Inequality in Public School Expenditures across Space and Time

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Abstract

We study spending per student across U.S. school districts and between cohorts within districts with a particular focus on state aid. Spending per student varies over time with local- and state-level income; however, state governments provide almost perfect insurance (risk sharing) against local income shocks, while per student spending is highly sensitive to shocks to state-level income. As a result, school spending varies across students within the same school district. State aid reacts only slowly to local income shocks, reducing the extent of risk sharing provided.

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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 now provide a form of risk sharing/income insurance for their local school districts. That is, a local school district that 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 the system of state education financing responds to fluctuations in income which allows us to also focus on disparities in resources over time, an issue that has not been previously addressed in the education finance literature.

The academic literature, starting with 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] Indeed, some studies are explicitly concerned with how mandates to address inequities impact the level of resources; 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 all this literature, however, is that it implicitly assumes that school district income is unchanging. Our direction is to examine the level of educational resources over time available to cohorts of students, assuming those students remain in the same school district over their entire K-12 experience. We summarize the

[1]The focus on school districts rather than individual income of students may be a consequence of the original *Serrano v. Priest* decision, a distinction that is important in a different context than the one we pursue here.

interaction between state governments and school districts using objective functions where both levels of government have preferences for school spending and for other (unspecified) uses of funds, while state governments also have preferences for equalization across districts.

Local school financing depends about equally on local resources raised by individual school districts and aid from the state government, so fluctuations in either the level of local resources or the level of state resources are important for resource disparities over time. An idiosyncratic shock may occur to an individual school district, such as the closing of a factory, and affect the tax base and funds raised locally. Conversely, a state-wide shock is likely to impact the resources available for education as most states impose balanced-budget rules, which limit the scope for expenditure smoothing. In either case, access to educational resources for individual students will be impacted, resulting in disparities of opportunity in access to resources over time. As state aid has become more sensitive to local resources, risk sharing across local districts in a state has become more substantial, with idiosyncratic local income shocks being compensated by changes in state aid. However, state aid only materialize with a time-lag, with the results that local income fluctuations are an important source of disparities in school spending. We find that the variance of K-12 resources over time by cohort is about 1/3 that of the between-school district variance at any one time, a not inconsequential amount. and that over 3000 (3.7%) of cohorts in our data receive less resources than a prior cohort, in spite of income growing over time on average.

We model school spending by state- and local governments with utility functions for school spending versus other spending and a desire for equality in school spending (state governments only), and a desire for slow adjustment of spending. We consider the objective function as an "as if" preference function, following Inman (1978), rather than a "deep" preference function for spending.[2] Further, we formulate the objective function in terms of

[2]A "deep" preference function for school spending would, at the practical level, be highly non-linear and hard to estimate, because of the interactions between local and state government decision makers and because local school district behavior is constrained by a myriad set of rules handed down by state governments. Particularly, slow adjustment is likely due to financing constraints that are complicated to model empirically. Formalizing such details is therefore beyond the scope of this paper.

county-level income. Traditionally, K-12 education in the United States has been provided by local governments financed through property taxes; however, it would be a daunting task to get a comprehensive sample of property values and the details of taxation are not part of our study which focuses on how school spending typically co-varies with income and not on the exact mechanism of taxation.

The state-local objective functions are intertwined and we can not solve for the response to state or local income shocks in closed form. Wee simulate the responses in order to illustrate three important dimensions of state education aid programs. First, our depiction of the distribution of average (steady-state in the model) per student expenditure as a function of income finds that state aid succeeds in equalizing school district per student expenditures, in particular, for the bottom quartile of the income distribution of school districts. Second, our simulations characterize how much risk sharing states provide to school districts; i.e., how much changes in state aid make up for local revenue shortfalls (or windfalls) caused by income shocks in the short- and long run. Specifically, we find that individual school district idiosyncratic income shocks are largely buffered by increases in state aid in the long run; however, it takes several years following a local income shock before state governments make up for the short-fall. Because of the income-conditioned features of state aid, we also find the amount of risk sharing varies inversely with the per capita income of districts. Third, school districts do not, in general, cushion reductions in state aid that result from state-level income shocks, although this varies with per capita income in that rich districts are able to use local property taxes to reduce the variation in expenditure induced by state aid shocks to a greater extent than middle- or low-income districts. Further, because lower income districts are more reliant on state aid, fluctuations in state aid are relatively more important the lower is school district income. Local governments on average offset a \$1 per student increase in state aid by about \$0.15 in the first year, and by about \$0.57 in steady state.[3]

Within-district inter-temporal disparities between cohorts are non-negligible with an av-

[3]We do not have the data to study how local districts allocate funds between schools.

erage cross-cohort standard deviation of expenditure per student about 28 percent as large as the analogous cross- district standard deviation. Our specification of the state government objective function is designed to estimate the state government response to disparities in education resources over time as well as cross-sectionally. Thus, the quality 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. We begin by discussing the data used in the empirical analysis in Section 2. We illustrate the differences in expenditure per student by district, and also demonstrate differences in expenditure by student cohort. We follow that by introducing and developing our theoretical 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.

2 Data

School districts in the United States are primarily organized in two different ways. Generally, school districts are independent local special purpose governments, which provide local schooling for (pre) K-12. These independent school districts have elected boards, which are exclusively responsible for handling policies such as setting property tax rates and issuing debt.[4] The other organizational form is as part of a general purpose government, in which case the budget, electoral authority, and all other actions are conflated with that general purpose government (Fischel, 2009). For our purposes, we will focus on school districts

[4]We use the indicator for independence that is encoded in the district identification variable for each school district by the Census Bureau.

that are independent to allow us to model state preferences exclusively for educational resources. Thus, we use school district finance data on enrollment, revenue in total and broken down by source, 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.

