_t^S = \mu_s + \zeta_t + \frac{\gamma-1}{\gamma}\log R_{t-1}^S + \frac{\kappa}{\gamma}\log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (total state aid), $\log R_{d,t}^S = \mu_{s,t} + \frac{\omega}{\eta}\log R_{d,t}^L + \frac{\eta-1}{\eta}\log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), and $\log R_{d,t}^L = \mu_s + \zeta_t + \frac{\xi-1}{\xi}R_{d,t-1}^L + \frac{\phi}{\xi}\log R_{d,t}^S + \frac{\theta}{\xi}\log(Y_{d,t}^L - R_{d,t}^L) + \epsilon_{3,d,t}$ (local revenue). $R_{d,t}^S$ is state aid to school district d in real per student dollars, $R_{d,t}^L$ is locally raised revenue of school district d in real per student dollars, Y_t^S is the real per capita personal income of state S, and $Y_{d,t}^L$ is real per capita income of school district d. Estimation includes year fixed effects and state dummies or state-year dummies as appropriate. Each column reports results from a different specification of the model. The benchmark estimates are in the first column for comparison purposes. The second column reports OLS estimates without using the IVs. The third column reports OLS estimates with $\log Y_t^S$ proxying for $\log(Y_t^S - R_t^S)$ and $\log Y_{d,t}^L$ proxying for $\log(Y_{d,t}^L - R_{d,t}^L)$. The fourth column reports the results when district-year observations with zero values for local revenue or state aid are dropped. The fifth column reports estimates when districts with at least one year of zero local revenue or state aid are dropped. The sixth column reports nonlinear GMM estimates. The seventh column reports estimates when county-level income is used only for the years when ACS data is available. ***,**,* represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Delta method standard errors (in parentheses) are clustered by state for results in the top panel and clustered by school district or by state-year, as appropriate, for results in the bottom two panels.

Table D2: Model Estimation Results: Robustness Checks, Part II

	(1)	(2)	(3)	(4)	(5)	(6)
			Total State Aid			
κ	1.669***	2.367***	1.669***	1.669***	1.361***	1.669***
	(0.394)	(0.653)	(0.394)	(0.394)	(0.444)	(0.394)
γ	3.029***	5.925***	3.029***	3.029***	3.222**	3.029***
	(0.692)	(1.042)	(0.692)	(0.692)	(1.343)	(0.692)
			State Aid to Districts			
η	5.480***	4.787***	5.146***	5.480***	6.372***	5.480***
	(0.338)	(0.303)	(0.334)	(0.646)	(0.445)	(0.338)
ω	−0.593***	−0.547***	−0.725***	−0.593***	−0.602***	−0.593***
	(0.014)	(0.031)	(0.016)	(0.027)	(0.016)	(0.014)
			Local Revenue			
ξ	3.818***	8.873***	3.566***	3.818***	6.934***	10.066***
	(0.443)	(0.619)	(0.671)	(1.481)	(1.216)	(0.391)
θ	0.773***	0.450***	0.767***	0.773***	0.944***	0.308***
	(0.023)	(0.133)	(0.028)	(0.101)	(0.038)	(0.026)
ϕ	−0.568***	−0.781***	−0.084**	−0.568***	−0.280***	−0.660***
	(0.028)	(0.044)	(0.040)	(0.133)	(0.053)	(0.065)

