

Inequality in Public School Expenditures across Space and Time

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Abstract

This paper broadens the study of educational resource disparities to include inter-temporal disparities which we show are significant between cohorts in identical school districts. State aid programs, designed to address disparities between school districts, provide partial insurance (risk sharing) against local income shocks because transfers are conditioned on income. To characterize this risk sharing, we estimate state and local government preference functions using data for 8,676 independent school districts for the years 1992 to 2014. Using the estimates, we simulate state and local government responses to local and statewide income shocks. Risk sharing for idiosyncratic local shocks is found to vary inversely with income while risk sharing for state-wide shocks is limited. The result is considerable disparities between resources for student cohorts within districts. JEL: I22, H72, H77

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1 Introduction

Over the last forty years, state governments have attempted to reduce resource disparities between school districts in K-12 education financing, often as a result of court decisions starting with the *Serrano v. Priest* decision in California in 1976. Specifically, most states now use some form of income-conditioned grants, where school districts with lower resources receive more state financial aid per student than do school districts with greater resources. One important, but perhaps unintended, consequence of this institutional change is that state governments provide a form of risk sharing/income insurance for their local school districts. That is, a local school district which loses resources due to a financial shock will receive at least partial compensation from state governments, because state aid to this now lower income school district will increase. Our research is an examination of how education financing responds to fluctuations in income at both the state and local level. This examination allows us to focus on disparities in resources over time, an issue that has not been previously addressed in the education finance literature despite its empirical importance.

Feldstein (1975) lays out the original research agenda determining how governments make their education finance choices. Later work, including Silva and Sonstelie (1995), has focused on disparities in overall education resources and, starting with Murray, Evans, and Schwab (1998), has focused on resources of the lowest income districts.¹ Some studies are explicitly concerned with how mandates to address inequities influence the overall level of resources for schools; see, e.g., Downes and Shah (2006) and the references cited therein. Hoxby (2001), in an influential article, studies states' school-finance designs and points out how they affect local incentives to raise funds, in the extreme forcing so much redistribution that local school districts have no incentive to raise revenue. A potential omission in this literature is that it implicitly assumes that school district income is unchanging. Our approach is to

¹The focus on school districts rather than spending on individual students may be a consequence of the original *Serrano v. Priest* decision. The importance of the distinction between district income and student income is recently discussed in Lafortune, Rothstein, and Schanzenbach (2018).

examine the level of educational resources available to different cohorts of students over time, assuming that students remain in the same school district over their entire K-12 experience.² We summarize the interaction between state governments and local school districts using objective functions where both levels of government have preferences for school spending and for other uses of funds, while state governments additionally have preferences for equalization across districts.

In general, local schools depend about equally on local resources raised by individual school districts and on aid from the state government, so fluctuations in either local or state resources are important determinants for resource disparities over time. For example, an idiosyncratic shock to an individual local school district, such as the closing of a factory, will affect the tax base and funds raised locally. Conversely, a statewide shock is likely to impact the resources available for education in all districts. As a result, an income reduction at the state level results in reduced state aid for all school districts. Irrespective of the source of cyclicalities, local or state responses to reduced resources will result in disparities in access to resources across students in different cohorts within the same school district. This is because the balanced budget rules under which virtually all states and local districts operate severely limit the scope for expenditure smoothing.

An important change in the institutional environment since *Serrano* is that state aid is sensitive to local school district income in almost all states. In part, our examination here is related to the Tinbergen problem, where our work suggests that policies aimed at leveling disparities in resources over time may differ from policies aimed at leveling income disparities at a given point in time.³ In creating a system to address resource inequality between districts, state governments have also, perhaps inadvertently, created a system that affects resource inequality over time. Our work here is an initial assessment of how those mechanisms operate, which may allow others to begin to make more pointed policy innovations that can attack dynamic resource disparities. For example, we find that the

²We assume for the paper that all cohorts attend the same district for all 13 years of their K-12 education.

³Tinbergen (1952) posits that a separate policy is needed to address each public goods problem.

variance of K-12 resources over time by cohort is about a quarter of that of the between-school district variance at any one time. Further, over 3,000 cohorts of students in our data (3.7 percent of the total) receive less resources than a prior cohort, in spite of income growing over time on average.

We model the choice of state and local governments’ school expenditure by specifying a preference function for school districts’ education spending compared with other spending. Additionally, for state governments, we include preferences for equality in school spending between districts. We consider the objective function an “as if” preference function, following Inman (1978), which characterizes government actions rather than the process by which government decisions are generated.⁴ Further, we characterize distinctions between school districts using per capita income.⁵ We estimate this preference model using data on the independent school districts in the US using data from 1992-2014 to generate preference parameters describing how state aid responds to differences between districts and over time.

To illustrate the impact of the estimated preference parameters for school resource disparities, we simulate governmental responses in three core dimensions. First, we illustrate outcomes as a function of school district income. We find that per student expenditures are successfully leveled for the bottom quintile of the distribution of average per capita income. Second, our simulations characterize the degree and distribution of risk sharing provided by state governments to school districts; specifically, we illustrate how income conditioned state aid reacts to local income fluctuations. We find that local idiosyncratic negative income shocks are largely buffered by increases in state aid in the long run, but it takes several years before state governments make up for shortfalls. Further, we find the degree of risk

⁴Describing aid by our “as if” preference function is quite different than the administrative characterization pursued by Jackson, Johnson, and Persico (2014). That is, they characterize aid plans by whether they are based on aid types such as District Power Equalization, but in fact find that most plans are hybrids between types. Lafortune, Rothstein, and Schanzenbach (2018) combine administrative decisions with one empirical characteristic (progressivity), but we believe our preference function parameters provide a nuanced description and allows description of all state plans including those designed without explicit court intervention.

⁵Traditionally, K-12 education in the United States has been provided by local governments financed through property taxes on both residential and commercial property. We use income to proxy this process.

sharing varies inversely with the per capita income of districts, which happens because state aid is conditioned on local resources. Third, we find that school districts do not, in general, cushion reductions in state aid that result from state-level income shocks. What is more, because low-income districts are relatively more reliant on state aid, fluctuations in state aid are more consequential, the lower is school district income.⁶

Using data from the independent school districts in the United States, we show that resource disparities over time are an important part of the overall story of resource disparities between students. While these are smaller than disparities between school districts at a single point in time, we find there is substantial variation in access to resources for students that never change school districts. Further, we find that income conditioning implies risk sharing through state government aid, but this aid does not provide insurance against statewide shocks.

Finally, the extent of risk sharing varies considerably depending on the position of a district in the state's distribution of income. The nature of risk sharing, measured by the extent and rapidity with which state aid replaces a loss of local education funds, is an important if heretofore implicit aspect of income conditioned state government education aid. We believe that this aspect of our work is novel, as previous research has not investigated the role of state education aid as an income insurance mechanism for school districts.

The rest of this paper proceeds as follows. In Section 2, we discuss the data used in the empirical analysis. We illustrate the differences in expenditure per student by district, and demonstrate differences in expenditure by student cohort. We also demonstrate that resource disparities over time are essentially uncorrelated with resource disparities at any one point in time. We develop our model of the education finance system in the United States in Section 3, and we perform simulations to illustrate the implications of the model in Section 4. A conclusion and discussion of fiscal federalism in the context of the public education system follows in Section 5.

⁶This result accentuates the importance of the Tinbergen problem. Our focus on the time series dimension has the potential to stimulate policy innovations aimed at reducing this negative impact.

2 Data

We focus our analysis on the dominant form of public education in the United States, which is independent school districts. Independent school districts are single purpose governments with schooling as their sole function (Fischel, 2009).⁷ Independent school districts have separately elected boards with responsibility for policies such as setting property tax rates and issuing debt. The school district finance data includes revenue in total and broken down by source, enrollment, and current and capital expenditure for independent school districts for the years 1992 to 2014 drawn from the U.S. Census Bureau’s Annual Survey of School System Finances.

In addition to limiting our data to independent school districts, we delete districts with less than 100 students. We also delete 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. Lastly, to use a balanced panel we exclude any districts that are not present in the data for the entire sample. 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.^{8,9}

Table 1 gives summary statistics for the key variables in our analysis. Clearly, the role of the state government is an important one, as it supplies 47.6 percent of total revenue on average, with local governments contributing on average 45.6 percent. The remainder is provided by the federal government. We ignore the federal government in the analysis below because federal resources are almost exclusively directed towards specialized functions, such

⁷We use the indicator for independence that is encoded in the district identification variable for each school district by the Census Bureau. The alternative important organizational form is school systems as part of a general purpose local government. Our focus on states with primarily independent school districts means we will exclude all school districts from Alaska, Hawaii, Maryland, Virginia, North Carolina, and the District of Columbia.

⁸Appendix Table A1 reports the number of independent school districts that remain in our sample for each state. There is a wide variety in the number of school districts across states, with a minimum of 3 in Rhode Island and a maximum of over 900 in Texas.

⁹There 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 these observations, as Appendix Table A3 demonstrates.

as school breakfast and lunch.¹⁰ Table 1 also demonstrates the significance of balanced budget constraints for local school districts. On average, school districts spend all of their annual revenue as they generally do not have savings accounts.

Table 1: Summary Statistics for Key Variables: Total Sample

Variable	Mean	Std Dev 1 (x districts)	Std Dev 2 (time)
<i>Per-Student Values (000s of 2009 dollars)</i>			
Total Revenue	10.74	3.80	2.08
Revenue from State Govt	5.11	2.38	1.24
Local Revenue	4.90	3.86	1.17
Total Current Expenditure	9.02	2.78	1.56
Total Revenue from Federal Govt	0.74	0.85	0.35
Total Capital Outlay	1.05	1.89	1.44
<i>Per-Capita Values (000s of 2009 dollars)</i>			
District Personal Income	30.55	5.92	4.36
State Personal Income	35.60	5.49	4.38

Notes: The table reports the 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 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 $[(1/n) \sum_i (X_{d,t} - \bar{X}_t)^2]^{1/2}$. “Std Dev 2” is defined as the cross sectional average of $[(1/T) \sum_t (X_{d,t} - \bar{X}_d)^2]^{1/2}$. In the top panel of the table, the denominator for each variable is the number of students in district d in year t . In the bottom panel of the table, the denominator for each variable is the total population in county c or state s in year t .

Table 1 also 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 level income.”¹¹

¹⁰The primary concern with the omission of federal aid is Title I aid for low income districts. Title I aid is small enough so that our results are not sensitive to its inclusion. While student income is important for school food aid, those resources are not generally fungible with other school expenditures.

¹¹We use county-level personal income from the Bureau of Economic Analysis, which is available for the entire time period of our analysis. The Census Bureau’s American Community Survey (ACS) has started

Table 2 reports the sources of fluctuations in school districts’ total revenue. The table shows that variation from state aid is equally as important as is variation in local revenue. Thus, fluctuations in state aid can contribute to disparities in access to educational resources across students in different cohorts.

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

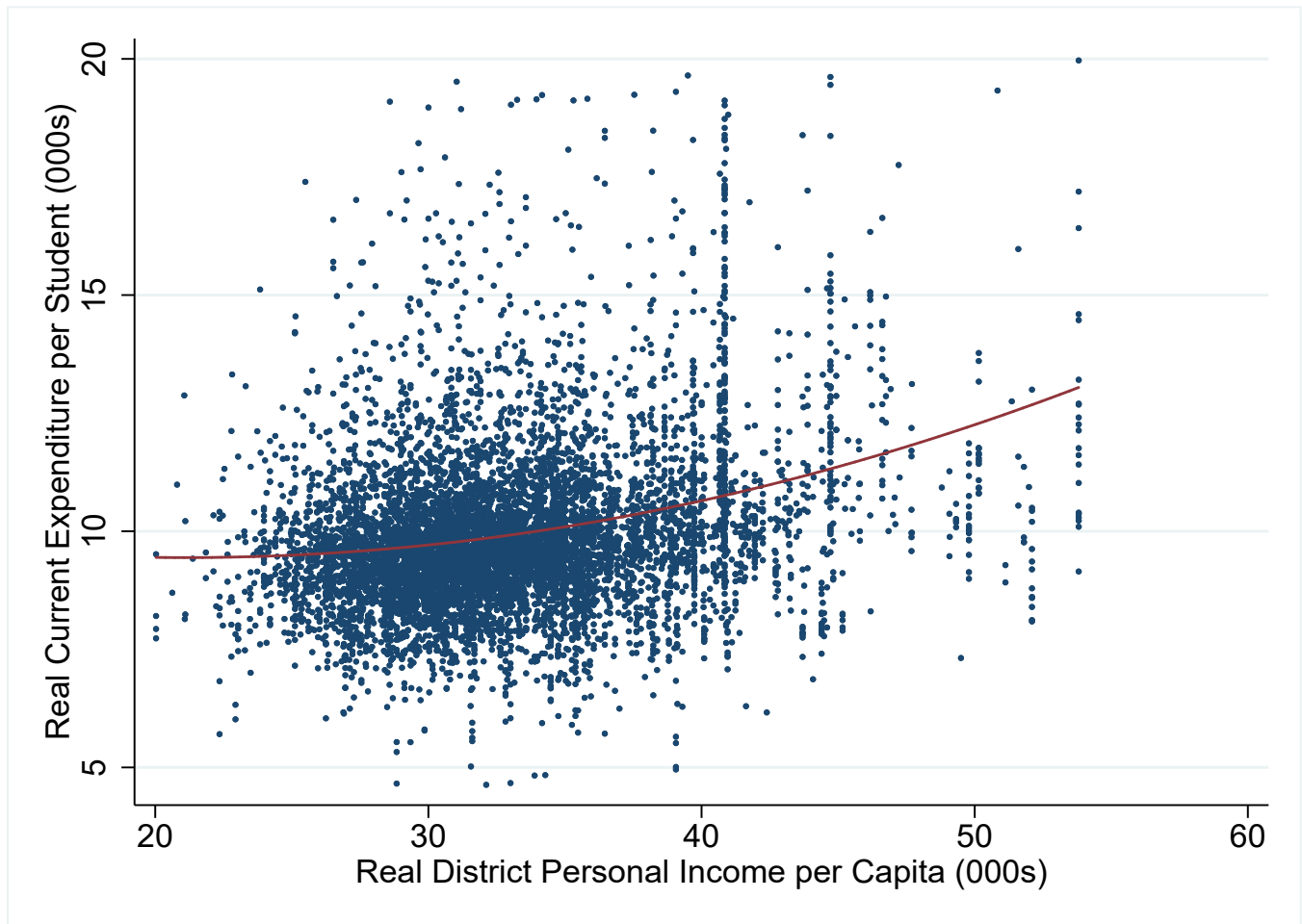
Revenue Source	(1)	(2)	(3)
State Aid	42.5 (3.7)	42.4 (3.7)	42.8 (3.8)
Local Revenue	43.4 (2.6)	43.7 (2.6)	42.9 (2.6)
Federal Revenue	14.1 (4.8)	13.9 (4.9)	14.3 (4.8)
Year Fixed Effects	No	Yes	No
District Fixed Effects	No	No	Yes

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 (col 1), real local revenue per student in district d in year t (2), and real federal revenue per student in district d in year t (3). 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.

Figure 1 depicts the classic problem that the earliest state court orders sought to address, namely cross-sectional resource disparities. This figure plots time-averaged real expenditures (less federal aid) per student as a function of time-averaged district per capita income using all of the independent school districts in our sample across the 45 states. It shows wide differences in expenditure not only between school districts with different per capita incomes, but also wide disparities in expenditures between school districts of equal incomes. That is, differences in education resources are not only a function of different constraints, they also reflect differences in implied preferences. Nonetheless, the fitted line in the figure shows that access to educational resources has been relatively equalized over school districts in the lower making income available by school district, but these data are only available going back to 2009 for the 5-year moving average. Our model estimates using ACS income are very similar to what we report below, but with considerably less precision.

segment of the income distribution, while for the upper segment local income is correlated with educational expenditures.

Figure 1: Average Annual Spending per Student



Notes: The figure plots the average of each district's sum of real total state and local revenue per student 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 with average state effects. 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) with resources more than \$20 thousand greater than the state-year average.

In addition to resource disparities across districts, resource constraints faced by school districts are not static. Table 3 shows the transition matrix using five year moving average per capita income in the districts from 1992-2014. The table makes clear that school districts can experience substantial changes in their position in the state-specific income distribution.

Mobility between income quintiles is perhaps surprisingly large, especially for the middle three quintiles of school districts. Of districts in the middle income quintile at the beginning of our data, for example, only 35 percent are still in the middle quintile by the end of our data in 2014. Even for school districts at the top or bottom quintile of the income distribution, moreover, there is significant mobility along the income distribution over time. Coupled with the importance of income differences in educational resources shown in Figure 1, the transition matrix illustrates the potential for substantial disparities in resources over time for a substantial number of student cohorts.

Table 3: Transition between Income Quintiles of School Districts Using 5-Year Moving Average, 1996-2014

	2014				
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 income quintile given by the row header in 1996 that is in the income quintile indicated by the column header in 2014. The starting year is 1996 as we consider a 5-year moving average with our sample starting in 1992.

One method by which we examine resource disparities over time is to evaluate the level of student resources assuming students do not change school districts. That is, we sum the level of real resources available to a student, assuming that student remains in the same school district for all 13 years of K-12 education and receives 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. The cohort analysis is summarized in Table 4, which reports that the average spending per student is about \$118 thousand in real 2009 dollars. The cohort calculation could allow some smoothing over the 13 years if lean years are compensated by abundant years, but despite that the within-district standard deviation

is more than 28 percent of the annual average cross-sectional standard deviation. In more than 3 percent of the cohorts, students receive fewer resources than their peers in the prior year. Further, despite the fact that the average growth in per student education spending of 2.02 percent is greater than average income growth, in over a quarter of the cohorts, students are educated in school districts in which education spending grew more slowly than income.