Using only independent school districts leads us to exclude all school districts from Alaska, Hawaii, Maryland, Virginia, North Carolina, and the District of Columbia. We also delete small school districts containing less than 100 students. There are 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. We drop these so as to avoid possible discontinuities in the district's income process. 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 annual frequency over 23 years in 45 states, resulting in a total of 199,548 district-year observations.[5]

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 as school breakfast and lunch, as well as some other specialized education programs. The table also demonstrates the significance of balanced budget constraints for local school districts. On average, school districts do not spend more than they raise in revenue, a feature that we will exploit in our theoretical model where we equate spending with revenue. Table 2, in addition, reports the sources of fluctuations on average in school districts' total revenue. While the quantitative significance of state aid enables the state to provide a risk

[5]Appendix 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.

sharing function for local districts that experience an idiosyncratic income shock, we also find that state aid is itself a substantial source of resource variation, contributing to disparities between student cohorts considerably; in fact, the variance decomposition shows state aid is virtually as important as that of local revenue.

Table 1 also provides statistics on personal income at the county and state levels. We assign each school district the per capita personal income of the county in which it is predominantly located, although we refer to this as "district level income," when convenient.[6]

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 per student as a function of time-averaged district per capita income using all of the 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 shows 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 reflect differences in implied preferences as well.

Further, there is evidence that the resource constraints faced by school districts are not static. Table 3 shows the transition matrix for average per capita income in the districts, and it makes clear that school districts can experience substantial changes in their position in the state-specific income distribution. The transition matrix between income quintiles is perhaps surprisingly rich, especially for the middle three quintiles of school districts. Of districts in the middle income quintile at the beginning of our data in 1992, 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.

[6] We use county-level personal income from the Bureau of Economic Analysis, which is available for a much longer period of time than personal income aggregated to the school district level, which can be obtained from the Census Bureau's American Community Survey (ACS), and is available only going back to 2009 for the 5-year moving average data. When a district crosses county lines, we use the county assigned by the Census based on the Federal Information Processing Standards (FIPS) codes.

A key contribution of our paper is to illustrate a problem that has been relatively neglected in the literature to this point; namely, that there is substantial variation in the level of education resources for students that remain in the same school district for their entire K-12 education. To examine this question, we sum the level of real resources available to a student, assuming that student remains in the same school district for 13 years and receives the average level of spending for all 13 years. We only perform this calculation for students that begin school in the years between 1992 and 2002, for whom we have information on a full 13-year primary and secondary education career. The cohort analysis is summarized in Table 4, which reports that the average spending per student is about $118K in real 2009 dollars. The standard deviation across districts is about a third of that level, but even within a single district students are exposed to considerable variation. Students in 3.3 percent of the cohorts are found to receive fewer resources than students in the previous cohort. Students in over a quarter of the cohorts are educated in an environment in which the income elasticity of per-student education spending is less than one.

While Table 4 presents an aggregate picture of overall resources available to each student cohort, Figure 2 reveals that there is quite rich heterogeneity according to a school district's income level. Each panel of Figure 2 is broken down by a school district's position in the national income distribution in 1992, the first year of our sample. Panel (a) demonstrates that average real education expenditures rise monotonically by quintile, with those school districts in the counties with higher levels of income spending more per student than those in less well-off areas. Further, as demonstrated by Panel (b), there is wider variation across cohorts over time in the richest school districts, and the cross-cohort variation is smallest in the poorest school districts. In our model, these facts can be explained by a risk sharing mechanism that varies with income in terms of how well it insures districts against idiosyncratic shocks.

Panel (c) shows that the highest-income quintile has much higher variation across districts than other quintiles, consistent with the idea that there are some school districts at the top end with extremely high spending-per-student figures. Panel (d) reports the share of cohort observations in each quintile, in which total spending over a student's educational career was lower than a student in the same district starting one year earlier. Interestingly, there is a U-shape in this measure relative to income. Middle-income students are the least likely to be exposed to reduced resources relative to their older peers, while the poorest students are the most likely. Panel (e) reports the same measure, only now comparing a student's total resources to those of a child starting school five years before her. Still, the middle-income students are least likely to be receiving less, but now, the richest students are most likely to be exposed to fewer resources than those who came before them.

Panel (e) illustrates the proportion of cohorts for whom spending on their education grew more slowly than overall income in their local area over the course of their educational career (so, the proportion of cohorts for whom the income elasticity of education spending was less than one). Again, middle income districts are the least likely to experience slower education spending growth than income growth, with only 28% of fourth-quintile students and 30% in that category, relative to 36% of the poorest students. When comparing cohorts to their peers entering school five years earlier, the pattern is similar, with only 22% of fourth-quintile students and 24% of middle-income students having a less-than-one income elasticity, compared with 31% of the poorest students.

Figure 3 depicts the time pattern of the share of students receiving less spending than previous cohorts (Panels (a) and (b)) or slower spending growth relative to income growth, again broken down by income quintile (Panels (c) and (d)). Cohorts starting school in the richest school districts in the 1990s were the most likely to be exposed to either reduced resources relative to those starting in earlier years or to spending growth that failed to track income growth. This pattern, however, does not completely continue into the early 2000s, however, as it is the richest students who are generally among the least likely to receive reduced expenditures relative to their peers or relative to income. Students starting school in the 2000s in the lowest-income districts are the most likely to experience such reductions. Students starting school in the 2000s in all income quintiles are generally more likely to experience reduced expenditures, as they were still in school at the time of the Great Recession, with its squeezes on state and local government finances.

Figure **??** shows spending growth for student cohorts over time in 5 school districts with relatively slow growth rates and 5 school districts with relatively rapid growth rates. In both cases, the relatively extreme cases are fairly spread out both with respect to geography and with respect to the initial nationwide income distribution.

Given the data on the behavior of education spending both in the cross-section and over time, the model that we develop in Section 3 must be capable of incorporating a number of important features. Education expenditures must, especially at the high end, be related to local incomes. State governments must have a preference for equalizing expenditures to at least some extent. The model must allow for school districts to shift places within the income distribution and require the state government to respond accordingly in its aid decisions. Further, state aid itself may need to be a source of fluctuations in spending, and these fluctuations might also be expected to be dependent on the income distribution in terms of their volatility. We next turn to describing a model that we believe incorporates all of these characteristics.