Notes: The table reports the parameters from estimating the equations $\log R_t^S = \mu_s + \zeta_t + \frac{\gamma-1}{\gamma} \log R_{t-1}^S + \frac{\kappa}{\gamma} \log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (total state aid), $\log R_{d,t}^S = \mu_{s,t} + \frac{\omega}{\eta} \log R_{d,t}^L + \frac{\eta-1}{\eta} \log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), and $\log R_{d,t}^L = \mu_s + \zeta_t + \frac{\xi-1}{\xi} R_{d,t-1}^L + \frac{\phi}{\xi} \log R_{d,t}^S + \frac{\theta}{\xi} \log(Y_{d,t}^L - R_{d,t}^L) + \epsilon_{3,d,t}$ (local revenue). $R_{d,t}^S$ is state aid to school district d in real per student dollars, $R_{d,t}^L$ is locally raised revenue of school district d in real per student dollars, Y_t^S is the real per capita personal income of state S, and $Y_{d,t}^L$ is real per capita income of school district d. Estimation includes year fixed effects and state dummies or state-year dummies as appropriate. Each column reports results from a different specification of the model. The benchmark estimates are in the first column for comparison purposes. The second column estimates the model with the instrumental variables technique introduced by Lewbel (2012). The third column uses annual growth in real county-level income per capita to backcast district income per household from the ACS sample. The fourth column clusters standard errors at the state-year level (instead of the district level, as in the benchmark). The fifth column limits the sample to only unified school districts that are marked as unified in every year of the sample. The sixth column substitutes the log of house prices for the log of local income in the local revenue equation and estimates the model via OLS. ***,**,* represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Delta method standard errors (in parentheses) are clustered by state for results in the top panel and clustered by school district or by state-year, as appropriate, for results in the bottom two panels.

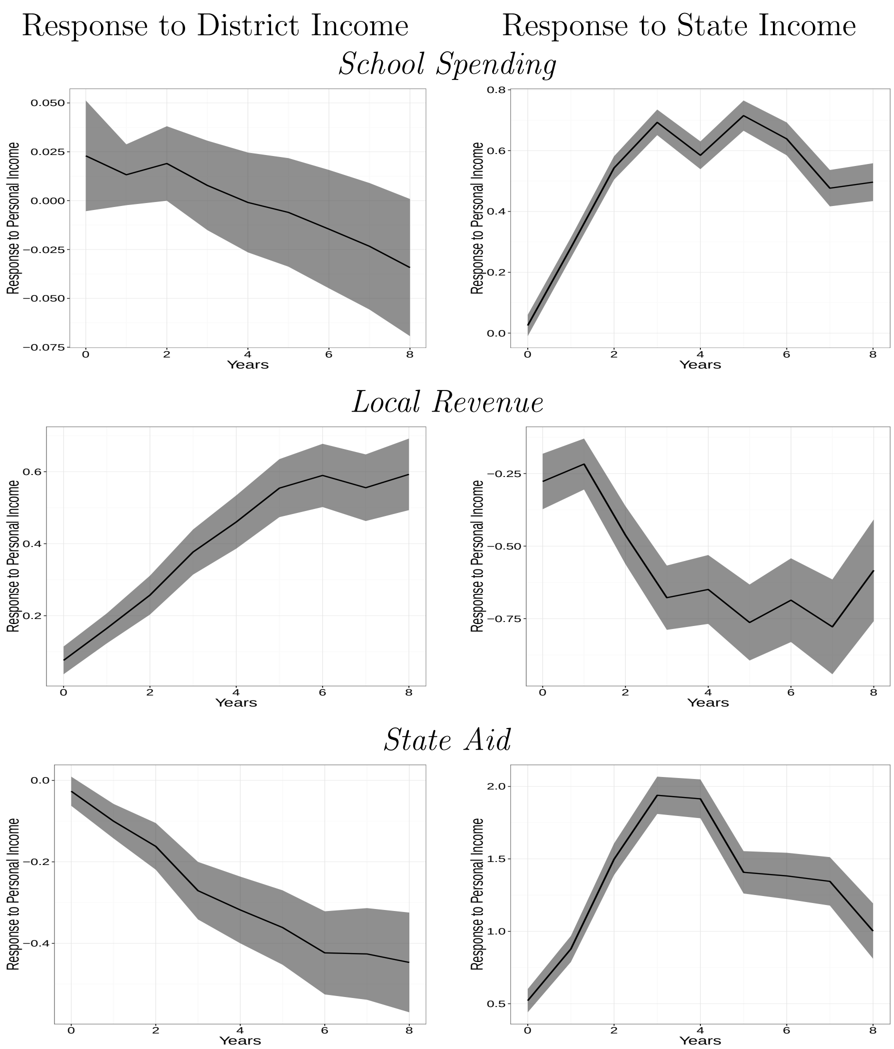
Table D3: Income and Lagged School Spending