Table 4: Summary Statistics of Resources 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 receiving lesser spending than Previous Cohort	3,188 (3.7% of total)
District-Cohort Observations Exposed to Lesser Resources 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)

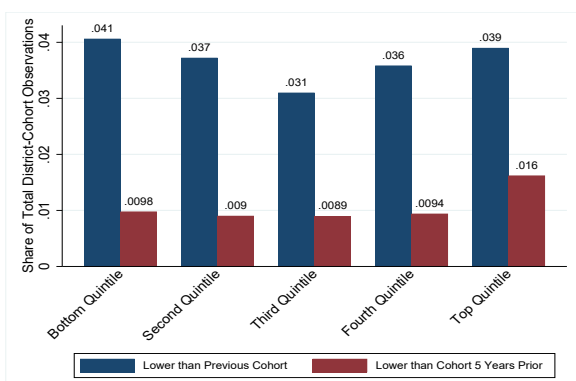
Notes: The table reports summary statistics for total resources for education (measured in 2009 dollars per student) that the average student in each school district would be exposed to over the course of their entire K-12 education career. The table includes only complete cohorts, covering students entering kindergarten in 1992 through 2002 in our sample. 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 the parentheses are calculated using the appropriate comparison cohorts.

2.1 Resource Disparities by Cohort are Unrelated to Income Levels

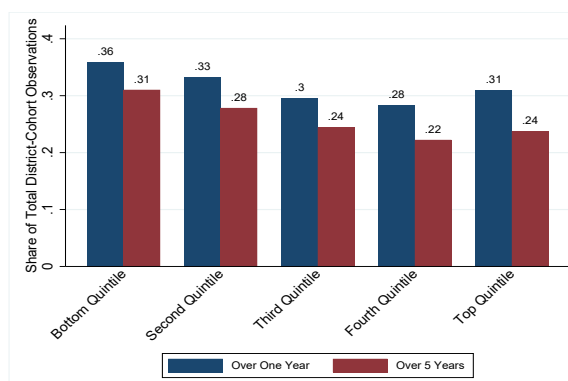
Figure 2 reveals that the time series disparities are roughly orthogonal to the cross-sectional disparities that have motivated the school finance literature. The top row of Figure 2 depicts the share of student cohorts which have experienced lower resources than earlier cohorts in the same school district. 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 resources than the previous cohort. For the top income quintile of school districts, however, 3.9 percent of the cohorts received fewer resources 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 resource reductions. Panel (b) shows a similar pattern of low growing expenditure years being relatively evenly distributed by income.

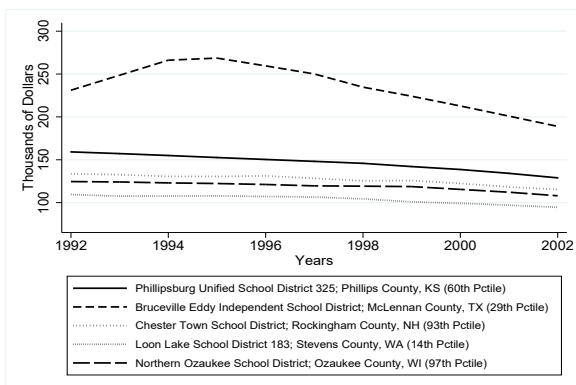
Figure 2: Changes in Spending by Cohort by Income Quintile
(Based on 1992 Income Quintiles)



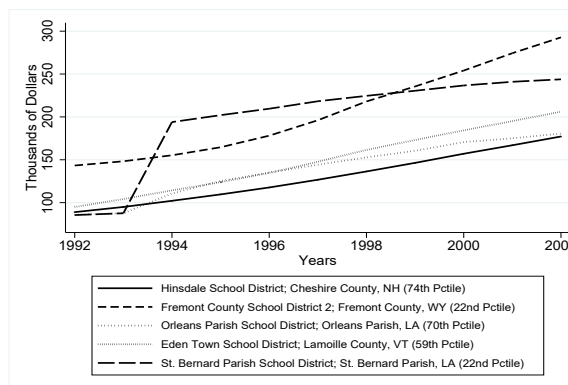
(a) Share of Cohorts Receiving Less Spending than Previous Cohort



(b) Share of Cohorts 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 total 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 education spending, and in the five districts with the fastest growth in education spending. The sample includes the complete cohorts, those entering kindergarten in 1992 through 2002.

The bottom row of Figure 2 illustrates the same point using individual school districts.

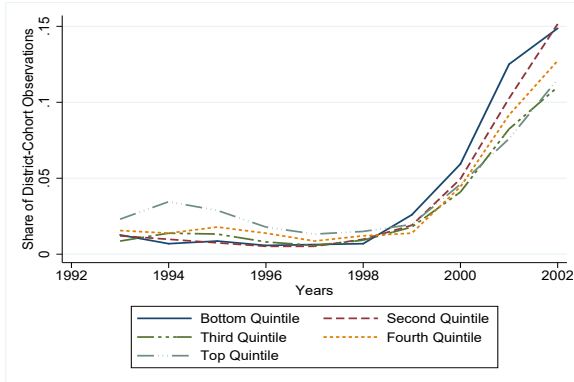
Panel (c) shows the five slowest growing school districts measured by expenditures per student. We see that districts with both high and low income at the start of the sample period have experienced reductions in schooling resources for cohorts over time. Similarly, Panel (d) shows the fastest growing districts in expenditures per student, and these districts likewise originated at very different points in the income spectrum. This preliminary evidence strongly suggests that education resource disparities over time is a problem distinct from disparities between school districts.

Figure 3 shows in a completely different way how disparities in resources over time are unrelated to disparities in resources across districts. The top row of the panel shows the annual share of cohorts experiencing resource reductions relative to previous cohorts in the same school district. We again separate cohorts according to income quintile. While we see that the Great Recession is associated with resource reductions in many districts, the top two panels show that these reductions were almost equally likely to be experienced by cohorts in the top income quintile districts as by those in the bottom quintile. The two panels in the bottom row of this figure show the same basic pattern for cohorts experiencing resource growth slower than income growth.¹²

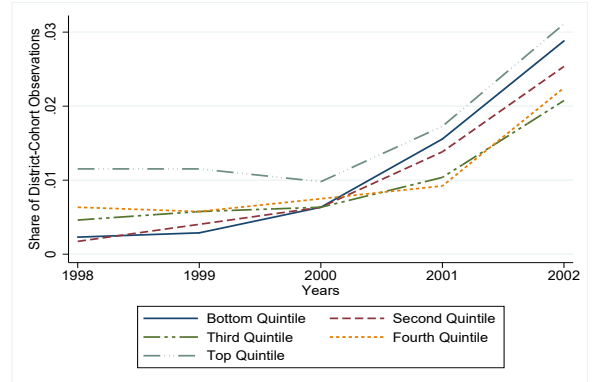
The model that we develop to characterize how state governments design their school aid systems is developed in Section 3 below. Given the discussion, the model must be capable of incorporating a number of important features. Total education expenditures by state governments must be a choice variable. It will need to be responsive to the federalist framework, and include how local governments respond to state government actions, and vice versa. The model will need to incorporate how both state and local governments respond over time to changes in income, and it must show the extent to which state governments express concern over disparities in access to educational resources between school districts, and over time. We next turn to describing a model that we believe incorporates all of these characteristics.

¹²Panel (d) is the only one in the eight panels of the two figures that suggests a correlation with income.

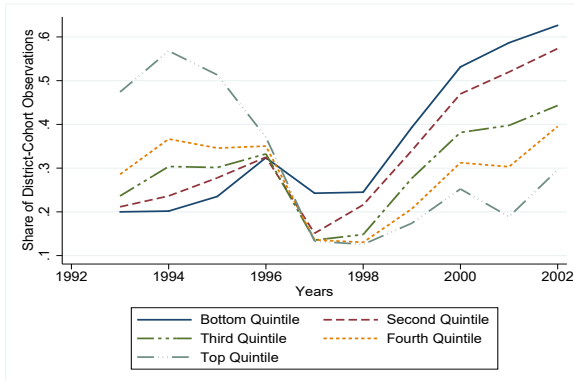
Figure 3: Evolution Over Time of Changes in Spending by Cohort by Income Quintile (Based on 1992 Income Quintiles)



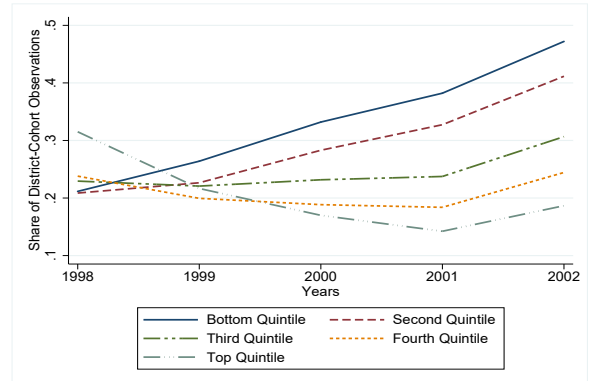
(a) Share of Cohorts Receiving Less Spending than Previous Cohort



(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 spending in a different comparison- either to the previous cohort, the five years' prior cohort, or more slowly than income in one or five years. Each district's cohort is 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 the full 13 years for the complete cohorts from 1992-2002.

3 A Preference Model for K-12 Education Finance

State governments are the institutions that design financial assistance programs for state aid to local school districts. State supreme courts then judge whether the state government aid system design is consistent with the state constitution. If not, the state government is required to develop a new system of school aid. Because of the challenges in state courts, and in anticipation of challenges, many states have built their school aid systems to address resource disparities between school districts. No court challenges have yet addressed educational resource disparities over time, but as discussed above, school aid systems have attributes that interact with resource variation resulting from income shocks at either the state or local level.

We therefore build a state government preference model by which state governments choose how to address resource disparities between districts.¹³ After estimation of the preference parameters, we examine through simulations how the aid system affects disparities that result from income shocks. The model incorporate the three choice variables discussed above, total state aid to local schools, the distribution of that aid across school districts, and all other goods. The model builds in a dynamic component by specifying total school aid as a function of previous total allocations and by specifying aid to each individual school district as a function of previous district allocations.¹⁴ We capture distributional preferences by weighting the distributional term by local district revenue, following the unequal concern specification in Behrman and Craig (1987).

The local government model describes the response of local school taxes to local income shocks and to state government aid. It is well established in the school finance literature that,

¹³Dupor and Mehkari (2015) develop a model in which school districts are presumed to behave as optimizing consumers. Their focus is only on school districts and they treat revenue as exogenous, while we model the interactions between school districts and state governments where school district revenue is an endogenous variable. The model in our paper also relates to the work of Fernández and Rogerson (1996) and Fernández and Rogerson (1998), in that it examines the distribution of resources across the income distribution for financing public education.

¹⁴Slow adjustment of spending to state and local income shocks is pervasive, as documented, for example, in Sørensen, Wu, and Yosha (2001).

despite “flypaper effects,” school taxes are reduced in response to state aid. By modeling this process explicitly, we incorporate how state governments take the local response into account in the aid granting decision..¹⁵

We use the models of state and local education choices to derive estimating equations, and we estimate the parameters using all 199,548 observations on independent school district expenditure choices. The estimated preference parameters are then used to examine how both state and local governments respond to income shocks.¹⁶ This examination reveals the extent of risk sharing based on an evaluation of both the speed and extent of governmental behavioral responses.¹⁷

3.1 State Government Behavior

The representative state government is assumed to have preferences over the level of total state aid to local districts, its distribution, and all other goods. We weight preferences for the distribution of aid by local revenue to capture concern over resource disparities, and dynamics are introduced by specifying state aid relative to past decisions. These features lead to the following preference function:

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

where $R_t^S = \Sigma_{d \in D} R_{d,t}^S$. The state is assumed to myopically solve its optimization problem separately in each period t .

Unequal concern is determined by the first term in the preference function, where a

¹⁵The “flypaper effect,” is where state “lump sum” aid is found to be more stimulative of government expenditure than would an equivalent increase in personal income. Buettner and Wildasin (2006) demonstrate that, on average, local governments tend to collect less revenue from local taxpayers when they receive an increase in vertical grants.

¹⁶We treat school district income as exogenous. Districts have many schools, and the purpose of our local model is the fiscal interaction with states. Thus, individual mobility is of secondary importance and we ignore it throughout.

¹⁷While there are differences between states, we find it preferable to study average behavior and leave estimation of individual state objective functions, and tests of which states might be empirically similar, to a separate study.

positive estimated ω indicates that states weight transfers more highly for districts with higher locally raised revenue per student, while a negative ω indicates states weight transfers more highly for districts with lower local revenue per student. η describes the degree of inequality aversion with respect to state-provided resources. If η is estimated to equal 1, states have no aversion to unequal state aid across districts, while a larger η indicates a state with a greater aversion to differences in state resources per student between districts. The aversion to differences is also pertinent to changes over time, where a larger η indicates states respond more slowly to changes over time.

Preferences over inequality in access to resources are specified relative to a reference level, $\frac{\widetilde{R_{d,t}^S}}{R_t^S}$. The reference level is specified as a function of the previous year's allocations, and thus introduces a dynamic dimension into the model which captures the significant lags in adjustment observed in the data.¹⁸ The model is agnostic about the exact motivation underlying the reference level. Reasonable theories would include adjustment costs associated with altering resource allocations from year to year, or the effect of political competition on policy choices as, for example, in the reversion level in the Structure Induced Equilibrium models first introduced by Shepsle (1979).

The second term in the equation captures the preferences derived from total state government education spending 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}_t^S , which depends on overall aid levels in the previous year.¹⁹

The final term in the equation captures preferences derived from funds not used for education, defined as personal income minus total education aid per capita.²⁰ κ captures

¹⁸Appendix Figures A2 and A3 report accumulated responses of various state finance variables to lagged changes in local and state personal income per capita using a distributed lag framework. These figures demonstrate that state aid and local resources adjust gradually to income changes, thus motivating our use of the reference level mechanism.

¹⁹To simplify the analysis, we assume that the state government is myopic with respect to its reference level of spending (or habit formation), in the sense that it does not internalize the effect of decisions in time t on preferences in time $t + 1$.

²⁰Baicker and Gordon (2006) find that increases in state aid partly result in lower aid to local governments for other purposes. Since we use single purpose school districts, however, this avenue is closed. Thus spending on other local purposes consists of taxpayers' private use of funds.

the concavity of welfare derived from other uses of income, both public and private. As either the γ or κ parameters approach unity, the state government becomes more tolerant of intertemporal fluctuations in total education spending or in other uses, respectively.²¹

We specify reference level resources as:²²

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

and

$$\log \left(\frac{\widetilde{R_{d,t}^S}}{R_t^S} \right) = \varrho^d + \log \left(\frac{R_{d,t-1}^S}{R_{t-1}^S} \right).$$

Estimating equations are derived assuming that the state government decides first how much to spend in total on education without regards to its distribution.²³ 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_t^S (holding the districts' shares constant):

$$(R_t^S)^{-\gamma} (\tilde{R}_t^S)^{\gamma-1} = (Y_t^S - R_t^S)^{-\kappa},$$

which can be solved for

$$\log R_t^S = \frac{\gamma-1}{\gamma} \log \tilde{R}_t^S + \frac{\kappa}{\gamma} \log(Y_t^S - R_t^S).$$

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

²¹Adding the net-of-tax term parameterized with κ completes the budget constraint for state residents, excepting federal aid which is omitted here.

²²The lagged terms will have parameters in the estimation, see Equation 1 below.

²³This could be rationalized by each school district being atomistic.

fixed effects for states and years, we arrive at the first estimating equation, showing the logarithm of total state education aid to be a function of total resources in the state and the state reference spending level:

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

From Equation 1, the preferences of state governments for total state education aid in the face of economic shocks are shaped by the parameter γ . For example, for constant κ , as γ is larger, the state government alters education aid less for any given shock. In the extreme, as $\gamma \rightarrow \infty$, the level of state aid approaches a random walk. The coefficient on income less spending on education depends on both the parameter on income, κ , and the parameter on state education spending, γ . Education spending is more sensitive to income changes the lower is γ and the higher is κ , illustrating the trade-off between the relative desire to keep education aid constant compared with the desire to keep other resource uses, including taxes, constant.

The term $\log(Y_t^S - R_t^S)$ is a function of the dependent variable and therefore correlated with the residual. Because school aid is a small fraction of state income, we assume state income is exogenous to school spending.²⁴ To account for simultaneity, we employ the contemporaneous value and four lags of log real state income per capita as instruments for the term $\log(Y_t^S - R_t^S)$ in the estimation.

The state's preferred distribution of education aid across school districts is derived from the first order condition of the preference function holding total state aid for education constant. Thus, we take the derivative of the first segment of the preference function with respect to aid distribution, subject to the total spending constraint,

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

²⁴Implicitly, this includes an assumption of Tiebout-mobility being negligible at the state level at the frequency of our data.

holding R_t^S constant. λ_t^S is a Lagrange Multiplier measuring the shadow welfare value of an extra dollar of total state government education spending. The first order condition for transfers to district d is

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

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 resource level we obtain (after absorbing the additional state-level term into the state-year dummy) the basis of the second estimation equation:

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

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

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

The second estimating equation shows that transfers to district d depend on the transfers in the previous year as captured by the parameter η on the second variable of the equation. η reflects the desire to protect transfers to local district d in the face of economic shocks. Additionally, both ω and η interact to describe the state response to local resources $R_{d,t}^L$. As ω is more negative, higher local resources will result in lower overall state aid to that district, holding η constant.