3 A Preference Model of the K-12 Education Finance System

To characterize how state governments and local districts allocate funding for schools, we present an optimizing model of state governments and school districts, where governments have preferences for school spending as well as for other spending while state government further have preferences for the distribution of aid across school districts.[7] The state govern-

[7]Dupor 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

ments' preferences for school spending in a school district is assumed to depend on locally raised revenue.[8] A important feature of the model permits estimation of the extent to which the state government and the school districts react to the decisions taken by the other, consistent with analyses of fiscal federalism.

The model implies risk sharing across school districts (via the state government) because the objective functions are formulated in term of annual spending, implying that spending adjust each period to economic shocks. The model, for both state and local actors, also allow for a time-varying reference level of welfare which is a function of allocations the previous year (equivalent to "habit formation" in the consumption literature)—slow adjustment of spending to state- and local income shocks is pervasive as documented in Sørensen, Wu, and Yosha (2001). We estimate the model for a "representative state" based on all of the observations in our dataset, and we perform simulations depicting a number of alternative scenarios that illuminate how our estimated parameters explain the outcomes of state government equalization efforts across school districts and over time.[9]

3.1 State Government Behavior

We assume that the representative state is comprised of D school districts, each of which is its own independent local government. The school districts are heterogeneous in terms of their income levels, but not with respect to their preferences.

The representative state government is specified to have preferences over the level of state provided resources in each independent school district, and to have preferences over the distribution of those resources across districts. The preferences are modeled with the

financing public education.

[8] This aspect is referred to as unequal caring in Behrman and Craig (1987), to differentiate it from aversion to inequality.

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

following criterion function:

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

where $R^S_t = \Sigma_{d\in D} R^S_{d,t}$ and the state myopically solves its optimization problem in each period t.

Unequal caring is determined by the first term, where a positive estimated ω indicates that states weigh transfers more highly for districts with higher locally raised revenue, while a negative ω indicates states weight transfers more highly for districts with lower local revenue. 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.

Preferences over inequality in access to resources are specified relative to a reference level, $\widetilde{\frac{R^S_{d,t}}{R^S_t}}$. The reference level is specified as a function of the previous year's allocations, and this introduces a dynamic dimension into the model, which captures the significant lags in adjustment observed in the data[10] and while we do not explore the underlying structure behind these lags, this may capture adjustment costs associated with altering resource allocations from year to year, or possibly the effect of political competition on policy choices, as in for example the reversion level in the Structure Induced Equilibrium models first introduced by Shepsle (1979).

The second term in the equation captures the utility 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, $\tilde{R}^S_t$ which depends on overall aid levels in the previous year.[11]

[10]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 and demonstrate that state aid and local resources take some time to adjust to income changes. This motivates our use of the reference utility mechanism.

[11]To simplify the analysis, we assume that the state government is myopic with respect to its reference

The final term in the equation captures the utility derived from all other goods, defined as personal income minus total education aid per capita.[12] κ captures 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 relatively more tolerant of intertemporal fluctuations in total education spending or other uses, respectively. Larger positive values, on the other hand, indicate greater willingness on the part of the state government to protect one spending flow or the other.[13]

We specify reference utility as

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

and

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

We derive estimating equations by first assuming the state government decides how much to spend in total on education. With the overall funding level fixed, we then assume the state decides how to allocate that funding across the various school districts. Thus, 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 (keeping the districts' shares constant):

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

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 $t+1$.

[12]Baicker and Gordon (2006) find that increases in state aid partly result in lower aid to local governments for other purposes—the utility of spending on other local purposes are here lumped in with all other non-school spending.

[13]Adding the net of tax term parameterized with κ completes the budget constraint for state residents, excepting federal aid. We omit federal aid from this equation altogether, because understanding federal education aid is outside of the scope of the current paper.

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 utility level, we arrive at:

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

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

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

From equation 1, the tendency for spending to stay constant is determined by the parameter γ; for example, for constant κ, if γ approach infinity, the level of state revenues is constant. The approximate elasticity of spending with respect to state-level income is $\frac{\kappa}{\gamma}$, which is higher the more concave the utility from other state-level uses of income and higher the lower γ, the interpretation being the sensitivity to income is determined by a trade-off between a wish to keep spending constant, as captured by γ, and a desire to minimize fluctuations in other spending, as capture by κ.

The term $\log(Y_t^S - R_t^S)$ is a function of the left-hand side variable and therefore correlated with the residual, but, because school aid is a small fraction of state income, we assume state income is exogenous to school spending and, 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 optimal distribution of education aid across the D school districts is derived from the first order optimality condition by taking the derivative of

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

holding R^S_t constant (assuming that aid to each school district is a negligible part of the total state spending on schooling). λ^S_t 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

$$(R^L_{d,t})^\omega (R^S_{d,t})^{-\eta} (\frac{1}{R^S_t})^{1-\eta} \left(\frac{\widetilde{R^S_{d,t}}}{R^S_t}\right)^{\eta-1} = \lambda^S_t \ .$$

We take logs and use state-year fixed effects to absorb state-level terms into λ^S_t, to obtain

$$-\eta \log R^S_{d,t} + \omega \log R^L_{d,t} + (\eta - 1) \log \tilde{R}^S_{d,t} = \Lambda^S_t \ .$$

Using the expression for the reference utility, we get (after absorbing the additional state-level term into the state-year dummy) the basis of the second estimation equation:

$$\log R^S_{d,t} = \frac{\omega}{\eta} \log R^L_{d,t} + \frac{\eta-1}{\eta} \log R^S_{d,t-1} + \Lambda^{S'}_t \ .$$

We substitute a set of state-year effects ($\mu_{s,t}$) for $\Lambda^{S'}_t$ to yield the second estimating equation:

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

The desire to keep transfers to local district d is captured by the parameter η, while the reaction to local spending is a trade-ff between this desire and the parameter ω, which captures the curvature of states utility from local spending—when ω is negative, the more likely the state-government is to off-set local spending the larger the numerical value of ω.