	County Income Growth	District Income Growth
Spending Growth$_{t-1}$	0.01***	0.02***
	(0.00)	(0.01)
Spending Growth$_{t-2}$	0.00	0.01
	(0.00)	(0.01)
Spending Growth$_{t-3}$	-0.00	
	(0.00)	
Spending Growth$_{t-4}$	-0.01^{***}	
	(0.00)	
Spending Growth$_{t-5}$	0.01***	
	(0.00)	
F-Statistic	13.72	6.11
Long-Run Effect of Spending Growth	0.00	0.02

Notes: Each column reports the regression coefficients on lags of current spending growth per student from a regression with the variable listed in the column header as the dependent variable. Each regression also includes lags of the dependent variable. The table also reports in the lower panel the F-statistic for a test of the null hypothesis that lags of spending growth do not Granger-cause the dependent variable, as well as the long-run cumulative dynamic multiplier on lags of spending growth. Standard errors are clustered at the level of school districts. ***,**,* represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

E Empirical Impulse Responses

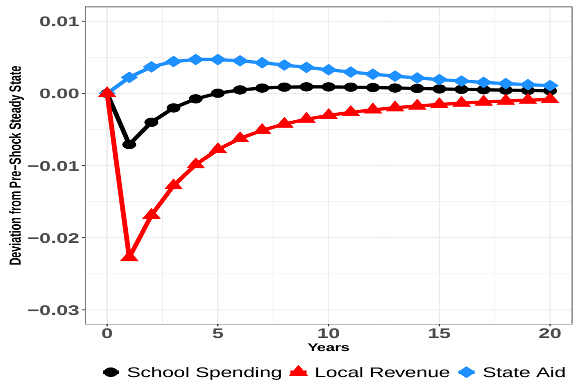
Figure E3: Responses to Income Innovations



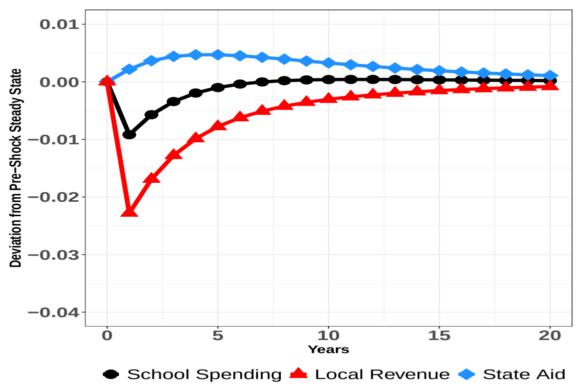
Notes: This figure displays the results from estimating $\Delta Z_{d,s,t} = \mu + \sum_{p=0}^{8} \alpha_p^L \Delta Y_{d,s,t-p} + \sum_{p=0}^{8} \alpha_p^S \Delta Y_{s,t-p} + \sum_{p=0}^{8} \gamma_{1,p} \Delta pop_{d,s,t-p} + \sum_{p=0}^{8} \gamma_{2,p} \Delta pop_{s,t-p} + \delta_t + \varepsilon_{d,s,t}$, where the left hand side gives the accumulated sums of α_p^L and the right hand side gives the accumulated sums of α_p^S (that is, the main effects in the regression) with 95% confidence bands. $\Delta Y_{d,s,t}$ denotes the change in the log of real personal income in district d in state s in time t and $\Delta Y_{s,t}$ denotes the change in the log of real personal income in state s in time t. The regressions include the contemporaneous value and eight lags of county and state population growth as well as year fixed effects.