Local school districts are expected to respond to the level of state aid as described in Section 3.2 below. Thus, we use the contemporaneous value and four lags of log real school district personal income per capita as instruments for $\log R_{d,t}^L$ in the estimation. Together, Equations 1 and 2 provide us with parameters that describe state government behavior with

respect to choosing the level of total state education aid to school districts, as well as its distribution across districts.

We believe this general model of how state governments address the issue of resource disparities is useful for characterizing both the response to disparities at any point in time, and for characterizing the dynamic patterns of the response. Our model captures the nuances of all the myriad program parameters without reliance on governments' specific administrative frameworks. Specifically, the parameters ω and η together describe the response of state aid to the level of local resources as shown in Equation 2. A negative value of ω implies that the state government tends to shift greater amounts of aid to districts with lower local resources. The higher is η , the more the state government desires to have equal aid for each local government, conditional on the value of ω . In a dynamic context, a higher value of η also means that the state government reacts only slowly to changes in income at the local level. Intuitively, a state government with a higher η is less willing to move resources from one district to another, so when a district receives an income shock, it takes the state relatively longer to respond.

3.2 Local School District Behavior

This section presents our model of how local school districts determine the level of local resources (taxes). Specifically, local school districts are assumed to decide on the level of resources versus other uses of income by selecting local school taxes. Independent school districts exclusively provide public education, so the trade-off is between school spending and private uses of funds. Because total school expenditure is the sum of state plus local resources, the goal of this component of the model is to illustrate the local offset of state aid. Additionally, we introduce dynamics through a reference level of local resources allowing us to assess the speed of local district responses to income shocks. The model below is specified for a single school district. For purposes of estimation, we assume all districts behave with

an identical preference function.²⁵

A local school district d is modeled to choose local school district revenue $R_{d,t}^L$ to maximize the following preference function:

$$\max_{R_{d,t}^L} (R_{d,t}^S)^{-\phi} \frac{1}{1-\xi} \left(\frac{R_{d,t}^L}{\tilde{R}_{d,t}^L} \right)^{1-\xi} + \frac{1}{1-\theta} (Y_{d,t}^L - R_{d,t}^L)^{1-\theta} .$$

As with the state government, we assume that the local government behaves myopically with respect to the reference spending level, \tilde{R}_d^L , which is assumed to follow the relation

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

The local preference function thus depends on three terms: state aid, local school resources, and local income net of taxes to pay for schools. The key relation of interest is local resources relative to the reference level, as this helps to inform the dynamic response of local school districts to variation in state aid ($R_{d,t}^S$), and to variation in local income net of school taxes ($Y_{d,t}^L - R_{d,t}^L$).

Maximizing the local objective function with respect to the choice of $R_{d,t}^L$ yields as a first order condition:

$$\left(\frac{R_{d,t}^L}{\tilde{R}_{d,t}^L} \right)^{-\xi} \frac{1}{\tilde{R}_{d,t}^L} (R_{d,t}^S)^{-\phi} - (Y_{d,t}^L - R_{d,t}^L)^{-\theta} = 0 ,$$

or after taking logarithms and rearranging

$$-\xi \log R_{d,t}^L - (1-\xi) \tilde{R}_{d,t}^L - \phi \log R_{d,t}^S = -\theta \log (Y_{d,t}^L - R_{d,t}^L) ,$$

²⁵Clearly, there are many reasons to expect differences in behavior between districts. Consistent with our estimation of a representative state, this model allows us to consider the interaction between state aid and local resources, and to estimate the relative importance of stability of resources over time for a representative district.

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

$$-\xi \log R_{d,t}^L - (1 - \xi)(\pi_0 + R_{d,t-1}^L) - \phi \log R_{d,t}^S = -\theta \log(Y_{d,t}^L - R_{d,t}^L) .$$

From this, we find

$$\log R_{d,t}^L = \pi + \frac{\xi - 1}{\xi} \log R_{d,t-1}^L - \frac{\phi}{\xi} \log R_{d,t}^S + \frac{\theta}{\xi} \log(Y_{d,t}^L - R_{d,t}^L) ,$$

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

$$\log R_{d,t}^L = \mu_s + \zeta_t + \frac{\xi - 1}{\xi} \log R_{d,t-1}^L - \frac{\phi}{\xi} \log R_{d,t}^S + \frac{\theta}{\xi} \log(Y_{d,t}^L - R_{d,t}^L) + \varepsilon_{3,d,t} . \quad (3)$$

Depending on the parameter ϕ , the school district may choose to offset part or all of state aid by tax reductions. A finding of $\phi = 0$ would imply that the school district does not take state aid into account when choosing local revenue, while $\phi > 0$ would suggest that increases in state aid do not increase spending on education dollar for dollar due to the negative sign on $\log R_{d,t}^S$. As $\phi \rightarrow 0$, the greater is the flypaper effect, such as discussed in Bradford and Oates (1971a) and Bradford and Oates (1971b) The ratio $\frac{\phi}{\xi}$ determines exactly how much local districts offset changes in state government transfers. Note that school districts are subject to laws set by the state government, so the estimated parameters for districts are hybrid parameters which incorporate school districts' preferences for tax levels as well as constraints imposed by the state.

In Equation 3, the desire to keep local school spending constant is captured by the parameter ξ , while θ/ξ is the (approximate) elasticity of local school spending with respect to local income. The simultaneous interaction between state government aid and local taxes dictates the use of instrumental variables (IVs). We use the contemporaneous value and four lags of both the logarithm of real state personal income per capita and the logarithm of real

school district personal income per capita to instrument for $\log R_{d,t}^S$ and $\log(Y_{d,t}^L - R_{d,t}^L)$.²⁶

4 Estimation Results

We estimate the three behavioral equations derived above; namely, the state choice over the level of state aid (Equation 1), the allocation of state aid to school districts (Equation 2), and local spending as a function of state aid (Equation 3). The estimation results are presented below in four parts. We first present the fundamental preference parameters that are just identified based on the reduced form estimates. Second, we present the model-implied steady state allocations of state aid to individual school districts. The key aspect of this presentation is to show differences by income, since the income conditioning of state aid is what generates the risk sharing function by the state government. The third set of results illustrates the response of school finance variables to income shocks at the state and local level, using simulation analysis. Finally, we illustrate the extent to which cohorts of students receive differential resources depending on when in the business cycle they attend school.²⁷ Specifically, these latter two parts of our analysis illustrate that an idiosyncratic negative local income shock generates additional state aid to compensate, depending on the income level of the school district. We also illustrate how an income shock to the state as a whole results in substantial resource disparities between student cohorts. The resulting shocks caused by state aid are more important the lower is a district's income since state aid comprises a larger share of total resources.

While we interpret our parameter estimates in light of our theoretical structure, the empirical results can also be given an atheoretic reduced form interpretation. We present reduced form estimation results for Equations 1, 2, and 3 in Appendix Table A2 without

²⁶For 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.

²⁷These results are driven by dynamics over time as channeled through the reference levels, as the resulting estimates reveal large differences between the initial impact of income shocks and the long run values.

reference to the model.²⁸ The estimated reduced form coefficients are highly statistically significant, so, for brevity, we will not comment further on the statistical significance of the parameters.²⁹

Overall state education aid. The preference parameters estimated from Equation 1 capture how state governments choose total education aid versus all other uses of income, public and private. γ is reflective of the curvature of preferences for education spending, while κ shows the tastes for all other goods. We estimate γ to be 3.029, while κ is estimated to be 1.669. These parameters imply that state governments have a stronger preference to protect education spending in the face of economic shocks than to protect taxation levels. The γ parameter is derived from a coefficient to lagged spending of 0.67 in the reduced form estimates reported in Appendix Table A2. The combination of the κ and γ parameters amount to an elasticity with respect to income of 0.551 in the reduced form.³⁰

Allocation of state education aid across school districts. The parameters η and ω are derived from estimation of Equation 2, which expresses state governments' preferences over the allocation of state aid across districts. The unequal caring parameter ω , which weights local resources in the objective function, is estimated to equal -0.59 . The negative value of ω implies that, all else equal, state governments desire to distribute more aid to school districts that have lower local revenue, a finding consistent with state governments incorporating court rulings (or anticipation of future court rulings) into their decision making regarding educational resource disparities.

The ω coefficient also relates to the work of Hoxby (2001) and Jackson, Johnson, and Persico (2016), who focus on the potential importance of inverted tax prices. From the reduced form coefficient in Appendix Table A2, we see that states are estimated to reduce aid

²⁸That is, we estimate the following relationships: $\log R_t^S = \mu_s + \zeta_t + a_1 \log R_{t-1}^S + a_2 \log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (state total education spending), $\log R_{d,t}^S = \mu_{s,t} + b_1 \log R_{d,t}^L + b_2 \log R_{d,t-1}^S + \epsilon_{2,d,t}$ (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).

²⁹Our results are robust to estimating a number of different specifications of the model. These estimates are reported in Appendix Table A3.

³⁰Literally, 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

Point Estimate	
Total State Education Spending	
κ	1.669*** (0.394)
γ	3.029*** (0.692)
State Aid to Districts	
η	5.480*** (0.338)
ω	-0.593*** (0.014)
Local Revenue	
ξ	3.818*** (0.443)
θ	0.773*** (0.023)
ϕ	0.568*** (0.028)

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 education spending), $\log R_{d,t}^S = \mu_{s,t} + \frac{\omega}{\eta} \log R_{d,t}^L + \frac{\eta-1}{\eta} \log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), and $\log R_{d,t}^L = \mu_s + \zeta_t + \frac{\xi-1}{\xi} \log R_{d,t-1}^L - \frac{\phi}{\xi} \log R_{d,t}^S + \frac{\theta}{\xi} \log(Y_{d,t}^L - R_{d,t}^L) + \epsilon_{3,d,t}$ (local revenue). All parameters are derived from the estimates reported in Appendix Table A2. $R_{d,t}^S$ is state aid to school district d at time t in real per student dollars, $R_{d,t}^L$ is locally raised 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 . Estimation includes year fixed effects and state dummies or state-year dummies as appropriate. ***, **, * 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.

to a district with a negative elasticity of 0.108 with respect to local spending, a fairly low “tax rate” on average. The estimate of η , however, also contributes to our understanding of how state governments use allocations of aid to address resource disparities. η is estimated to be 5.480, derived from the coefficient of 0.818 on lagged district-level aid. The estimate for η yields a relatively steep curvature implying 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 are, on average, expressing considerable “stickiness” in aid levels over time, a finding which works against state flexibility in adjusting aid to changes in local economic activity.

Local school district spending. The response of local school districts to allocations of state education aid is captured by our estimates of Equation 3. The parameter ξ is estimated at 3.82, which is derived from the coefficient to lagged local spending of 0.738. The estimate of 3.82 implies that school districts have a fairly high degree of aversion to intertemporal fluctuations in education funding, suggesting local districts place some value on intertemporal risk sharing. 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. These preferences for continuity in funding not only speak to intertemporal equity, but suggest that poorly targeted institutions such as the well-known lag in property tax appraisals are consistent with preferences that could be addressed by more explicit policy that aids smoothing.

The parameter ϕ captures substitution of local spending in response to fluctuations in state aid, with the reduced form elasticity in Appendix Table A2 taking a low value of -0.148 . This implies that school spending overall is quite sensitive to state-level transfers as we will show in more detail through simulations below. The low coefficient also illustrates the flypaper effect on transfers from the state government, as an increase in transfers from the state is met by only a small decline in locally raised revenue.

4.1 Steady State Behavioral Implications

This section presents simulations of education resource outcomes based on the estimated preference parameters above. The simulations allow us to understand how much state governments narrow resource disparities, and they allow us to determine the extent of the risk sharing function in the face of income shocks to local districts. Our simulation is constructed for a synthetic state with 200 atomistic 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 of 3.45 and standard deviation of 0.18, which is the average mean and standard deviation of log school district income from state-year cells. The model assumes that the budget is balanced, so that current expenditure equals total revenue, which is the sum of local revenue and state education aid.³¹

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.³² The second target is for transfers from the state to make up 54 percent of the sum of state transfers and local revenue across all districts as in the data.³³

Figure 4 contains the model-implied steady state distributions of the three main variables in the analysis, namely, local revenue per student, state aid per student, and current expenditures per student. Each panel plots an outcome variable against school districts' steady state income. Panel (a) simulates locally raised revenue per student and, unsurprisingly, the relationship between steady state income and local revenue is upward sloping and nearly linear in spite of state education aid. Panel (b) shows how state transfers per student vary

³¹As throughout, we ignore federal aid. See footnote 10

³²This is equivalent to about 2 percent of income being devoted to education as students comprise about 14 percent of the population.

³³The data description is in Table 1. Further, for the purpose of the simulations, calibrating the model to these moments in the data effectively determines the values of χ^S and π in the model discussed in Sections 3.1 and 3.2. In our estimation, these parameters are absorbed by state fixed effects. Our calibration procedure thus ensures that our synthetic state is a composite of all the states in our dataset.

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 transfers to local school districts rise at an increasing rate as local per capita income falls.

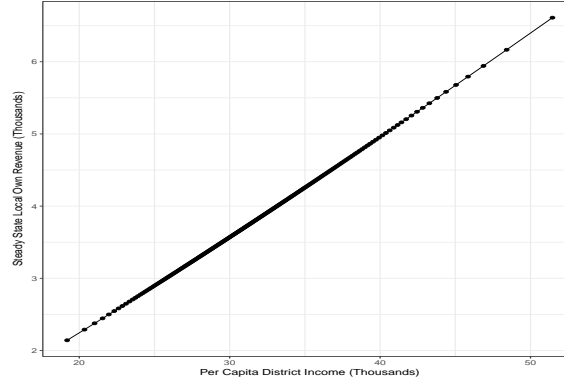
Panel (c) of Figure 4 depicts arguably the most important of the relationships, which is how total current expenditures per student vary with the per capita income of school districts. This panel demonstrates the net sum of the relationships in Panels (a) and (b). The figure shows that the lowest income school districts do not have the lowest level of resources, 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 education resources climb with per capita income for districts with income above the 14th percentile. The results here illustrate the influence of the estimated inequality aversion, as well as the negative weight on local income (the unequal caring).

4.2 Risk Sharing

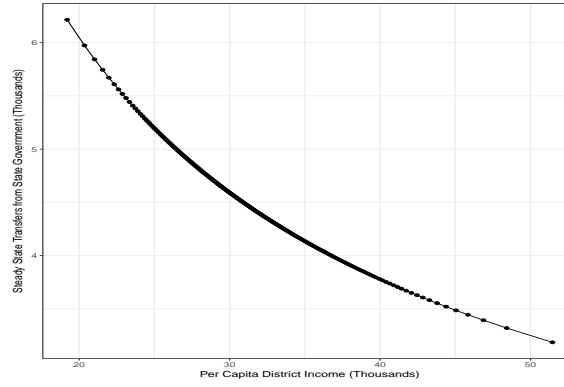
Because state governments seek to correct income disparities, state aid programs serve as risk sharing mechanisms. This section presents an evaluation of the risk sharing mechanisms at both the state and local government level, and for various time horizons. We show that idiosyncratic negative local income shocks to an individual district are met by increased state aid to an extent dependent on the income level of the district. Statewide shocks, on the other hand, are found to be transmitted to all districts and are not effectively buffered by local tax increases. To illustrate the impact of income shocks on the level and distribution of educational resources, we focus on districts with median per capita income that also face the highly persistent AR(1) income dynamics. That is, we assume each school district's logarithm of personal income per capita is drawn from an autocorrelated process with normal errors and an AR coefficient of 0.98 (the value estimated from the data).³⁴ Our model is

³⁴Using the Im, Pesaran, and Shin (2003) panel unit root test, we reject a nonstationary income process at the school district level.

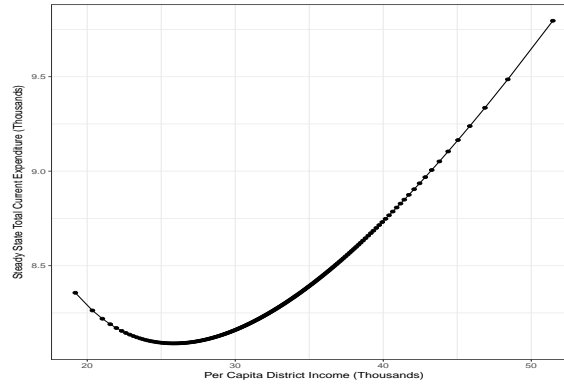
Figure 4: Model-Implied Steady State Distributions



(a) Locally Raised Revenue per Student



(b) State Transfers per Student



(c) Total Current Expenditure per Student

Notes: The figure shows the steady state distribution implied by the theoretical model for locally raised revenue, transfers from the state government, and total current expenditure (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 pooled sample, reported in Table 5.

flexible enough to accommodate a number of other kinds of shocks, and Figures A4 to A12 in the appendix illustrate the model’s predictions for the effects of shocks of varying degrees of persistence and at different levels of aggregation.³⁵

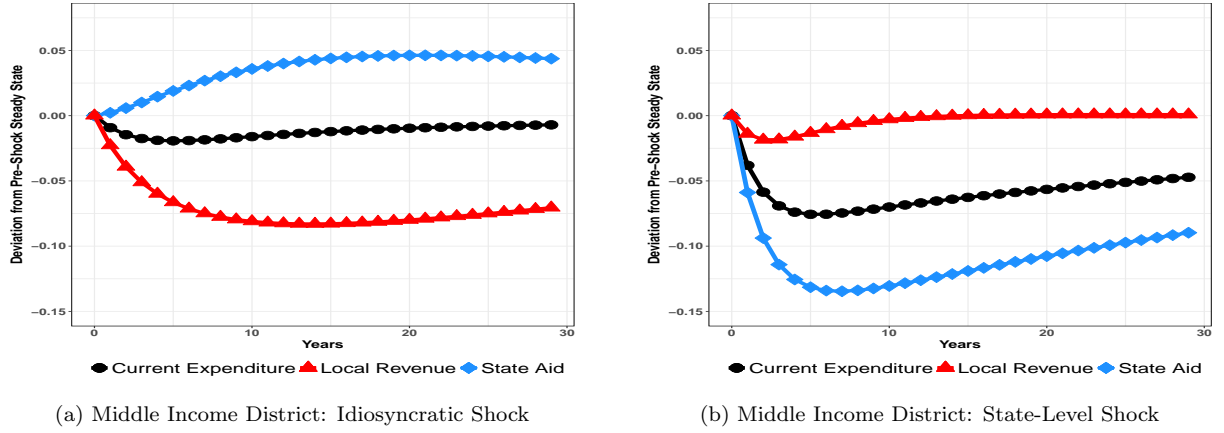
4.2.1 District and State Income Shocks

Panel (a) of Figure 5 depicts the effects of an idiosyncratic shock to a single local district, while Panel (b) illustrates the impact of a statewide income shock. The negative income shock we depict is worth 10 percent of steady state income for a school district at the median of the representative state’s income distribution. For the local idiosyncratic shock, we see from Panel (a) that the school district reduces locally raised revenue. At the trough, local revenue falls by more than 8 percent between 10 and 15 years after the occurrence of the income shock. As local revenue falls, state aid rises because of the state government’s tastes for equalization, captured by the negative value of the parameter ω . At the same time, the high value of η implies that the state is reluctant to change (or constrained from changing) aid values from the level 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, spending returns to its steady state value, aided in part by the relatively slow return of state aid to its pre-shock level. Despite the state government’s desire to correct disparities in resources, students attending school following the negative income shock receive fewer resources than students who are fortunate enough to avoid that time period.