To account for the simultaneous determination of $\log R^L_{d,t}$ (described in Section 3.2), we use the contemporaneous value and four lags of log real school district (county) personal income per capita as instruments in the regression 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 school districts.

It may be helpful at this stage to take stock of the important role played by two parameters influencing the allocation of state aid across districts, namely ω and η. A negative value of ω means that the state government does tend to shift greater amounts of aid to districts with a lower ability to raise local resources, consistent with moves toward income-conditioned aid in recent decades. 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 means that the state government reacts to changes in income at the local level more slowly. 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 more time to respond accordingly.

3.2 Local School District Behavior

We model local taxes collected for schools given the level of state education aid.Estimation of the local behavioral model completes our depiction of fiscal federalism in school finance, because we assume that total school resources are the sum of state aid and local taxes.

The local school district d is modeled to choose local revenue $R^L_{d,t}$ to fund schooling so as to maximize the following criterion function:

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

As 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

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

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. Our specification, via the parameter ϕ, allows that 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, but $\phi > 0$ would suggest that increases in state aid induce lower weight on the local revenue term, meaning that spending on education does not increase dollar for dollar with an increase in state aid. The model's description of local government behavior is completed by the post-tax income term, where θ reflects the extent to which local governments are willing to to alter local tax rates to maintain local school spending.

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

$$(\frac{R_d^L}{\tilde{R}_d^L})^{-\xi} \frac{1}{\tilde{R}_d^L} (R_d^S)^{-\phi} - (Y_d^L - R_d^L)^{-\theta} = 0 \ ,$$

or

$$-\xi \log R_d^L - (1-\xi)\tilde{R}_d^L - \phi \log R_d^S = -\theta \log(Y_d^L - R_d^L) \ ,$$

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

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

and adding an error term, plus fixed effects for years and states, we get a third estimating equation:

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

In equation (3), the desired 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. Further, the ratio $\frac{\phi}{\xi}$ determines how much local districts off-sets changes in state-government transfers.

We use the contemporaneous value and four lags of both log real state personal income per capita and log real school district (county) personal income per capita in equation 3 to instrument for $\log R^S_{d,t}$ and $\log(Y^L_{d,t} - R^L_{d,t})$. We consider this reasonable because school spending is a small fraction of local income.[14] [15]

4 Estimation Results

We estimate the three behavioral equations enumerated above—the estimates are pooled and reflect a "composite" state, as we use the entire national data set of independent school districts.[16]

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 Table A2 without reference to

[14] At longer frequencies, income is likely to be endogenous to school spending at the local level because, say, wealthy people may migrate to better school districts, which may have higher spending. However, unless mobility across counties were massive and instantaneous, this would not lead to much bias in our regressions. In either event, the contribution of the present paper is not in finding the exact response of state aid to local school spending (in reality, it is determined by much more complicated mechanisms), but rather our contribution is in pointing out the dynamic patterns that have been heretofore ignored.

[15] For all three estimating equations the estimation results are not qualitatively sensitive to the length of the lags used as instruments. Further, the results are similar if we specify reference utility as being a weighted average of the previous two periods.

[16] There is no reason to expect all states to have the same preference parameters. However, the pooled estimates clearly highlight the intertemporal issues that have received little attention.

the model.[17] The reduced-form coefficients are highly statistically significant, so, for brevity, we will not comment further on the statistical significance of the parameters. Our estimates reveal large differences between the initial impact of income shocks and the long run values. The reduced form results imply the model parameters in Table 5 as the model is exactly identified with a one-to-one mapping between the structural parameters and the reduced form parameters.

Overall state education aid. The structural parameters estimated from equation 1 captures how state governments choose total education aid versus other public expenditures or not raising taxes. The estimate of γ is 3.029, which implies that states have a strong desire to keep school spending constant over time, which implies a coefficient to lagged spending of 0.67 in the reduced form estimates reported in the reduced-form Table A2. The curvature of the utility of other uses of state-level income (κ is 1.669), which in conjunction with the value of κ, leads to an elasticity of 0.551 in the reduced form.[18]

Allocation of state education aid across school districts. The parameter, η, which captures "habit formation" is estimated with a large magnitude of 5.480, implying a reduced form coefficient to lagged district-level aid of 0.818, which together with the corresponding term for overall state spending implies that state governments, on average, are expressing a considerable unwillingness to adjust aid levels or adjust the allocation of aid around in order to address income shocks. The parameter ω, which is the unequal caring parameter, which weights local resources in the objective function is estimated to equal -0.593. The negative value of ω implies that, all else equal, state governments desire to distribute more aid to school districts that have lower revenue from local sources, maybe suggesting that states have incorporated court ruling to address educational resource disparities. This coefficient relates to the work of Hoxby (2001) and Jackson, Johnson, and Persico (2016), who focus

[17]That is, we estimate the following relationships: $\log R^S_t = \mu_s + \zeta_t + a_1 \log R^S_{t-1} + a_2 \log(Y^S_t - R^S_t) + \epsilon_{1,s,t}$ (state total education spending), $\log R^S_{d,t} = \mu_{s,t} + b_1 \log R^L_{d,t} + b_2 \log R^S_{d,t-1} + \epsilon_{2,d,t}$ (state aid to districts), and $\log R^L_{d,t} = \mu_s + \zeta_t + c_1 \log R^L_{d,t-1} + c_2 \log R^S_{d,t} + c_3 \log(Y^L_{d,t} - R^L_{d,t}) + \epsilon_{3,d,t}$ (local revenue).

[18]Literally, the coefficient to $\log(Y^S_t - R^S_t)$ 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.

on the potential importance of inverted tax prices—from the reduced form coefficient in Table A2, we see that states are estimated to reduce aid to a district with a negative elasticity of 0.108 with respect to local spending, a fairly low "tax rate" on average.