F Model-Implied Impulse Responses. i.i.d. Income Shocks

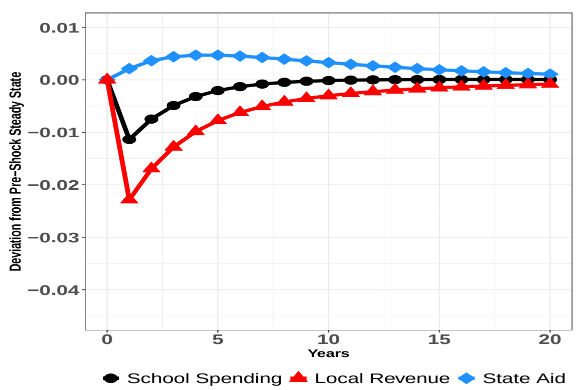
Figure F1: Impulse Responses for i.i.d. Local Income Shocks



(a) Poor District: Benchmark Parameters



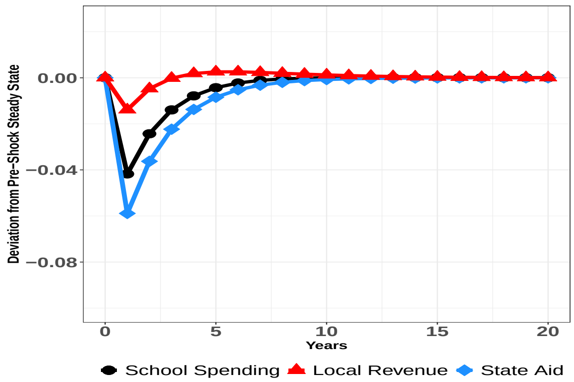
(b) Middle District: Benchmark Parameters



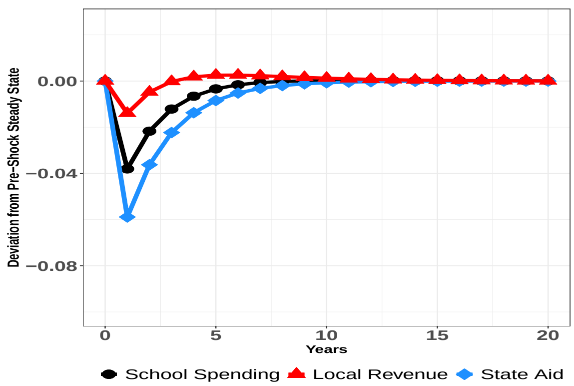
(c) Rich District: Benchmark Parameters

Notes: The figure shows the model implied responses of locally raised revenue, state aid, and school spending (all in log per student terms) to a negative income shock of 10 percent of steady state local income, assuming an AR parameter for income of 0.

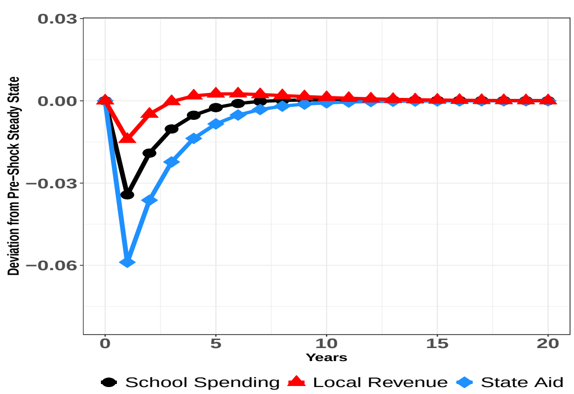
Figure F2: Impulse Responses for State-Level i.i.d. Income Shocks



(a) Poor District: Benchmark Parameters



(b) Middle District: Benchmark Parameters



(c) Rich District: Benchmark Parameters

Notes: The figure shows the model implied responses of local revenue, state aid, and school spending (all in log per student terms) to a negative income shock of 10 percent of steady state local income that simultaneously affects all school districts, assuming an AR parameter for income of 0.