State Buffer of Local Idiosyncratic Shocks. The extent of the risk sharing response with respect to the local idiosyncratic shock depends on the income level of the school district.

³⁵These include shocks to income processes with autoregressive coefficients of 0 or 1 at the district level, state level, and all-but-own district level for low, high, and middle-income districts.

Figure 5: School Finance Variables: Impulse-Response Functions



Notes: The figure shows, in terms of log deviation from the steady state without a shock, the model-implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (all in log per student terms) to a negative income shock of 10 percent of steady state local income. Panel (a) offers model-implied responses conditional on an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and Panel (b) offers model-implied responses in the 50th income percentile conditional on a statewide income shock.

Table 6 summarizes the responses at different time horizons following a 10 percent income shock. The Table illustrates how variation in local incomes cause considerable differences in the resulting outcomes from an economic shock. 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 equal at all points along the income distribution, so we focus on the spending responses. At all horizons following the shock and for all three districts reported, spending 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 resources in steady state than it does for the other richer districts, so a state aid response that is equal in percentage terms is a much larger increase in total resources for the poor district. Similarly, the decline in local revenue, while proportionally the same as in other districts, is comparatively small in terms of dollars. Eight years after the negative income shock worth 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. These results demonstrate that the risk sharing mechanism inherent in the state government having an income-conditioned state aid system is more effective for school districts at the bottom of the income distribution.

Table 6: School District Responses to 10% Income Shock: Model Implied Risk Sharing Across Income Distribution

	Steady State	<i>Current Expenditure</i>			
		Impact	1 year after	3 years after	8 years after
Rich (85th pctlile)	\$8589	−\$98 (−1.1%)	−\$159 (−1.8%)	−\$217 (−2.5%)	−\$228 (−2.7%)
Middle (50th pctlile)	\$8222	−\$76 (−0.9%)	−\$120 (−1.5%)	−\$155 (−1.9%)	−\$139 (−1.7%)
Poor (15th pctlile)	\$8099	−\$57 (−0.7%)	−\$88 (−1.1%)	−\$103 (−1.3%)	−\$62 (−0.8%)
	Steady State	<i>State Aid</i>			
		Impact	1 year after	3 years after	8 years after
Rich (85th pctlile)	\$3925	+\$8 (+0.2%)	+\$23 (+0.6%)	+\$57 (+1.4%)	+\$130 (+3.3%)
Middle (50th pctlile)	\$4454	+\$10 (+0.2%)	+\$26 (+0.6%)	+\$65 (+1.5%)	+\$148 (+3.3%)
Poor (15th pctlile)	\$5054	+\$11 (+0.2%)	+\$30 (+0.6%)	+\$74 (+1.5%)	+\$168 (+3.3%)
	Steady State	<i>Local Revenue</i>			
		Impact	1 year after	3 years after	8 years after
Rich (85th pctlile)	\$4664	−\$107 (−2.3%)	−\$183 (−3.9%)	−\$280 (−6.0%)	−\$371 (−8.0%)
Middle (50th pctlile)	\$3768	−\$86 (−2.3%)	−\$148 (−3.9%)	−\$226 (−6.0%)	−\$300 (−8.0%)
Poor (15th pctlile)	\$3045	−\$69 (−2.3%)	−\$119 (−3.9%)	−\$182 (−6.0%)	−\$242 (−8.0%)

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 AR(1) dynamics with an autoregressive parameter of 0.98.

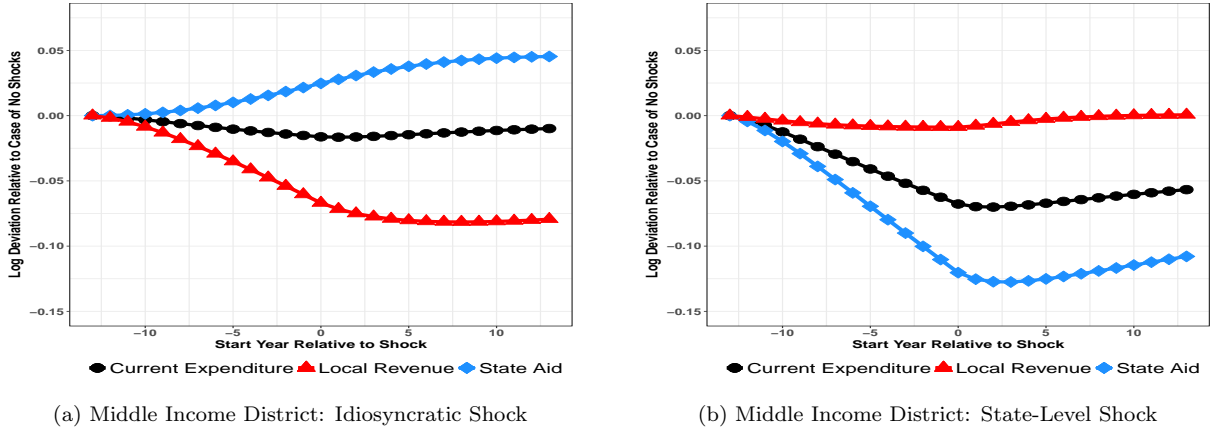
Timing of Risk Sharing Response. Irrespective of a school district’s income, the lag in income insurance causes substantial intertemporal disparities as students exposed to the

shock and its aftermath receive differential resources compared to students who avoid the episode. Figure 6 illustrates this phenomenon assuming 10 percent negative shocks. As in Figure 5, 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 6 measures the number of years after the negative income shock that a given student starts kindergarten.³⁶ 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 fewer resources 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 resources, around 2 percent of total spending 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 which might have offset the local revenue drop.

Local Buffer of State Shocks. One may imagine that, just as state aid buffers a fall in local revenue, local revenue may serve as a self-insurance mechanism in the face of a drop in state aid. This does not generally play out in practice, however, because a statewide income shock, by construction, affects each constituent local district. Panel (b) of Figure 5 shows the effects of an assumed negative 10 percent state-level shock on the median-income school district’s finance variables. State aid falls considerably, by close to 15 percent at the trough, which is about 8 years after the shock occurs. Local revenue also falls in the near term, though by less as the local tax effort increases. Our parameter estimates indicate that school districts are more willing to shift resources to education purposes from private spending than are states, as state governments also value smoothness in expenditures on other programs and in tax revenues. This explains the relatively modest fall in locally raised

³⁶We assume throughout that each student remains in the same school district for the entirety of their primary and secondary education career.

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



Notes: The figure depicts, in terms of log deviation from the steady state without a shock, the total education resources received by 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 conditional on an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and Panel (b) offers model-implied responses in the 50th income percentile conditional on a statewide income shock.

resources relative to the state cuts. Despite the 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 disturbance. 30 years later, spending in the middle-income district has still not recovered fully.

We repeat our cohort analysis for the statewide shock in Panel (b) of Figure 6. This figure demonstrates that a student starting school in the same year that a statewide economic downturn begins is exposed to considerably reduced resources (around 7 percent lower) for their entire tenure in elementary and secondary school, compared with a student not exposed to the state-level shock. Again, this is because of the sharp fall in state aid provided to the district and an insufficient response of local revenue.³⁷ Cohorts starting school long after the state shock occurs have to contend with reduced education resources relative to those not

³⁷Appendix Figure A6 shows the responses if a local district does not experience the state shock occurring in all other districts. In this case, local revenue does rise to partially offset the loss in state aid. Nonetheless, there are substantial resource disparities remaining.

attending school in any year affected by the state-level shock.

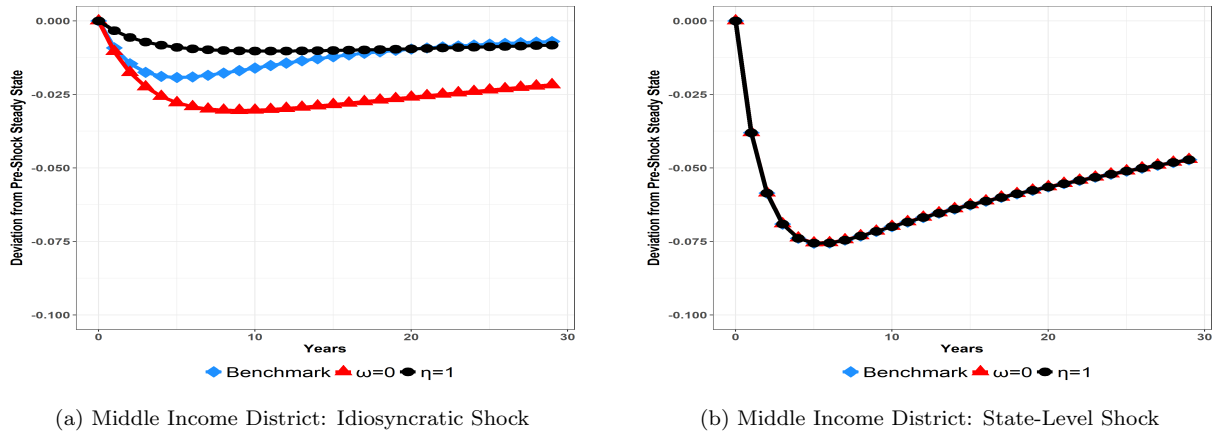
4.2.2 Sensitivity to Equity Parameters

We illustrate the importance of the state government’s risk sharing efforts by running simulations of the model with alternative preference parameters. Specifically, we illustrate two special cases, one by setting the inequality aversion parameter $\eta = 1$, and another by setting the unequal caring parameter $\omega = 0$. Setting $\eta = 1$ implies no inequality aversion on the part of state governments with respect to state aid and, simultaneously, a willingness to shift resources from one school district to another so that there are no delays in response to income shocks. Setting $\omega = 0$ removes the unequal caring motivation which means all districts are treated equally in terms of education aid.

Figure 7 contains the responses of expenditures per student to a 10 percent negative shock to a middle-income district and to the state as a whole. For comparison, the benchmark responses with the actual estimated coefficients are also plotted alongside the counterfactual responses. Following a negative idiosyncratic local shock to a single district, Panel (a) shows spending per student falls a lot further and faster when $\omega = 0$ than when state governments confer disproportionate aid to lower revenue school districts. The lack of state government sensitivity to income means that previously expenditure per student bottoms at around 1.9 percent below the steady state level using the estimated benchmark parameters. In contrast, the simulation shows the fall is closer to 3 percent when there is no income-conditioned aid. What is more, spending remains suppressed for a much longer period of time after the shock. Nearly 30 years later, spending is more than a full percentage point lower relative to the situation governed by the estimated benchmark parameters.

The case where $\eta = 1$ specifies that state governments do not exhibit inequality aversion in the allocation of state aid. In this case, as seen in Panel (a) of Figure 7, the decline in expenditure that results from income shocks is much shallower and less steep, at least initially, than in the benchmark case. This is because in the face of income shocks, state

Figure 7: Total Current Expenditure: Impulse Response Functions for Alternative Parameters



Notes: The figure shows, in terms of deviation from the steady state, the model implied responses of total current expenditure (in log per student terms) to a negative income shock of 10 percent of steady state local income, assuming a number of different model parameterizations. We assume state governments do not exhibit unequal caring across school districts, i.e., we set $\omega = 0$, or adjust allocations immediately in response to shocks and do not have inequality aversion with respect to state aid, i.e., we set $\eta = 1$. The baseline response is included for comparison. Panel (a) offers model-implied responses to an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and Panel (b) offers model-implied responses in the 50th income percentile conditional on a statewide income shock. The three scenarios in this panel overlap because state governments do not respond to the local shock.

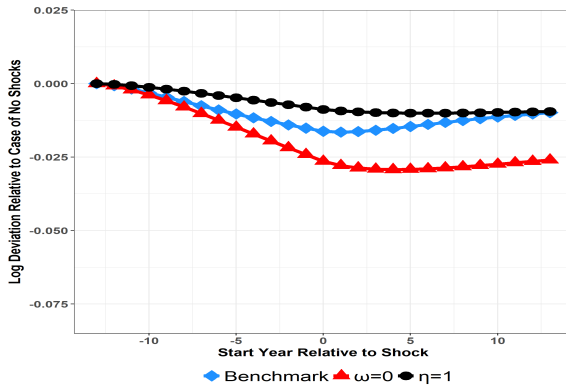
governments are much more willing to shift resources to affected districts and away from districts not experiencing an income shock. As a result, the risk sharing mechanism is more flexible because states choose to respond more rapidly. The relatively rapid response means cohorts starting school amid a local downturn under this regime experience reduced declines in their total resources relative to their unaffected peers, compared with the benchmark scenario. That the responses are similar by twelve years out does not protect against the additional disparities.

In sharp contrast to the idiosyncratic local income shocks, Panel (b) of Figure 7 illustrates that the preference parameters regarding inequality aversion η or unequal caring ω do not significantly influence the risk sharing attributes of state aid in the presence of a state-level shock. Changes in the preference parameters are not found to influence the allocation of education resources among districts or over time. This is because with all districts suffering proportionately from an economic downturn, the state government has little incentive to alter its existing allocations of state aid among the school districts within the state.

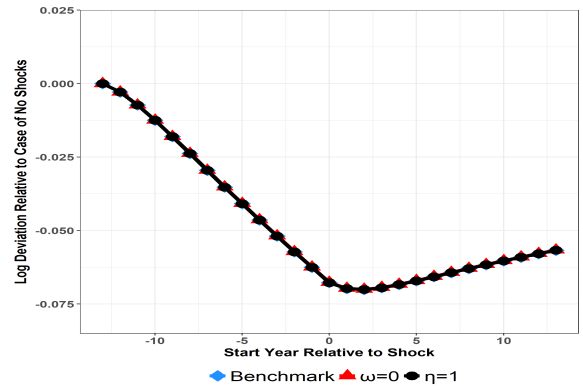
The income shock without preferences for income-conditioned aid has dramatic implications for spending over the course of a student's entire career, as can be observed in Panel (a) of Figure 8. A student starting kindergarten under an $\omega = 0$ regime in the year of an idiosyncratic local income shock must contend with overall resources close to 3 percent lower than a peer who started 13 years earlier. Panel (a) also shows cohorts starting after the shock have even fewer resources than students starting in the year of an income shock. The recovery of total education spending over a student's career is also much slower when $\omega = 0$ than in the benchmark results. Thus, aid programs that result from unequal caring preferences are found to reduce the losses of total career education resources that result from income shocks by more than half.

Panel (b) of Figure 8 reinforces the result illustrated in Figure 7 that the preference parameters regarding inequality aversion η or unequal caring ω do not significantly influence the risk sharing attributes of state aid in the presence of a state-level shock. That is, for a

Figure 8: Model-Implied Evolution of Total Spending over Educational Career by Cohort: Alternative Parameters



(a) Middle Income District: Idiosyncratic Shock



(b) Middle Income District: State-Level Shock

Notes: The figure depicts, in terms of log deviation from the steady state without a shock, the response of total education resources received by a cohort of students over their entire K-12 career to a negative income shock of 10 percent of steady state local income, assuming a number of different model parameterizations. The x-axis measures the timing of the start of the cohort's educational career relative to the timing of the shock. We assume state governments do not exhibit unequal caring across school districts, i.e., we set $\omega = 0$, or adjust allocations immediately in response to shocks and do not have inequality aversion with respect to state aid, i.e. we set $\eta = 1$. The baseline response is included for comparison. Panel (a) offers model-implied responses to an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and Panel (b) offers model-implied responses in the 50th income percentile conditional on a statewide income shock. The three scenarios in this panel overlap because state governments do not respond to the local shock.

middle income district the evolution of state aid and of local resources is highly correlated. Despite that correlation, for example, local revenue shown towards the bottom of Table 6 shows a slower decline than the simulated income drop, suggesting an increase in local tax effort. The simulation results in Panel (b) here, however, indicate these tax increases are small relative to the impact of state-wide economic shock thus illustrating the need for a stronger risk sharing mechanism for state shocks.