Local school district spending. The parameter ξ is estimated at 3.82, which implies a coefficient to lagged local spending of 0.738, implying that districts have a fairly high degree of aversion to intertemporal fluctuations in education funding. 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 school spending with respect to local income of 0.202. This might not be a surprising considering the property-tax based framework for local school financing in the United States because house values often reacts with a lag to local income fluctuations. The parameter ϕ, captures substitution of local spending in response to fluctuations in state aid, with the reduced form elasticity, in 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. 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 a only a small decline in locally raised revenue.

4.1 Steady State Behavioral Implications

In this section, we use the model parameters to simulate education resource outcomes across school districts. This process will allow us to understand the extent to which state governments have narrowed resource disparities, and it allows us to determine the efficacy 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, log personal income per capita is constructed as $\log y^S = \log(\frac{1}{D}\sum_{d=1}^{D}\exp(\log(y_d^L)))$. The stationary distribution is a log normal with mean of 3.43 and standard deviation of 0.18, which is the average mean and standard deviation of log county 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.[19]

We calibrate the intercepts in the model to match two important features of the data. First, we impose that, in the steady state, per-pupil state spending on education as a share of per-capita income matches the sample mean. Second, we choose the intercepts such that state aid transfers make up 54 percent of the sum of state transfers and local revenue across all districts as in the data.[20]

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 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 varies with the per capita income of school districts. This panel demonstrates the net sum of the relationships in panels A and B. This figure shows that the lowest income school districts have a bit of a U-shape.The figure also illustrates, however, that K-12 education resources climb with per capita income for districts with income above about the 14th percentile. The results illustrated here incorporate the estimated inequality aversion, as well as the negative weight on local income (the unequal

[19] As throughout we continue to ignore federal aid.

[20] The data are 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 of the states in our dataset.

caring).

4.2 Risk Sharing

We next turn to evaluating our model's predictions for how state and local governments respond to various kinds of income shocks. We focus especially here on the effects of idiosyncratic and state-level shocks on a school district with median per-capita income, assuming AR(1) income dynamics.We assume that each school district's log personal income per capita is drawn from autocorrelated processes with normal errors.[21] Our model is, however, flexible enough to accommodate a number of other kinds of shocks as well, so Figures A4 to A12 in the appendix illustrate the model's predictions for the effects of white noise shocks (that is, with no autoregressive income dynamics), transitory, and permanent shocks at the district level, state level, and all-but-own district level for low-, high-, and middle-income districts.

4.2.1 District and State Income Shocks

Figure 5 depicts the effects of first an idiosyncratic (Panel A) and then state-level (Panel B) negative income shock equivalent to 10 percent of steady state income on a school district at the median of the state-wise income distribution. After the shock occurs, we observe that the school district must reduce locally raised revenue, since its available economic resources have declined. 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, and the school district shifts down the state's income distribution, state aid rises due to the negative value of ω (that is, the state wants to provide more resources to school districts unable to provide for themselves). At the same time, the high value of η implies that the state cannot (or does not desire to) respond quickly to the shock, and the rise in state aid is less steep than is the decline in local revenue. The result is that, for several years following the income less, expenditure per student lies below the district's steady state level. The trough in expenditure

[21] A regression of log real per capita county income on its own lag, with or without a time trend, leads to a highly precisely estimated AR coefficient of 0.98.

occurs within 5 years, and is around 2 percent lower than steady state spending. In the long run, as income recovers along with local revenue, spending returns to its steady state value, aided in part by the relatively slow return of state aid to its pre-shock level. Thus, for a middle income school district, there is a substantial amount of risk sharing for education provided by the state government, though it is far from perfect. For several years after a negative shock, spending on education is lower than its pre-shock level, though not as low as it might have been.

Table 6 summarizes the responses with respect to the same kind of shock at different time horizons for 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 proportionally the same in percentage terms is a much larger increase in real dollar terms. Similarly, the decline in local revenue, while proportionally the same as in other districts, is much less for a poor district 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 only fallen by less than 1 percent. In contrast, in the rich district, it has fallen by more than 2.5 percent. 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.

Because expenditures per student remain below their steady state level for several years after the occurrence of a shock, a student entering school during an inauspicious period may wind up being exposed to substantially fewer resources than one who started a few years earlier or later. Figure 6 illustrates this phenomenon, with the idiosyncratic shock under consideration treated in Panel A. The horizontal axis in Figure 6 measures the years relative to the occurrence of the negative income shock that a given student starts kindergarten.[22] For example, "0" means that a student started kindergarten in the same year that the income shock occurred. A value of 1 means that they started kindergarten a year after the impact of the shock, and −1 indicates that they started school a year before its happening. The figure illustrates that students starting school up to 12 years before the negative income disturbance and for many years after are negatively affected by it, in terms of being exposed to fewer resources over their entire career than a student whose years in school are entirely unaffected by the shock. The student starting in the year of the shock experiences the most dramatic decline in overall resources, around 2 percent of total spending over their 13 years in school relative to her peer that started 13 years before the shock. A student starting school contemporaneously with the shock is exposed to the bulk of the overall decline in local resources, but must wait several years for state aid to increase meaningfully enough to begin to offset the local revenue drop.

In the face of a negative state-wide income shock (equal to 10% of steady state income), however, the risk sharing mechanism provided by the state government breaks down, which is to be expected, since there can be no insurance for aggregate income shocks. Panel B of Figure 5 shows the effects of the state-level shock on the median-income school district's school finance variables. State aid falls considerably, by more than 15 percent at the trough, which is about 8 years after the shock occurs. Local revenue also falls in the near term, though not as much. Our parameter estimates indicate that school districts are more willing to shift resources to education purposes (in this case, from private spending) than are states, who also value smoothness in expenditures on other programs and in tax revenues. This explains the relatively modest fall in locally raised resources. That said, the effect on expenditures per student is still quite large. 5 years after the state-wide income shock, spending in the middle-income district is about 7.5 percent lower than it was before the disturbance. 30

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

years later, spending in the middle-income district has still not recovered fully.

We repeat our cohort analysis for the state-wide shock in Panel B of Figure 6. This figure demonstrates that a student starting school in the same year that a state-wide 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. Cohorts starting school long after the state shock occurs will have to contend to reduced education resources relative to those not attending school in any year affected by the state-level shock.