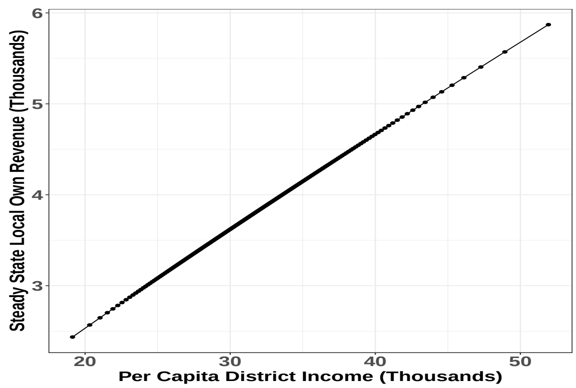
G Analysis with Parameters Estimated with District Income

Table G1: School District Responses to 10% Local Income Shock. Components of School Revenue

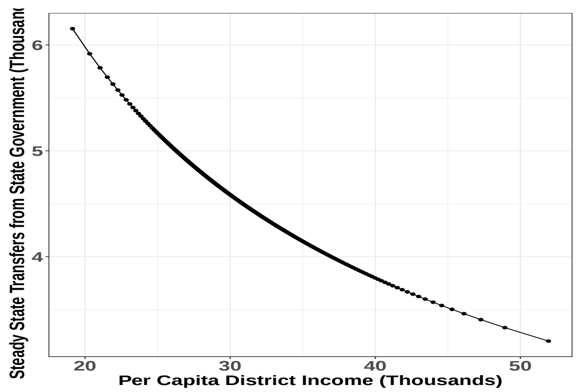
	School Spending				
Pctile:	Steady State	Impact	1 year after	3 years after	8 years after
Rich (85th)	\$8383	−\$76 (−0.9%)	−\$116 (−1.4%)	−\$143 (−1.7%)	−\$128 (−1.5%)
Middle (50th)	\$8220	−\$61 (−0.7%)	−\$91 (−1.1%)	−\$104 (−1.3%)	−\$71 (−0.9%)
Poor (15th)	\$8226	−\$48 (−0.6%)	−\$69 (−0.8%)	−\$68 (−0.8%)	−\$17 (−0.2%)
	State Aid				
	Steady State	Impact	1 year after	3 years after	8 years after
Rich (85th)	\$3939	+\$8 (+0.2%)	+\$25 (+0.6%)	+\$61 (+1.5%)	+\$132 (+3.3%)
Middle (50th)	\$4450	+\$10 (+0.3%)	+\$29 (+0.7%)	+\$70 (+1.6%)	+\$150 (+3.4%)
Poor (15th)	\$5029	+\$11 (+0.3%)	+\$33 (+0.7%)	+\$79 (+1.6%)	+\$170 (+3.4%)
	Local Revenue				
	Steady State	Impact	1 year after	3 years after	8 years after
Rich (85th)	\$4445	−\$86 (−1.9%)	−\$141 (−3.2%)	−\$204 (−4.6%)	−\$259 (−5.8%)
Middle (50th)	\$3770	−\$73 (−1.9%)	−\$120 (−3.2%)	−\$173 (−4.6%)	−\$220 (−5.8%)
Poor (15th)	\$3198	−\$62 (−1.9%)	−\$102 (−3.2%)	−\$148 (−4.6%)	−\$187 (−5.9%)

Notes: The table reports the model-implied steady state values of total expenditure, state aid, and local revenue for a "rich" district (85th percentile of the distribution), "middle-income" district (50th percentile of the distribution), and "poor" district (15th percentile of the distribution), as well as the changes in each variable in dollar and percentage point terms on impact, and one, three, and eight years after the shock. The changes are in response to an idiosyncratic 10 percent negative shock to local income, assuming that each district's income process is characterized by an AR(1) model with an autoregressive parameter of 0.98.

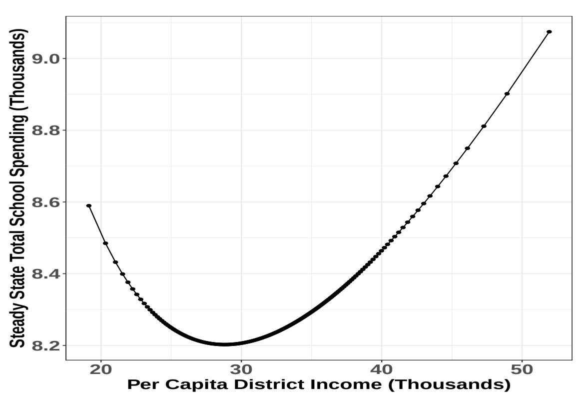
Figure G1: Model-Implied Steady State Distributions