5 Conclusion

This paper broadens the traditional view of education inequities by considering the dynamic impact of economic fluctuations. In particular, by relaxing the implicit assumption that inequities are static, we are able to more fully explore the dynamic aspects of education finance systems. We believe the disparities we demonstrate here suggest that explicit policy attention to the problems created by economic cyclicalities merit attention.

Specifically, we believe our paper opens the door to consideration of policies that would assist governments in smoothing consumption over time. Clearly, most balanced budget restrictions actually work against this need (Poterba, 1994). Our work here does not address all of the ramifications, but nonetheless provides a first look at whether governments are interested in, or capable of, accomplishing consumption smoothing by using a risk sharing mechanism. Our research provides evidence about three crucial pieces to any systematic risk sharing mechanism. First, we show that there is a potential need. That is, because of economic cyclicalities, education expenditures fluctuate with changes in revenue, and these fluctuations create disparities in access to resources among children that attend school at different points in the business cycle. Second, we show that income conditioned state aid provides a mechanism by which school districts suffering a negative idiosyncratic local shock can receive partial compensation from state governments. That this compensation varies with average income across school districts, and is not necessarily timely, is a consequence

perhaps of risk sharing not being its original goal.

Third, we find that state governments do not have a parallel mechanism to smooth state government economic fluctuations. That is, resource shocks to the state government are likely to be highly correlated with economic shocks to the local governments. Thus, local districts face a reduced ability to increase local taxes simultaneously with reductions in state aid since both governments face resource reductions. Further, in some states local taxes may be restricted as part of the drive to reduce resource disparities across districts. In any case, we find that fluctuations in state aid to local districts are an important source of disparities over time between cohorts of students. Previous work on unemployment insurance savings accounts (Craig, Hemissi, Mukherjee, and Sørensen, 2016) suggests that with the proper institutional environment, state governments can manage economic fluctuations better on average than individual households. Our conclusion from these findings is that it would be potentially useful to consider a policy that could provide risk sharing for state governments. If that policy could sharpen the response of state aid to local economic shocks, it would be a further gain.

References

- BAICKER, K., AND N. GORDON (2006): “The Effect of State Education Finance Reform on Total Local Resources,” *Journal of Public Economics*, 90(8-9), 1519–1535.
- 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.
- BRADFORD, D. F., AND W. E. OATES (1971a): “The Analysis of Revenue Sharing in a New Approach to Collective Fiscal Decisions,” *The Quarterly Journal of Economics*, 85(3), 416–439.
- (1971b): “Towards a Predictive Theory of Intergovernmental Grants,” *The American Economic Review*, 61(2), 440–448.
- BUETTNER, T., AND D. E. WILDASIN (2006): “The Dynamics of Municipal Fiscal Adjustment,” *Journal of Public Economics*, 90(6-7), 1115–1132.
- 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.
- DOWNES, T. A., AND M. P. SHAH (2006): “The Effect of School Finance Reforms on the Level and Growth of Per-Pupil Expenditures,” *Peabody Journal of Education*, 81(3), 1–38.
- DUPOR, B., AND M. S. MEHKARI (2015): “Schools and Stimulus,” Federal Reserve Bank of St. Louis Working Paper 2015-004A.
- FELDSTEIN, M. S. (1975): “Wealth Neutrality and Local Choice in Public Education,” *The American Economic Review*, 65(1), 75–89.
- 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. (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.
- INMAN, R. P. (1978): “Testing Political Economy’s ‘As If’ Proposition: Is the Median Income Voter Really Decisive?,” *Public Choice*, 33(4), 45–65.
- JACKSON, C. K., R. C. JOHNSON, AND C. PERSICO (2014): “The Effect of School Finance Reforms on the Distribution of Spending, Academic Achievement, and Adult Outcomes,” NBER Working Paper 20118.
- (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.
- 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.
- MURRAY, S. E., W. N. EVANS, AND R. M. SCHWAB (1998): “Education-Finance Reform and the Distribution of Education Resources,” *The American Economic Review*, 88(4), 789–812.

- POTERBA, J. M. (1994): “State Responses to Fiscal Crises: The Effects of Budgetary Institutions and Politics,” *Journal of Political Economy*, 102(4), 799–821.
- SHEPSLE, K. A. (1979): “Institutional Arrangements and Equilibrium in Multidimensional Voting Models,” *American Journal of Political Science*, 23(1), 27–59.
- SILVA, F., AND J. SONSTELIE (1995): “Did *Serrano* Cause a Decline in School Spending?,” *National Tax Journal*, 48(2), 199–215.
- SØRENSEN, B., L. WU, AND O. YOSHA (2001): “Output Fluctuations and Fiscal Policy: U.S. State and Local Governments 1978-1994,” *European Economic Review*, 45(7), 1271–1310.
- TINBERGEN, J. (1952): *On the Theory of Economic Policy*. North-Holland, Amsterdam, the Netherlands.

A Decomposing Cross-Sectional and Time Series Inequality in Public Education Expenditures

To assess what our model might teach us about the sources of cross-sectional inequality, we conduct a stochastic simulation of our model, allowing the school districts in our synthetic state to be buffeted by statewide and idiosyncratic shocks. Specifically, we draw 200 district income levels from a normal distribution with mean and variance found in the pooled data. Then, we allow income in each district to evolve as follows:

$$y_{d,t}^{(k)} = \alpha y_{d,t-1}^{(k)} + (1 - \alpha) \bar{y}_d^{(k)} + \epsilon_t^{(k)} + \epsilon_{d,t}^{(k)} . \quad (4)$$

Here, $y_{d,t}^{(k)}$ denotes income in district d in period t for simulation k , and $\bar{y}_d^{(k)}$ is steady state income for that district. α represents the persistence of the AR(1) income process observed in the data, and we set α to be 0.98, estimated from an AR(1) regression in the data. Then, for each period in the model,³⁸ we solve the simultaneous game and collect the vector of state transfers and local revenue. For each non-discarded period, we calculate the cross-sectional standard deviation and then the average cross-sectional standard deviation across all 23 years. We report the average value of this average standard deviation across all 500 simulations.

We allow our districts to be affected by aggregate, state-level shocks, denoted by $\epsilon_t^{(k)}$, which is drawn from a normal distribution with mean 0 and standard deviation equal to the growth rate of state personal income in the data, namely 2.4 percent. Our districts are also buffeted by idiosyncratic income shocks, denoted here by $\epsilon_{d,t}^{(k)}$, itself a mean zero process with standard deviation of 3.5 percent. This is the standard deviation in the data of $\Delta y_{c,s,t} - \Delta y_{s,t}$, or the idiosyncratic component of local income growth, removing state-level effects.

³⁸Each simulation (k) comprises a simulated 100 periods, but we calculate statistics only over the last 23 periods in each simulation, which matches the number of years in our data. The additional periods for which we run simulations help remove the influence of initial conditions.

For our benchmark model, with the parameters provided by our empirical estimates, the top row of Appendix Table A4 reports the average cross-sectional standard deviation of expenditures in the steady state of the model and in the presence of shocks to income. In the presence of shocks (in the column denoted “Stochastic” in the table), we find an average cross-sectional standard deviation of log expenditures around 0.13, which is quite close to the average within state-year cross-sectional standard deviation of around 0.15 that we observe in the data. Our model predicts that, with the baseline parameterization, the cross-sectional standard deviation of log expenditure per student will be around 0.034 in steady state. This suggests that, in steady state, with no income shocks, the average state is willing to tolerate a modest amount of variation in spending per student, on the order of 3.4 percent. This is about 23 percent of the cross-sectional variation observed in the data.

If 23 percent of the observed variation in expenditure per student is explained by states’ steady state preferences, then that implies that the remainder of the variation is explained by shocks and states’ and districts’ adjustments to them. To assess the relative importance of different aspects of the model for explaining cross-sectional variation, we alter one parameter at a time and compare the resulting average cross-sectional standard deviation to that observed in the benchmark model. We start by shutting down slow adjustment of state aid to local shocks, which is equivalent to setting $\eta = 1$.³⁹ Shutting down slow adjustment of state aid reduces the cross-sectional standard deviation of expenditure per student in the presence of income shocks by about 1 percentage point.

We do not find any effect on the cross-sectional variation in expenditures by shutting down slow adjustment of total state spending, which involves setting $\gamma = 1$. We do, however, find that slow adjustment of local revenue raising to shocks substantially contributes to cross-sectional disparities in expenditures. Setting $\xi = 1$, which removes any influence of lagged local revenue on current local revenue brings the standard deviation of spending down to around 81 percent of that in the benchmark parameterization. This simulation evidence

³⁹Note that, in Equation 3.1, the coefficient on lagged state aid is $\frac{\eta-1}{\eta}$, such that setting $\eta = 1$ is equivalent to setting this coefficient to 0 and making state aid insensitive to aid in the previous period.

might imply then that slow adjustment of local governments to shocks is a more important determinant of cross-sectional variation than slow adjustment of the state government to the same shocks.

We also evaluate the relative importance of states' preferences for allocating more aid to poor districts (captured by the parameter ω) and local districts' willingness to offset increases in state aid by reducing local revenue (captured by the parameter ϕ). Our empirical estimate of ω is -0.593 , so we experiment with setting ω to the extreme values of 0 and -1 . In the former case, state aid allocations are insensitive to local revenue, and in the latter case, state aid moves in an inversely proportional manner with changes in local revenue. In the steady state, we find that either extreme value of ω leads to a much higher cross-sectional standard deviation of expenditures, with a 16.5 to 29.7 percent increase relative to the benchmark parameterization. This is because, when $\omega = 0$, relatively high income school districts spend much more than other school districts and the poorest school districts spend very little. When $\omega = -1$, the U-shape relationship between income and expenditure is much more symmetric than we find in our benchmark parameterization. Away from the steady state, too, variation increases when ω moves to either 0 or -1 . All of this implies that the intermediate level of ω that we find in the data helps considerably to dampen variation in expenditures.

Next, we turn to the local governments' offset parameter, ϕ , which we estimate to be 0.568. As in the case of ω , we assess the model's predictions of cross-sectional variation for more extreme values of $\phi = 0$ or $\phi = 1$. In the former case, local districts do not react at all to changes in state aid, while in the latter case, they react in an inversely proportional manner. When $\phi = 0$, we find a considerable reduction in variation to only 64.5 percent in the steady state relative to the benchmark and about 90 percent of the benchmark when districts are subject to shocks. This implies that districts' tendencies to offset increases in state aid by reducing revenues (or alternatively, the lack of a perfect "flypaper" effect) impedes states' abilities to reduce cross-sectional inequality. Accordingly,

allowing states to offset state aid even more leads to considerable increases in cross-sectional spending inequality, in the steady state and in the presence of shocks.

Finally, we examine which preferences are most important for within-district fluctuations over time. In many cases, the preferences that deliver cross-sectional variation are also those that produce time series variation. Removing slow adjustment in state aid brings the standard deviation down to about 94 percent of the benchmark case, while imposing that local districts respond to shocks immediately reduces variation to about 83.4 percent, relative to our estimated parameters. By moving the ω and ϕ parameters to more extreme values, we can increase the within-district standard deviation.

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 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.

Table A2: Model Estimation Results: Reduced Form

	Point Estimate
	Total State Education Spending
Lagged Total State Education Spending	0.670*** (0.075)
State Income Net of Total Education Spending	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*** (0.030)
State Aid to Districts	-0.148*** (0.020)
District Income Net of Education Spending	0.202*** (0.023)

Notes: The table reports estimates from the equations $\log R_t^S = \mu_s + \zeta_t + a_1 \log R_{t-1}^S + a_2 \log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (state total education spending), $\log R_{d,t}^S = \mu_{s,t} + b_1 \log R_{d,t}^L + b_2 \log R_{d,t-1}^S + \epsilon_{2,d,t}$ (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). All regressions are performed using contemporaneous values and four lags of state and local personal income as instruments. $R_{d,t}^S$ 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 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 A3: Model Estimation Results: Robustness Checks

	Benchmark	OLS	Drop Zero Values	Drop Districts with Zero Values	GMM	ACS School District Income	County Income in ACS Sample
Total State Education Spending							
κ	1.669*** (0.394)	2.251*** (0.644)	1.669*** (0.394)	1.670*** (0.393)	1.669*** (0.394)	-0.479 (1.113)	-0.479 (1.113)
γ	3.029*** (0.692)	5.135*** (0.868)	3.029*** (0.692)	3.036*** (0.697)	3.029*** (0.692)	0.425 (0.940)	0.425 (0.940)
State Aid to Districts							
η	5.480*** (0.338)	5.424*** (0.256)	6.402*** (0.232)	6.446*** (0.237)	5.383*** (0.313)	5.059*** (0.719)	6.127*** (0.852)
ω	-0.593*** (0.014)	-0.424*** (0.017)	-0.590*** (0.014)	-0.591*** (0.014)	-0.596*** (0.014)	-0.742*** (0.023)	-0.621*** (0.024)
Local Revenue							
ξ	3.818*** (0.443)	9.168*** (0.305)	3.822*** (0.437)	3.787*** (0.434)	3.601*** (0.388)	2.891*** (0.516)	2.752*** (0.422)
θ	0.773*** (0.023)	0.547*** (0.038)	0.770*** (0.023)	0.769*** (0.023)	0.725*** (0.021)	0.492** (0.197)	0.961*** (0.162)
ϕ	0.568*** (0.028)	0.695*** (0.039)	0.572*** (0.027)	0.574*** (0.027)	0.628*** (0.024)	0.583** (0.283)	0.336 (0.221)

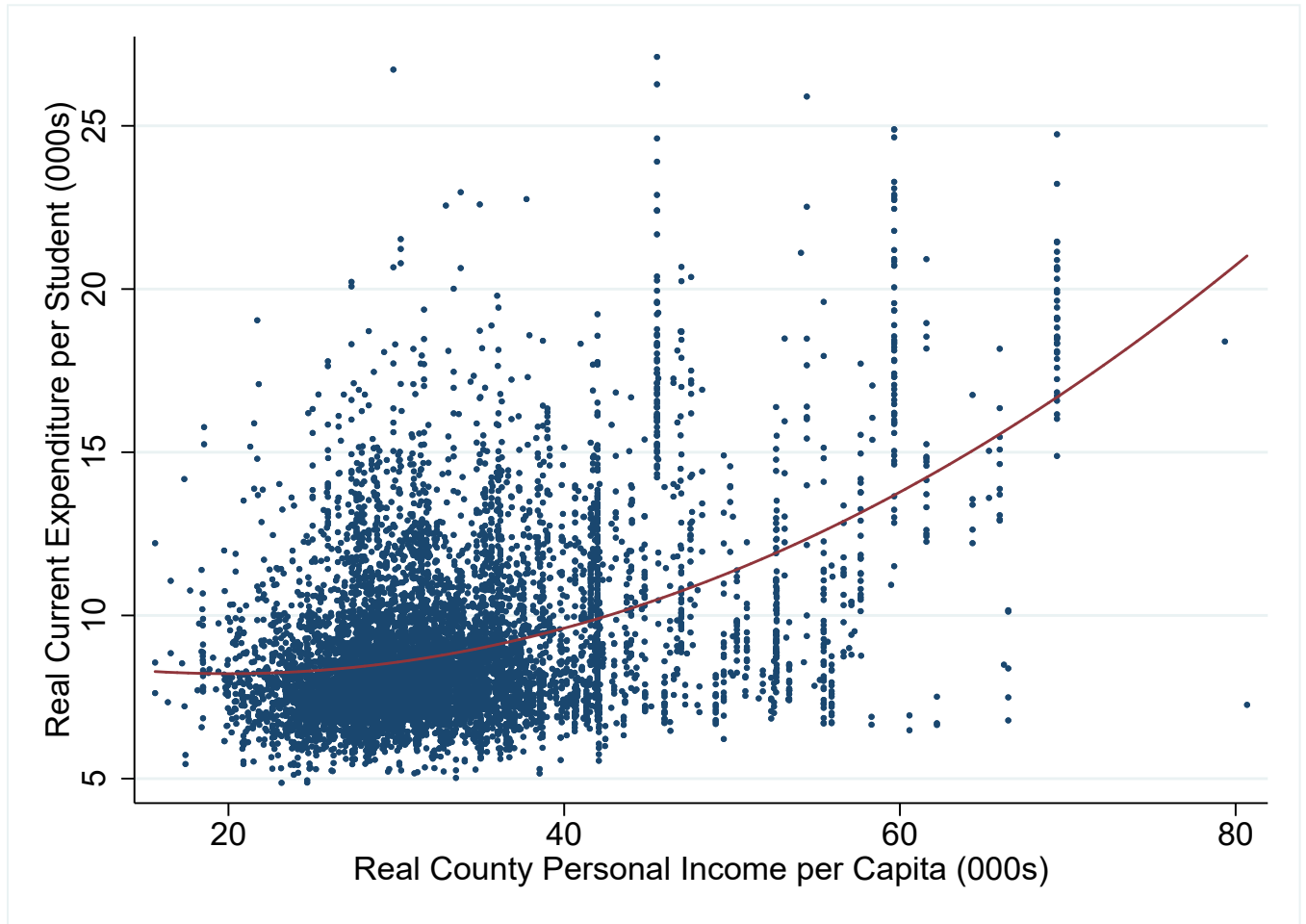
Notes: The table reports the parameters from estimating the equations $\log R_t^S = \mu_s + \zeta_t + \frac{\gamma-1}{\gamma} \log R_{t-1}^S + \frac{\kappa}{\gamma} \log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (total state education spending), $\log R_{d,t}^S = \mu_{s,t} + \frac{\omega}{\eta} \log R_{d,t}^L + \frac{\eta-1}{\eta} \log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), and $\log R_{d,t}^L = \mu_s + \zeta_t + \frac{\xi-1}{\xi} \log R_{d,t-1}^L - \frac{\phi}{\xi} \log R_{d,t}^S + \frac{\theta}{\xi} \log(Y_{d,t}^L - R_{d,t}^L) + \epsilon_{3,d,t}$ (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. The third column reports the results when district-year observations with zero values for local revenue or state transfers are dropped. The fourth column reports estimates when districts with at least one year of zero local revenue or state aid are dropped. The fifth column reports nonlinear GMM estimates. The sixth column reports estimates when the five-year moving average of income aggregated to the school district level in the American Community Survey is used instead of county personal income. The seventh column reports estimates when county 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 for results in the bottom two panels.