These results paint a stark portrait of the ramifications of the state government's large role in education finance. While the state government can (to varying degrees of effectiveness depending on a district's place in the income distribution) cushion idiosyncratic negative changes in income with increases in state aid, an aggregate (or state-level) shock leaves all districts in the state with fewer resources to devote to education, because of the substantial declines in state aid. This leads to intertemporal inequities as cohorts starting school in the year of the shock or in ensuing years must make do with less than their peers who started kindergarten in previous years.

4.2.2 Alternative Parameterizations

Given the strong influence of the inequality aversion parameter (η) and the unequal caring parameter (ω), it may be interesting to learn how outcomes might be different if these parameters took on different values relative to those we estimate. Two special cases, in particular, are worthy of attention. The first is to set $\eta = 1$, which would imply no inequality aversion on the part of state governments with respect to state aid and, simultaneously, a greater willingness to shift resources from one school district to another (so that there is no slow adjustment in response to income shocks). The second is to set $\omega = 0$, which removes the unequal caring motivation. Figure 7 contains the responses of expenditure per student to a transitory 10 percent negative shock to a middle-income district and to the state as a whole. For comparison, the benchmark responses are also plotted alongside the counterfactual responses.

Following an idiosyncratic shock, it is interesting to note that spending per student falls a lot further and faster when $\omega = 0$, that is, when state governments do not care to shift more aid to low-revenue school districts. Whereas expenditure per student bottoms at around 1.9 percent below the steady state level using our estimated parameters, when there is no income-conditioned aid, the fall is closer to 3 percent. 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 our estimated parameters.

This has dramatic implications for spending over the course of a student's entire career, as might be observed in Panel A of Figure 8. A student starting kindergarten under an $\omega = 0$ regime in the year of an idiosyncratic income shockmust contend with overall resources close to 3 percent lower than a peer who started 13 years earlier, and those cohorts starting school in subsequent years must deal with even less. The recovery of total education spending over a student's career is also much slower than in the case that $\omega < 0$, as in our benchmark framework. Thus, unequal caring might be said to reduce the losses of total career education resources that result from income shocks by more than half.

Next, we consider the case that $\eta = 1$, or that state governments do not exhibit any 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 much less steep than in the benchmark case. This is because, in the face of income shocks, state governments are much more willing to shift resources away from other districts not experiencing an income shock to the one that is affected. Thus, the risk sharing mechanism is much more complete, because states are able to respond more quickly. As would be expected, 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. Therefore, a state government's inequality aversion with respect to state aid impedes the insurance against local income shocks, at least in the short run.

With respect to state-level income shocks (Panel B of both Figures 7 and 8), it is apparent that changing the values of η or ω does not influence the allocation of education resources among districts or over time. This is because, with all districts suffering equally 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.

5 Conclusion

This paper has attempted to expand the lens through which inequities in access to education resources are viewed. The traditional view has developed under the implicit assumption that inequities between school districts are static. Recent work (cites***) has started to expand that view to include disparities over time, and our paper more fully explores the dynamic aspects of education finance systems. Specifically, we estimate a preference function to represent how state governments distribute state education aid across school districts and over time. Because state aid is conditioned on the level of income, it is of necessity sensitive to income changes over time- whether temporary or permanent. We therefore use our preference function estimates to evaluate the ability of state aid to address inequities in education resources across both space and time.

Our results on the effectiveness of state aid for reducing inequities span three dimensions, namely the differences between school districts arising from how state aid responds to disparities in local revenue, changes over time in school district resources due to idiosyncratic local shocks, and differences over time induced by changes in the level of state aid. We find that state governments behave as though they have concerns over the resources of the lowest income districts by granting them relatively larger aid levels. These aid increments appear to approximately level the educational resources for the lowest quartile by income of school districts. For districts with average incomes above the bottom quartile, however, educational resources are still found to increase with per capita income.

We find that state government aid responds slowly to temporary shocks, suggesting that were the response to changes in income faster, there might be welfare-enhancing gains in this dimension. For example, we find it takes five years for a poor districts resources to recover from a one-year temporary shock, and eight years or longer for middle or higher income school districts to recover. We show that students in school during the shock and recovery periods therefore receive access to substantially fewer resources than students in a district with similar income that is fortunate enough to avoid such shocks.

State education aid provides some level of risk sharing for school districts. The fact that state aid is, on average, over 45 percent of total K-12 education expenditures facilitates the performance of this function. However, when most (or all) of the state experiences an income shock, changes in state aid transmit that shock throughout all of the school districts in the state whether or not the individual district also shares in the shock. Our work illustrates this in two ways. First, we find that even without a correlated local shock, a shock to state income takes five to eight years for rich school districts to recover, partly by increasing local revenue and partially through the recovery of state aid. Low and middle income districts, however, for whom state aid is more important, unsurprisingly do much worse. Their local revenue response is relatively muted in dollar terms, and they must wait much longer for spending to recover. We also show the impact of the shock and slow recovery on between-cohort disparities even within the same school district, and find that these impacts are also quantitatively important.

On average state government institutions that are responsive to the dynamics of economic shocks are rare. In the case of state aid for school districts, we have demonstrated that the state government provides risk sharing, whether this is an intended or unintended consequence of its concern over disparities between school districts. Given the many dimensions of policy embedded within state government aid plans, it appears likely that the operation of the risk sharing mechanism could be improved for cases of isolated local income shocks. On the other hand, our work also illustrates serious shortcomings in the level of risk sharing available when there are income shocks hitting a large portion of the state, and likely only the federal government would be able to create institutions for insurance of such shocks. 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. This suggests that serious attention to the institutional environment can potentially address education resource disparities in a more comprehensive manner than is currently the case.