(a) Local Revenue per Student



(b) State Aid per Student



(c) School Spending per Student

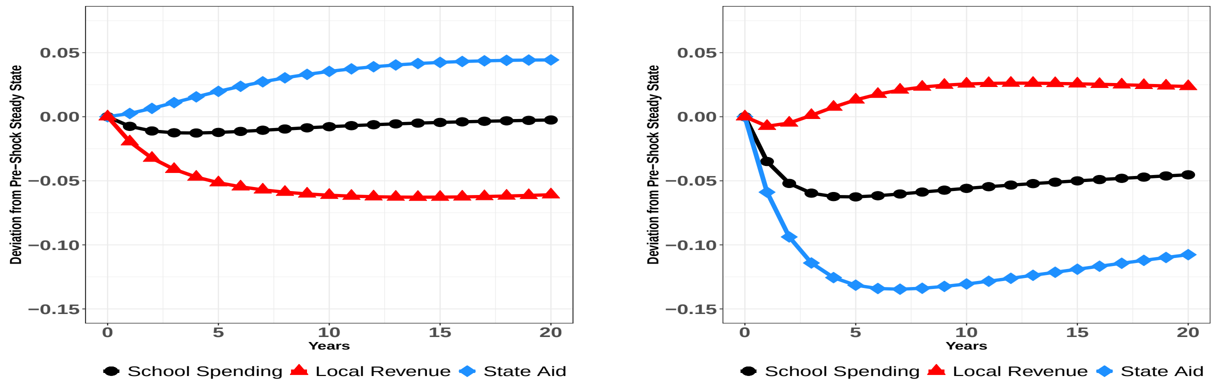
Notes: The figure shows the steady state distribution implied by the theoretical model for local revenue, state aid, and school spending (all in per student terms), conditional on an income distribution with mean and standard deviation taken from the pooled data. Model parameters are based on the estimated preferences using the pooled sample, reported in Table 5.

Table G2: Model-Implied District-Level Incidence of Income Shocks

	Idiosyncratic Shocks		Aggregate Shocks	
	Rich Districts		*Rich Districts*	
	Impact	8 years after	Impact	8 years after
Size of income shock	\$3603	\$3088	\$3603	\$3088
Incidence on Students	2.1%	4.1%	7.2%	12.2%
Incidence on Other Districts	0.3%	4.4%	0.9%	2.1%
Incidence on Taxpayers	97.6%	91.5%	92.0%	85.6%
	Middle Districts		*Middle Districts*	
	Impact	8 years after	Impact	8 years after
Size of income shock	\$2989	\$2561	\$2989	\$2561
Incidence on Students	2.1%	2.8%	9.4%	17.9%
Incidence on Other Districts	0.4%	6.0%	0.0%	0.1%
Incidence on Taxpayers	97.5%	91.3%	90.5%	82.0%
	Poor Districts		*Poor Districts*	
	Impact	8 years after	Impact	8 years after
Size of income shock	\$2479	\$2125	\$2479	\$2125
Incidence on Students	2.0%	0.8%	12.6%	25.6%
Incidence on Other Districts	0.5%	8.1%	−1.3%	−3.2%
Incidence on Taxpayers	97.5%	91.1%	88.7%	77.6%

Notes: The table reports the model-implied decompositions of income changes for a "rich" district (85th percentile of the distribution), "middle-income" district (50th percentile of the distribution), and "poor" district (15th percentile of the distribution) on impact and eight years after the shock. The top row of each panel reports the numerical pre-tax income change for a 10 percent income shock. The second row of each panel reports the change in local revenue for school districts owing to lower local income. The third row reports the change in state aid as a fraction of the income shocks. The fourth row reports the change in state taxes paid as a share of the income shocks (for state aid throughout the state), and the fifth row reports the changes in local income after accounting for the changes in local taxes. In the calculation, each district's income process is modeled as an AR(1) process with an autoregressive parameter of 0.98.