Table A4: Model Simulation Results: Variation in Expenditure per Student

Specification	Cross-Sectional Standard Devia- tion	Standard Devia- tion	Standard Deviation over Time
	Steady State	Stochastic	
Benchmark	0.034	0.131	0.124
Relative to Benchmark			
$\eta = 1$ (No Slow Adjustment of State Aid)	1.000	0.922	0.938
$\gamma = 1$ (No Slow Adjustment of Total State Spending)	1.000	0.995	0.989
$\xi = 1$ (No Slow Adjustment of Local Revenue)	1.000	0.806	0.834
$\omega = 0$ (Equal State Aid across Districts)	1.950	1.165	1.012
$\omega = -1$ (Greater State Aid to Poor Districts)	1.776	1.297	1.079
$\phi = 0$ (No Local Offsets of State Aid)	0.645	0.902	1.029
$\phi = 1$ (Greater Local Offsets of State Aid)	1.698	1.187	1.003

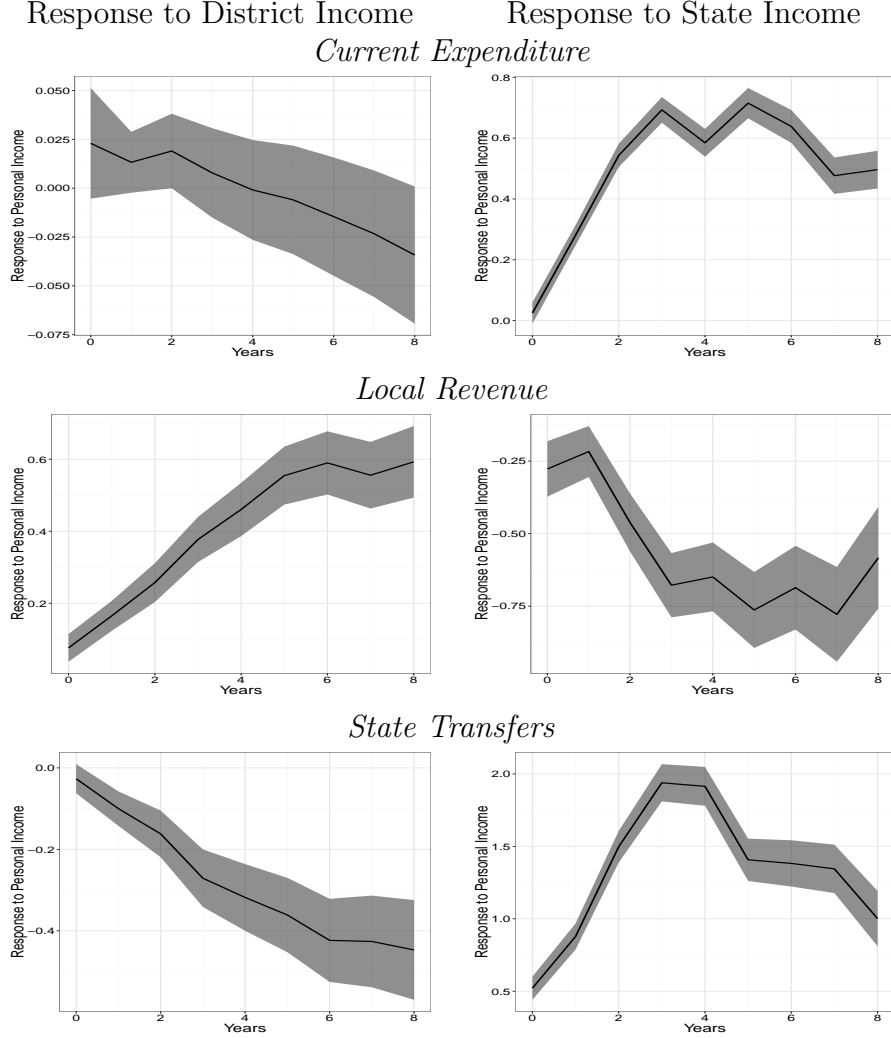
Notes: The table reports the standard deviations of per student expenditure in the steady state and averaged over 500 simulation sequences. For reference, the average cross-sectional standard deviation in 1,035 state-year cells is about 0.15. The average within-district standard deviation across 8,676 school districts is 0.173. The row headed “Benchmark” simulates the model with our benchmark estimated parameterization. The values for each subsequent row report the standard deviations of the steady state cross-sectional standard deviation, the average stochastic cross-sectional standard deviation, or the average standard deviation over time within districts for various permutations of the key parameters, expressed relative to the benchmark values. The row headed $\eta = 1$ refers to a model where the state government responds immediately to local income shocks in making state aid allocations (i.e. there is no slow adjustment of state aid). The row headed $\gamma = 1$ refers to a model in which the state government responds immediately to a state income shock in setting its overall budget for state aid (no slow adjustment in total expenditure on state aid). The row headed $\xi = 1$ refers to a model where the school districts respond immediately to local income fluctuations (no slow adjustment in local own revenue). The row headed $\omega = 0$ refers to a model where the state government’s aid allocations are insensitive to local revenue raised. The row headed $\omega = -1$ refers to a model where the state government reduces aid allocations one-for-one with local revenue raised. The row headed $\phi = 0$ refers to a model where local revenue is insensitive to the amount of state aid received. The row headed $\phi = 1$ refers to a model where local revenue falls one-for-one with state aid received.

Figure A1: Average Spending per Student



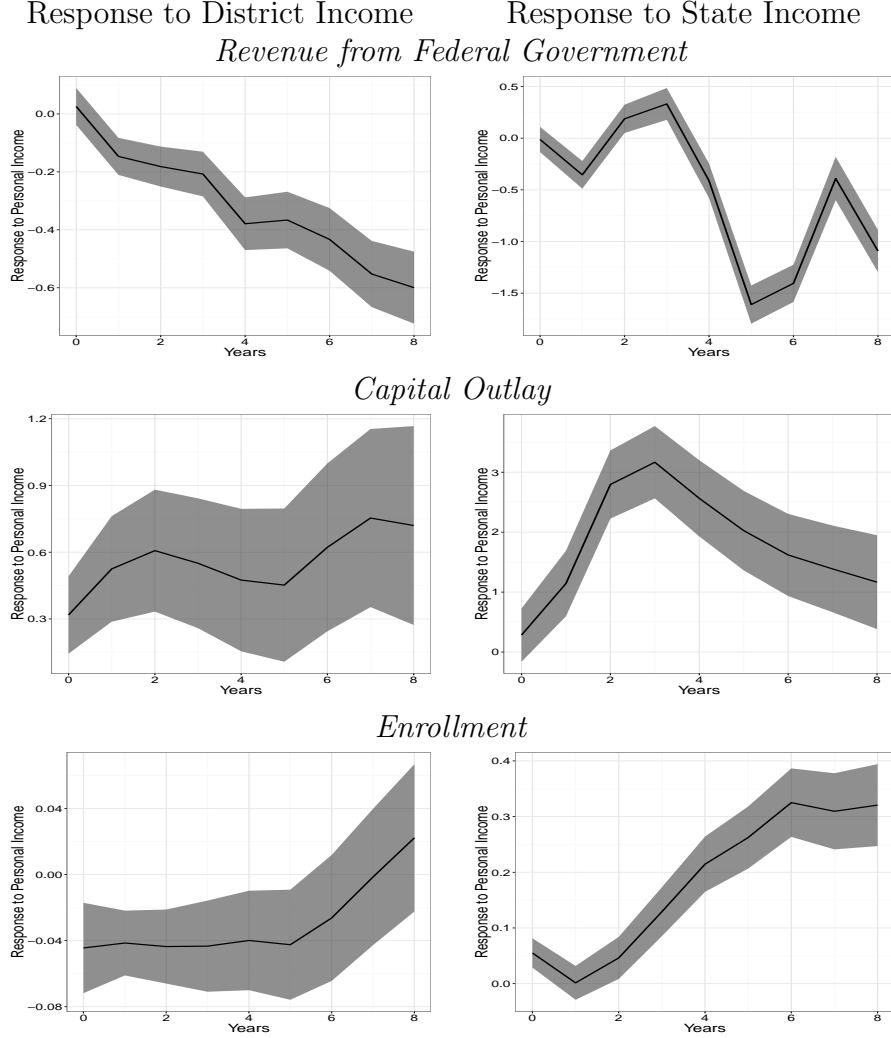
Notes: The figure plots the average of each district's real spending per student over the sample period (1992-2014) against the average of its per capita income over the sample period (1992-2014), along with a fitted quadratic regression line. It excludes outlier districts wherein income per person averaged more than \$100 thousand over the sample or expenditures per student averaged more than \$39 thousand over the sample.

Figure A2: Responses to Income Innovations



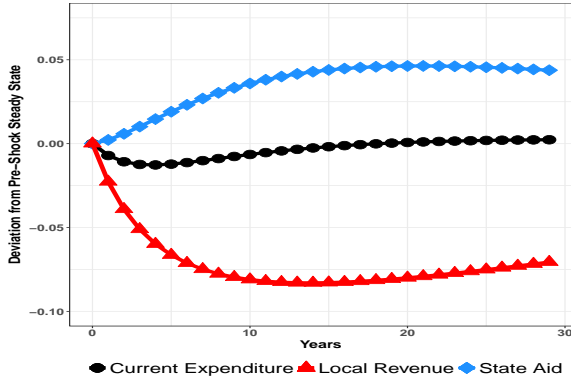
Notes: This figure displays the results from estimating $\Delta Z_{d,s,t} = \mu + \sum_{p=0}^8 \alpha_p^L \Delta Y_{d,s,t-p} + \sum_{p=0}^8 \alpha_p^S \Delta Y_{s,t-p} + \sum_{p=0}^8 \gamma_{1,p} \Delta pop_{d,s,t-p} + \sum_{p=0}^8 \gamma_{2,p} \Delta pop_{s,t-p} + \delta_t + \varepsilon_{d,s,t}$, where 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 growth 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.

Figure A3: Responses to Income Innovations

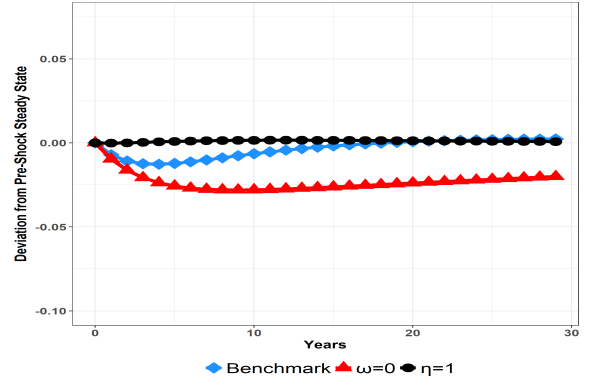


Notes: This figure displays the results from estimating $\Delta Z_{d,s,t} = \mu + \sum_{p=0}^8 \alpha_p^L \Delta Y_{d,s,t-p} + \sum_{p=0}^8 \alpha_p^S \Delta Y_{s,t-p} + \sum_{p=0}^8 \gamma_{1,p} \Delta pop_{d,s,t-p} + \sum_{p=0}^8 \gamma_{2,p} \Delta pop_{s,t-p} + \delta_t + \varepsilon_{d,s,t}$, where 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 growth 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.

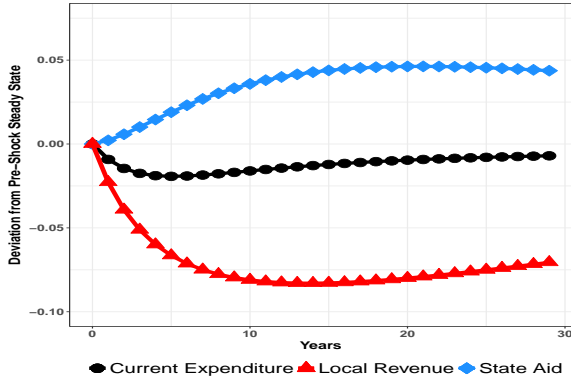
Figure A4: Model-Implied Responses to a Local Income Shock in a Single District



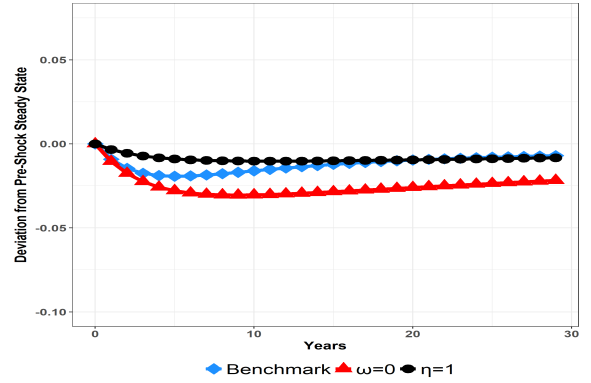
(a) Poor District: Benchmark Parameters



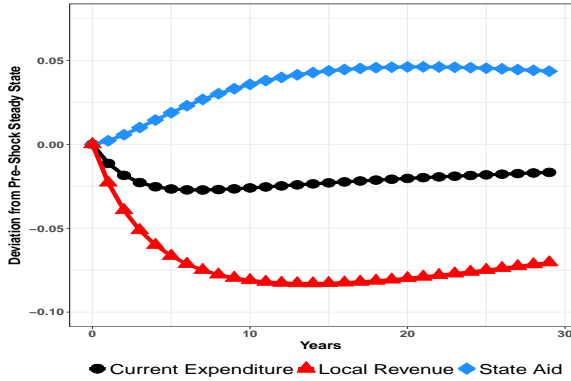
(b) Poor District: Alternative Parameters



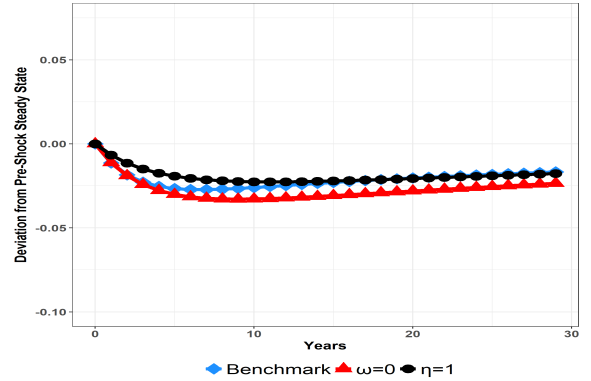
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



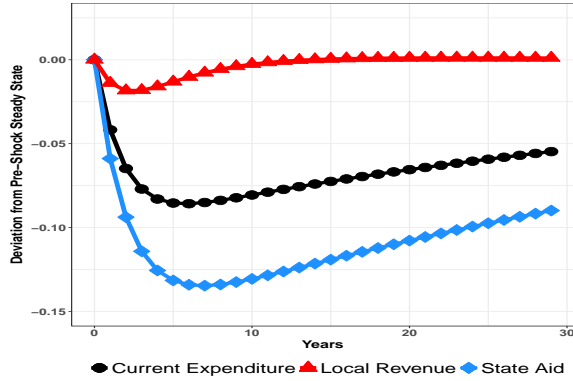
(e) Rich District: Benchmark Parameters



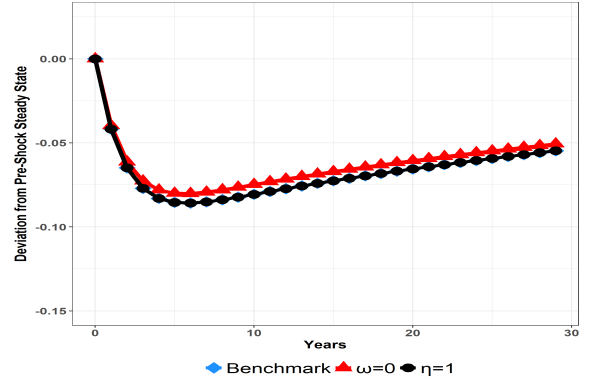
(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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 0.98. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.