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Table 1: Summary Statistics for Key Variables: Total Sample

Variable	Mean	Std Dev 1	Std Dev 2
	Per-Student Values		
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
	Per-Capita Values		
County Personal Income	30.55	5.91	4.36
State Personal Income	35.60	5.49	4.38

Notes: The table reports the summary statistic of the different types of revenues and incomes for the sample of 8676 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 $[(1/n)\sum_i (X_{d,s,t} - \bar{X}_{s,t})^2]^{1/2}$. "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 school 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 2: Variance Decomposition of Total Revenue of School Districts (Percent)

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

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

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: The row header and the column header show the quintile of state-specific five year moving average of per capita income distribution of school districts in the beginning of our sample and the end of our sample respectively. Each cell of the table reports the percentage of the of total school districts in the income quintile in 1996 is in the income quintile in 2014. The starting year is 1996 as we consider 5 year moving average with our sample starting in 1992.

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. Complete education career resources are available for cohorts entering kindergarten in 1992 through 2002 in our sample. The calculations assume that a student stays in the same school district over the whole 13 years. The last four rows of the table show the number of district-cohort observations who received a lower spending or had spending growing slower than the income relative to older cohorts (one year and five years older). The percentages in the parentheses are calculated using the total district-cohort observations that were there in older cohorts.

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)

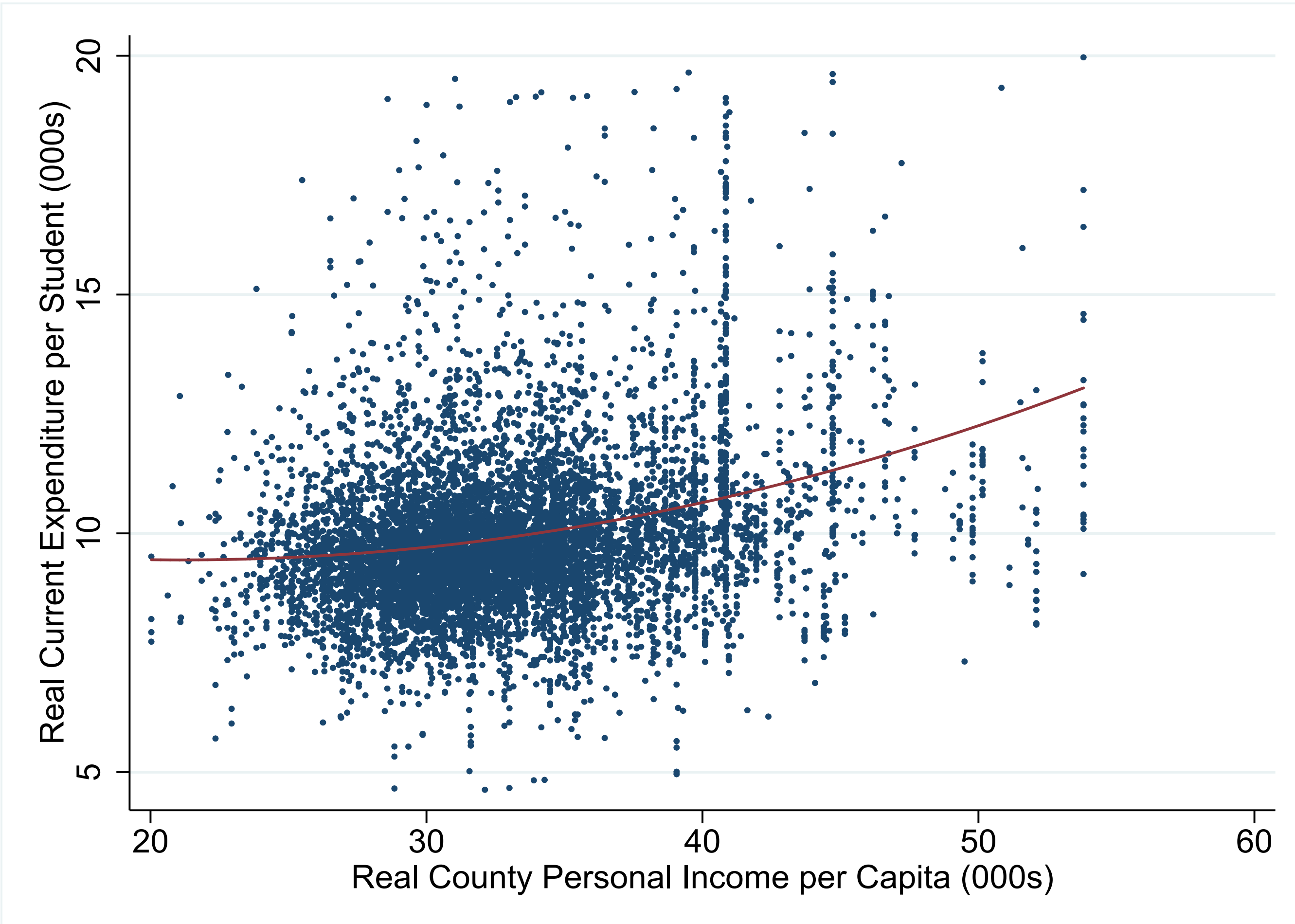
Notes: The table reports the parameters from estimating the equations $\log R_t^S = \mu_s + \zeta_t + \frac{\gamma-1}{\gamma}\log R_{t-1}^S + \frac{\kappa}{\gamma}\log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (total state education spending), $\log R_{d,t}^S = \mu_{s,t} + \frac{\omega}{\eta}\log R_{d,t}^L + \frac{1-\eta}{\eta}\log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), and $\log R_{d,t}^L = \mu_s + \zeta_t + \frac{\xi-1}{\xi}R_{d,t-1}^L - \frac{\phi}{\xi}\log R_{d,t}^S + \frac{\theta}{\xi}\log(Y_{d,t}^L - R_{d,t}^L) + \epsilon_{3,d,t}$ (local revenue). All parameters are derived from the estimates reported in Table A2. $R_{d,t}^S$ is state aid 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 the county in which school district d is located. Estimation includes year fixed effects, county and/or state dummies as appropriate. ***,**,* represent statistical significance at the 1%, 5%, and 10% levels, respectively. Delta method standard errors (in parentheses) are clustered by state for results in top panel and clustered by school district for results in bottom two panels.