Figure G2: School Finance Variables: Impulse-Response Functions

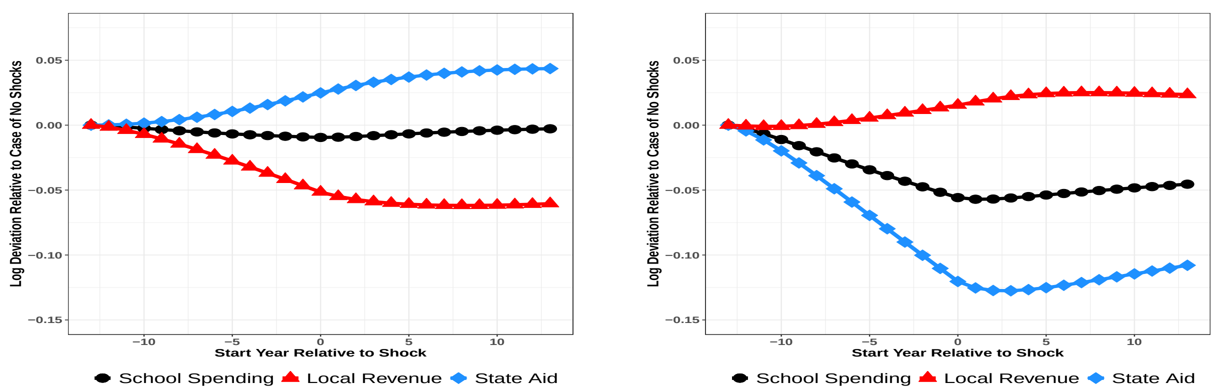


(a) Middle-Income District: Idiosyncratic Shock

(b) Middle-Income District: State-Level Shock

Notes: The figure shows, in terms of log deviations from steady state, the model-implied responses of local revenue, state aid, and school spending (all in per student terms) to a negative income shock of 10 percent of steady state income. Panel (a) shows responses to an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and Panel (b) shows responses of the median district to a statewide income shock.

Figure G3: Model-Implied Evolution of Total Spending over Educational Career by Cohort

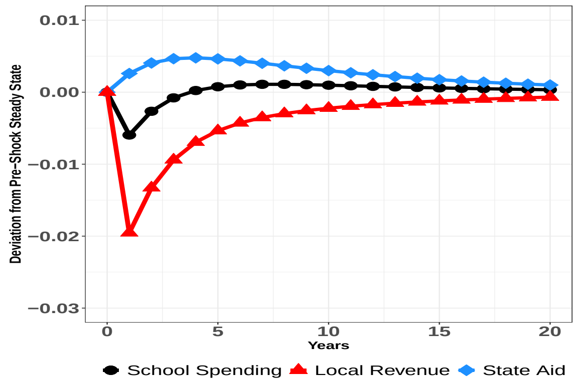


(a) Middle-Income District: Idiosyncratic Shock

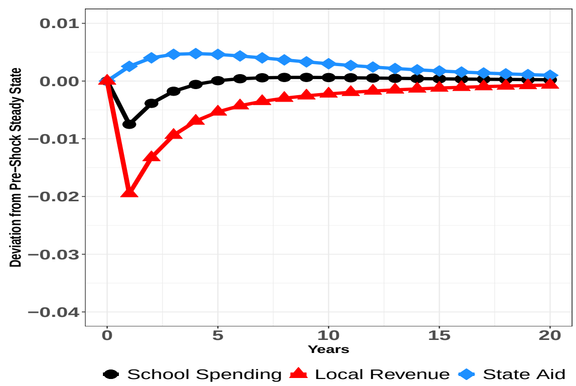
(b) Middle-Income District: State-Level Shock

Notes: The figure depicts, in terms of log deviation from steady state, the total school spending for a student cohort over their entire K-12 career, as it varies with when they start school in relation to a negative income shock of 10 percent. The x-axis measures the timing of the start of the cohort's educational career relative to the timing of the shock. Panel (a) offers model-implied responses to an idiosyncratic income shock, and Panel (b) offers model-implied responses conditional on a statewide income shock in the 50th income percentile, both for a district at the 50th percentile of the state income distribution.