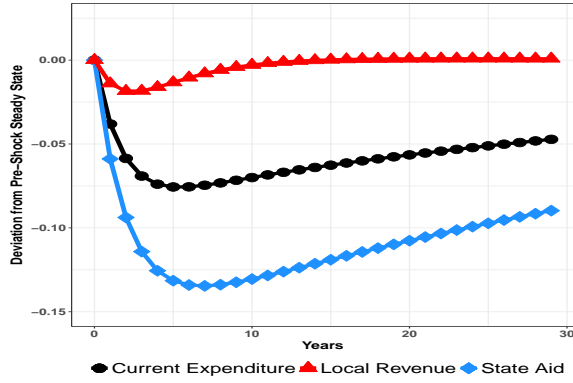
Figure A5: Model-Implied Responses to an Income Shock in All Districts



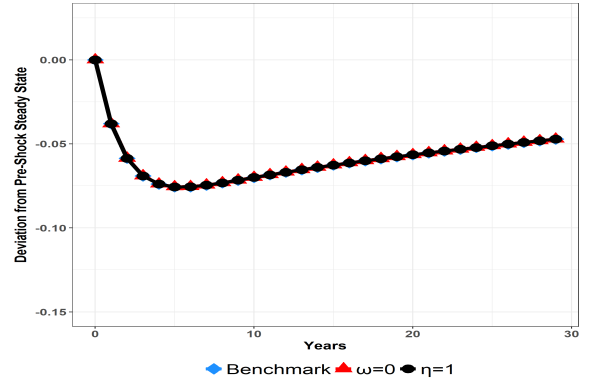
(a) Poor District: Benchmark Parameters



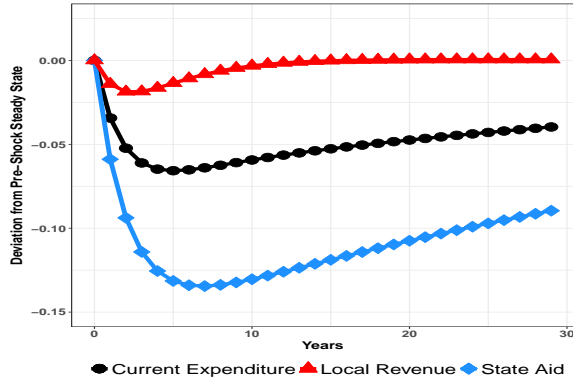
(b) Poor District: Alternative Parameters



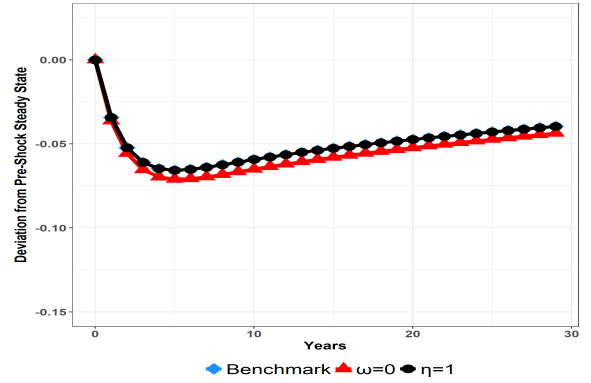
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



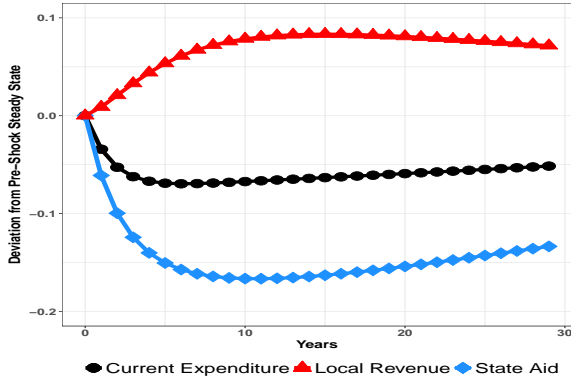
(e) Rich District: Benchmark Parameters



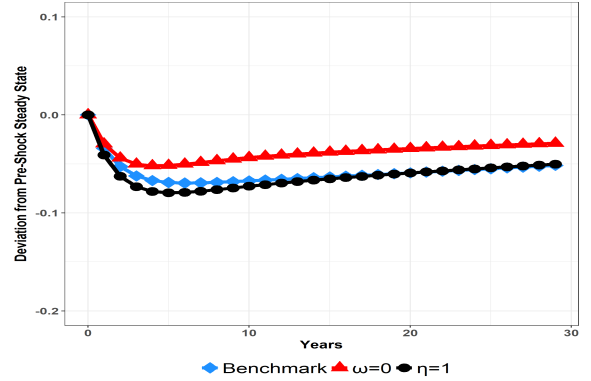
(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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 0.98. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.

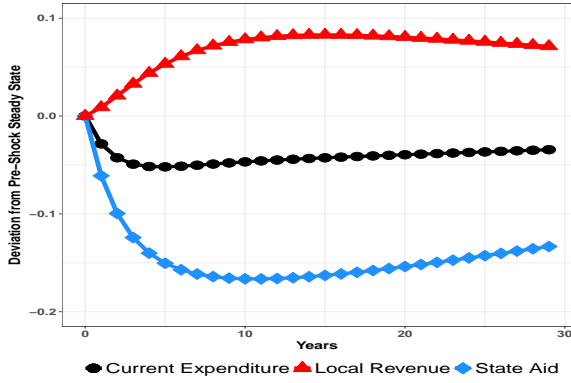
Figure A6: Model-Implied Responses to Income Shocks in All Other Districts



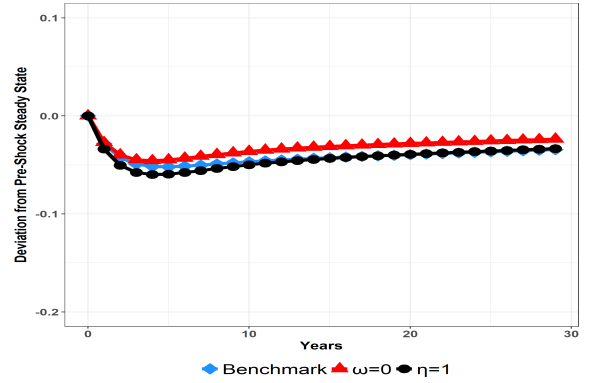
(a) Poor District: Benchmark Parameters



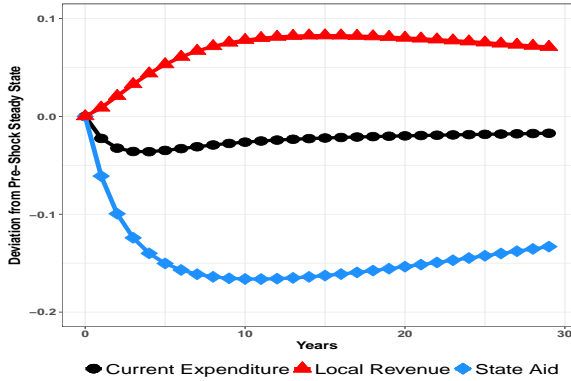
(b) Poor District: Alternative Parameters



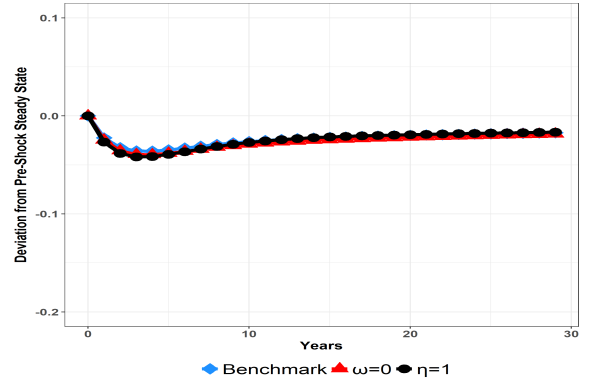
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



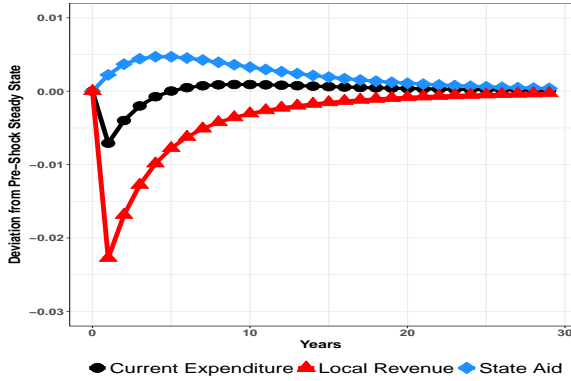
(e) Rich District: Benchmark Parameters



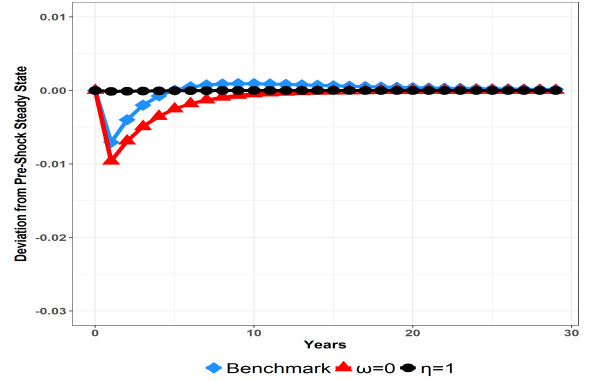
(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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, except for the one depicted, assuming an AR parameter for income of 0.98. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.

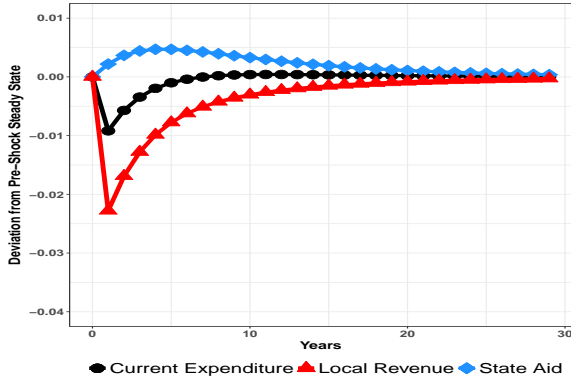
Figure A7: Model-Implied Responses to a Local Income Shock in a Single District



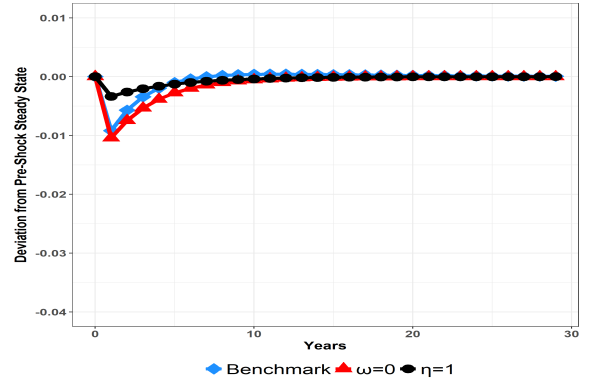
(a) Poor District: Benchmark Parameters



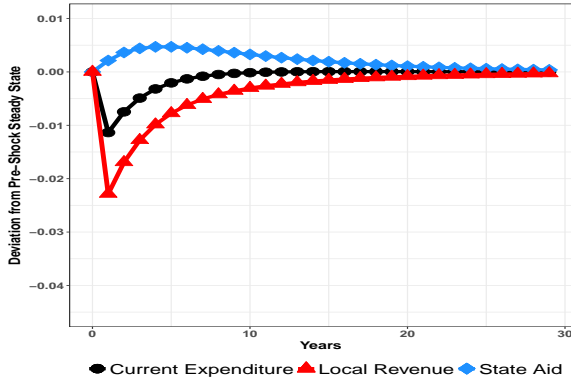
(b) Poor District: Alternative Parameters



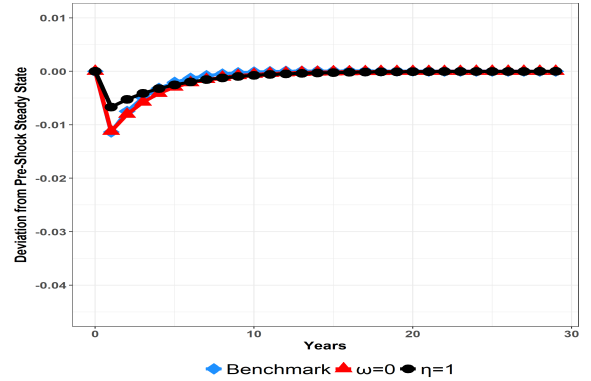
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



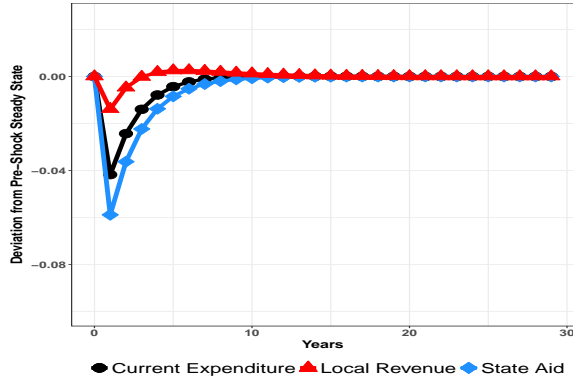
(e) Rich District: Benchmark Parameters



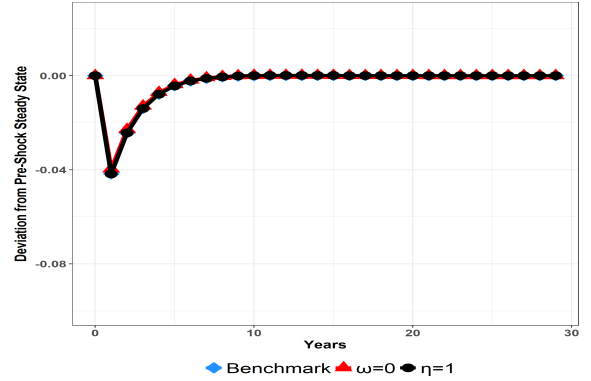
(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.

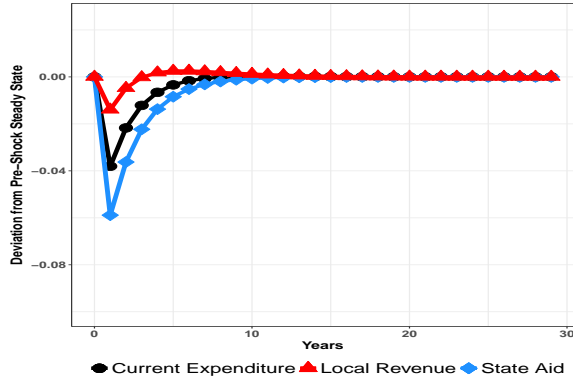
Figure A8: Model-Implied Responses to an Income Shock in All Districts



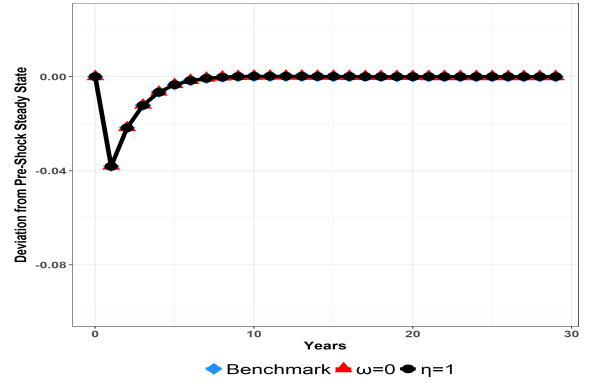
(a) Poor District: Benchmark Parameters



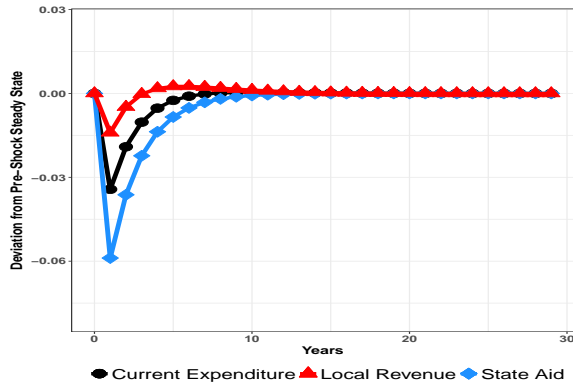
(b) Poor District: Alternative Parameters



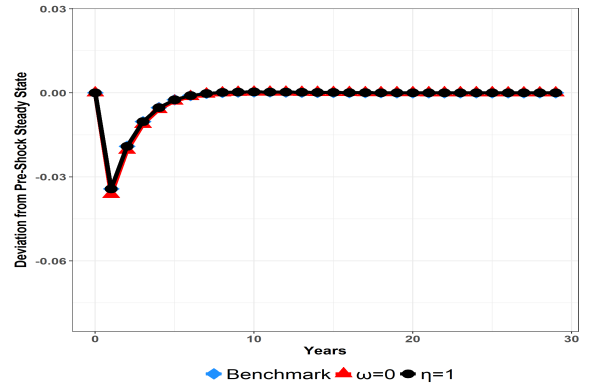
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



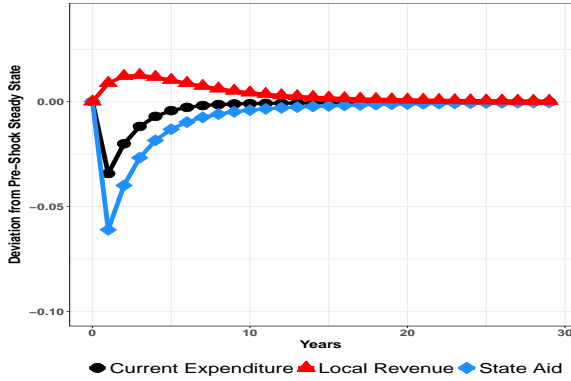
(e) Rich District: Benchmark Parameters



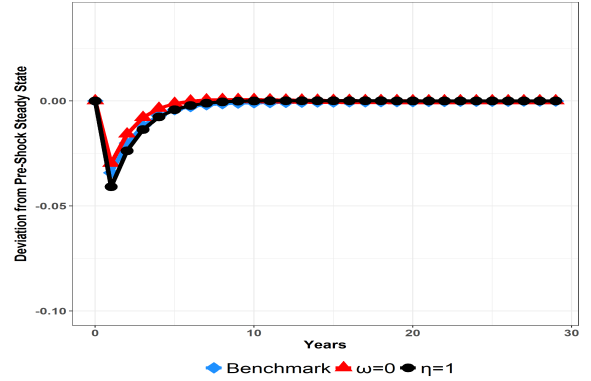
(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.

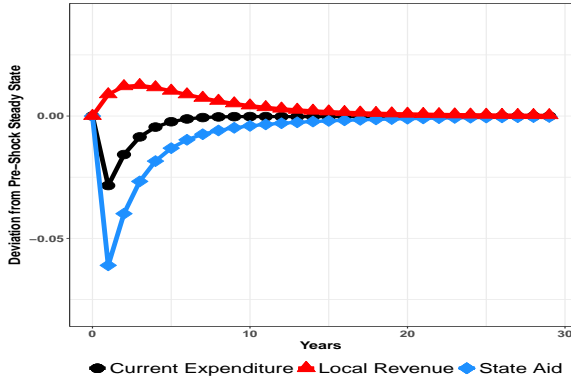
Figure A9: Model-Implied Responses to Income Shocks in All Other Districts



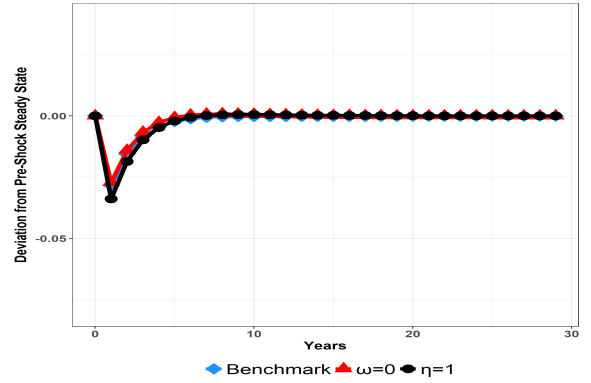
(a) Poor District: Benchmark Parameters



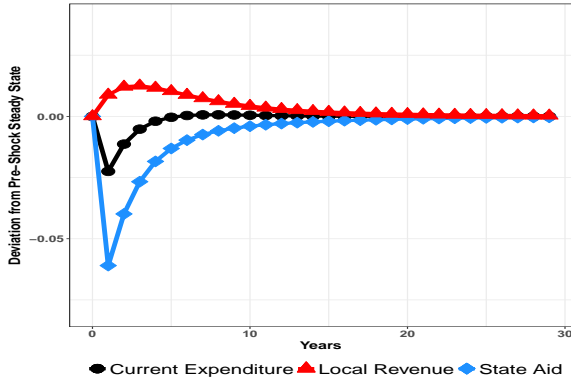
(b) Poor District: Alternative Parameters



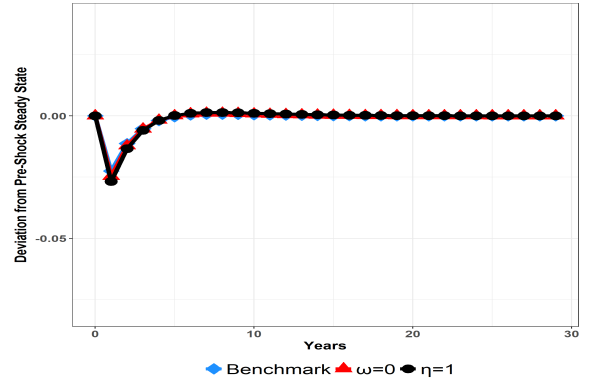
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



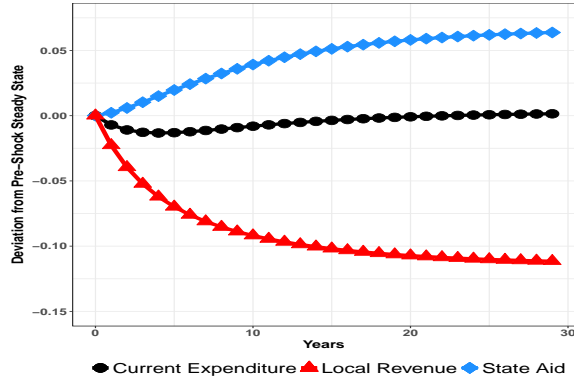
(e) Rich District: Benchmark Parameters



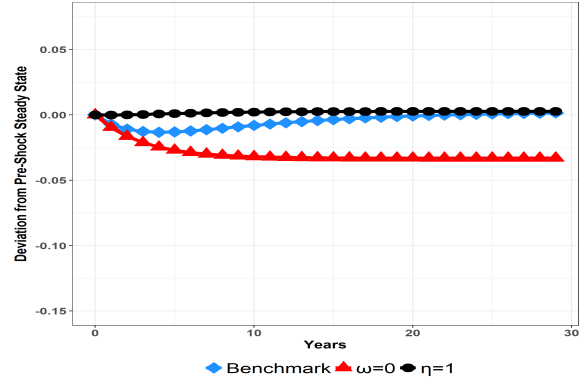
(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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, except for the one depicted, assuming an AR parameter for income of 0. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.

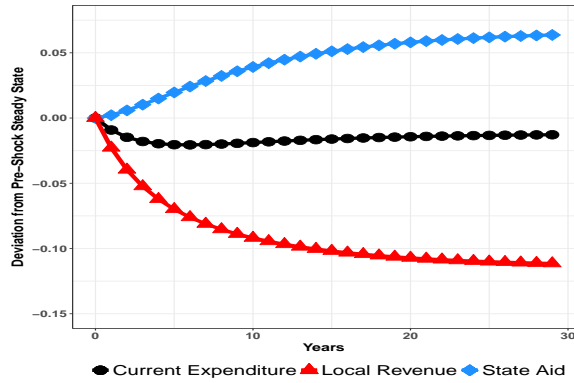
Figure A10: Model-Implied Responses to a Local Income Shock in a Single District



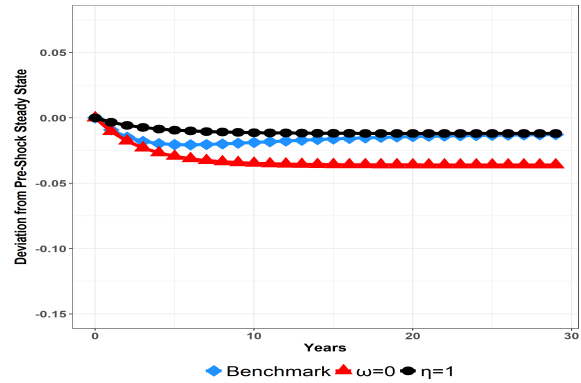
(a) Poor District: Benchmark Parameters



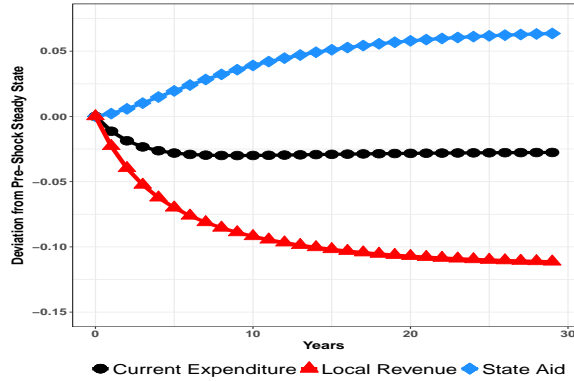
(b) Poor District: Alternative Parameters



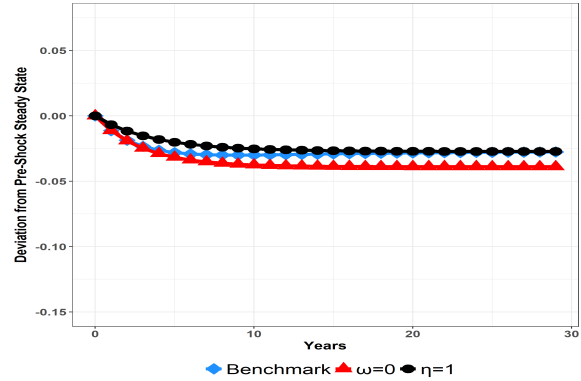
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



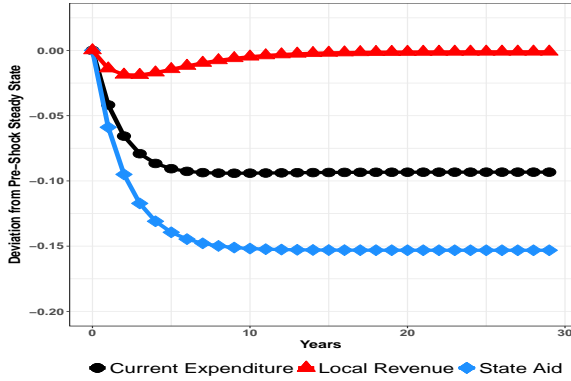
(e) Rich District: Benchmark Parameters



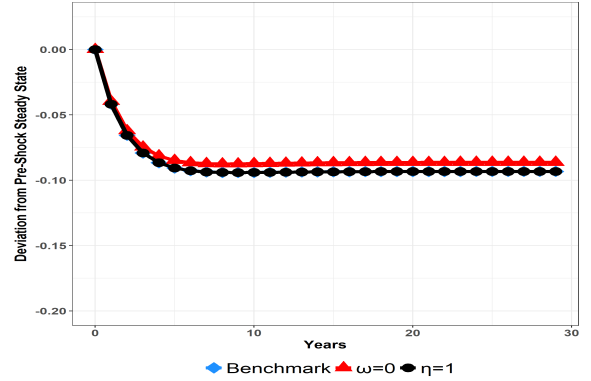
(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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 1. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.

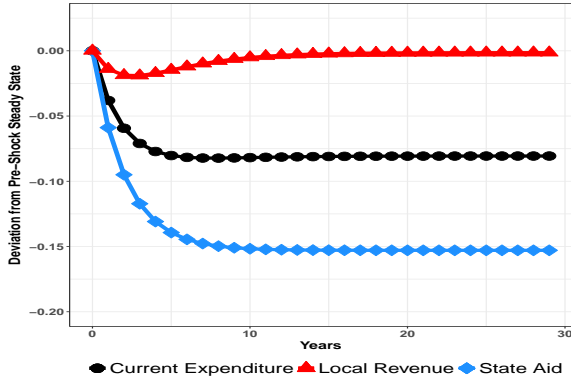
Figure A11: Model-Implied Responses to an Income Shock in All Districts



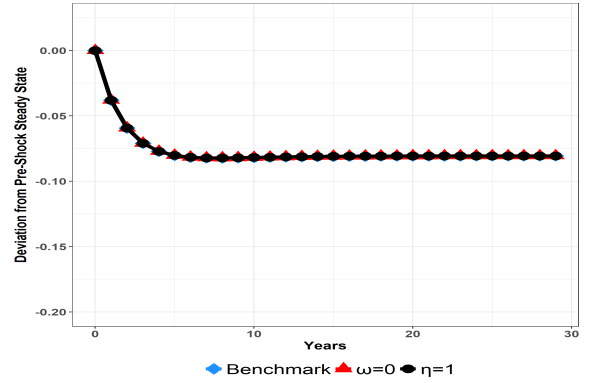
(a) Poor District: Benchmark Parameters



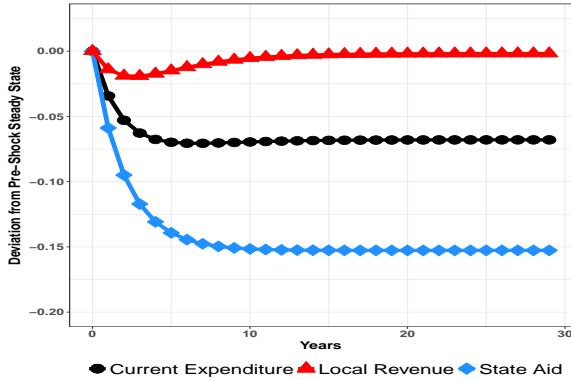
(b) Poor District: Alternative Parameters



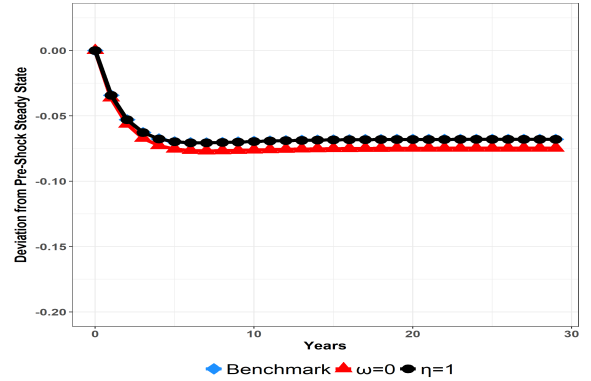
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



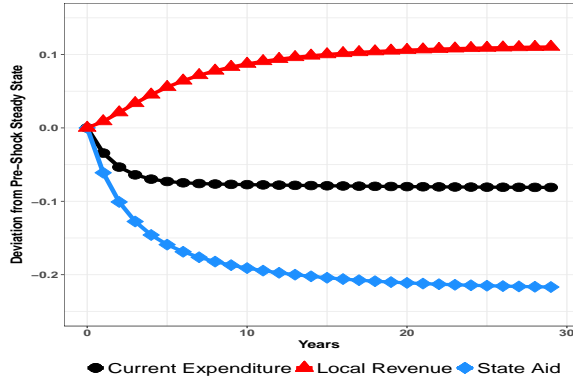
(e) Rich District: Benchmark Parameters



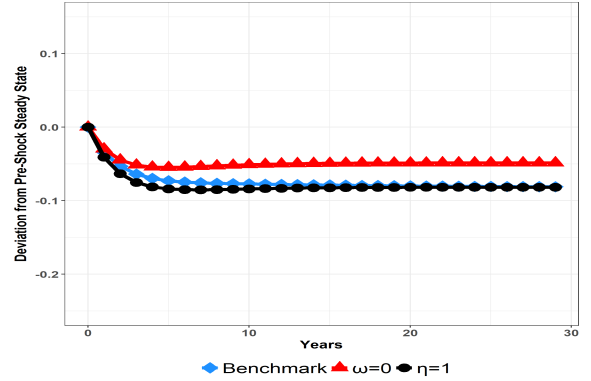
(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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 1. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.

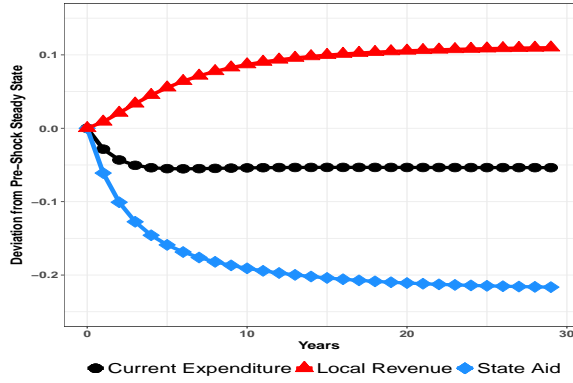
Figure A12: Model-Implied Responses to Income Shocks in All Other Districts



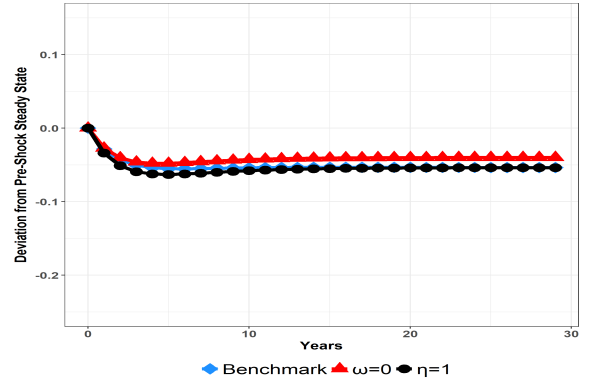
(a) Poor District: Benchmark Parameters



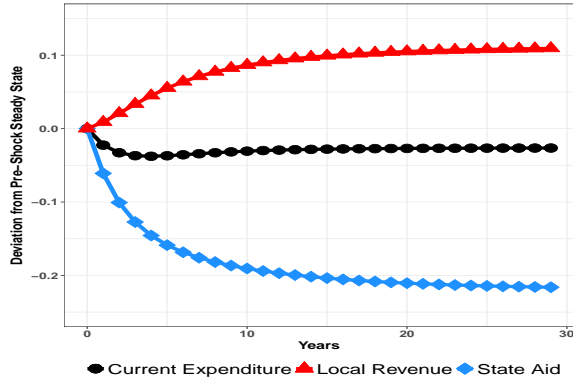
(b) Poor District: Alternative Parameters



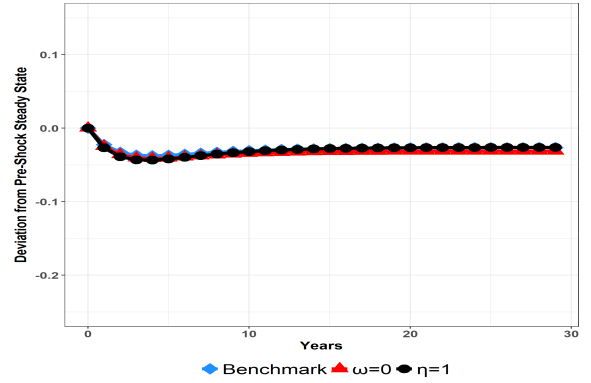
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



(e) Rich District: Benchmark Parameters



(f) Rich District: Alternative Parameters

Notes: The figure shows the model implied responses of locally-raised revenue, transfers from the state government, and total current expenditure (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, except for the one depicted, assuming an AR parameter for income of 1. The left-hand column offers model-implied responses based on the estimated parameters (benchmark parameters), whereas the right-hand column provides model-implied responses (of expenditures only) assuming state governments do not care about equalizing spending across districts, i.e., setting $\omega = 0$, or adjust allocations immediately in response to shocks, i.e., setting $\eta = 1$.