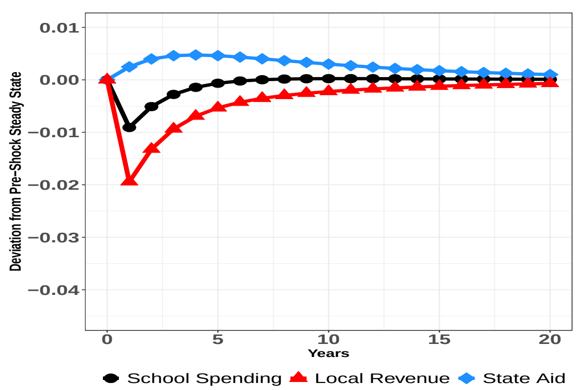
Figure G4: Impulse Responses for i.i.d. Local Income Shocks



(a) Poor District: Benchmark Parameters



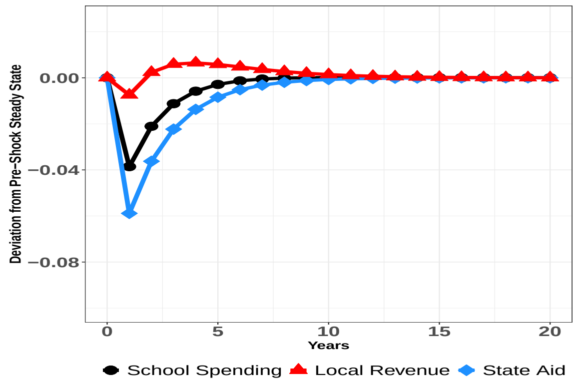
(b) Middle District: Benchmark Parameters



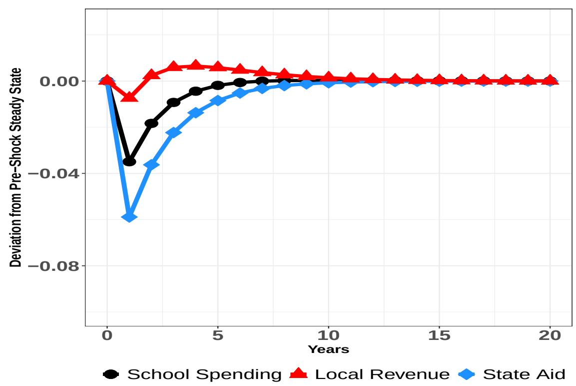
(c) Rich District: Benchmark Parameters

Notes: The figure shows the model implied responses of locally raised revenue, state aid, and school spending (all in log per student terms) to a negative income shock of 10 percent of steady state local income, assuming an AR parameter for income of 0.

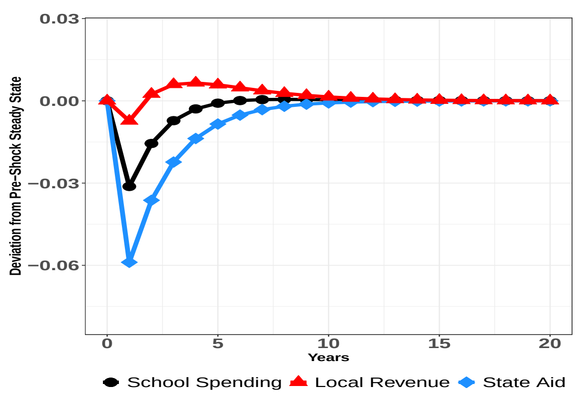
Figure G5: Impulse Responses for State-Level i.i.d. Income Shocks



(a) Poor District: Benchmark Parameters



(b) Middle District: Benchmark Parameters



(c) Rich District: Benchmark Parameters

Notes: The figure shows the model implied responses of local revenue, state aid, and school spending (all in log per student terms) to a negative income shock of 10 percent of steady state local income that simultaneously affects all school districts, assuming an AR parameter for income of 0.