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

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

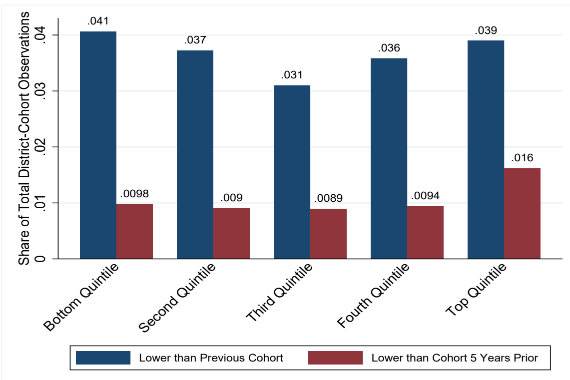
Notes: The table reports the model-implied steady state values of total expenditure, state aid, and local revenue for a "rich" district (85th percentile of the distribution),“ middle income" district (50th percentile of the distribution), and "poor" district (15th percentile of the distribution), as well as the changes in each variable in dollar and percentage point terms on impact, and three and eight years after the shock. The changes are in response to an idiosyncratic 10% 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.

Figure 1: Average Spending per Student

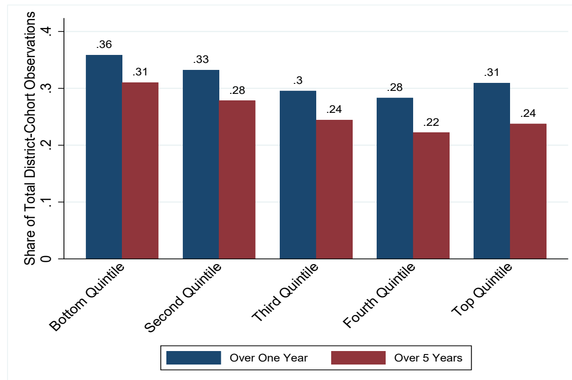


Notes: The figure plots the average of each district's sum of real local revenue per student and real state aid per student over the sample period (1992-2014) against the average of its per capita income over the sample period (1992-2014), along with a fitted quadratic regression line. State-year fixed effects are removed from each district's value and the average values over the entire sample added back in. The figure excludes districts wherein income per person averaged more than \$51.5 thousand over the sample or less than \$19.2 thousand over the sample as well as those districts whose sum of state aid and local revenue was more than \$20 thousand greater than the state-year average.

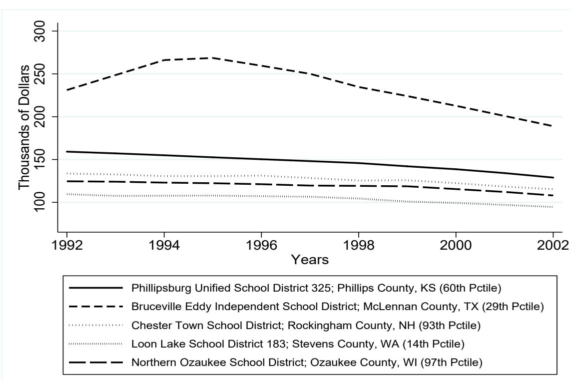
Figure 2: Distribution of Changes in Spending by Cohort Over Time (Based on 1992 Income Quintiles)



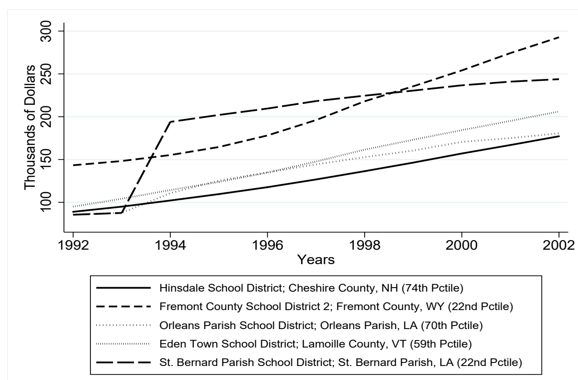
(a) Share of Cohorts Receiving Less Spending than Previous Cohort



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



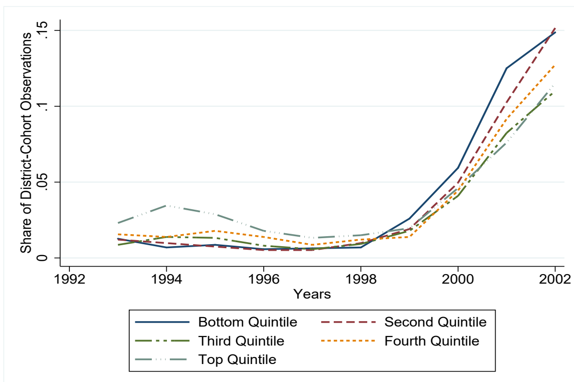
(c) Slowest Growth in Spending



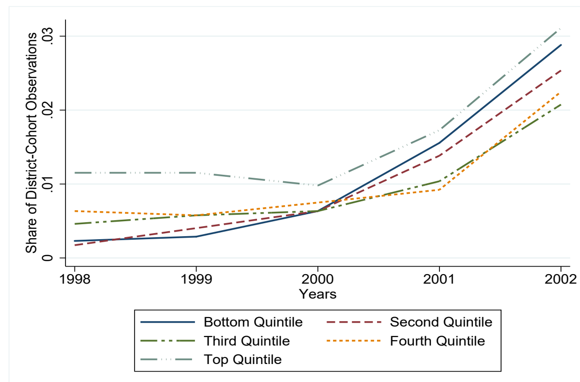
(d) Fastest Growth in Spending

Notes: The top two panels in the figure reports a different summary statistic for total spending per student in a cohort covering all of primary and secondary education, according to which income quintile that student's school district was in at the beginning of our sample period (1992). The bottom two panels report total spending per cohort over time in the five school districts with the slowest growth in education spending per cohort and in the five districts with the fastest growth in education spending per cohort. Complete education career resources are available for cohorts entering kindergarten in 1992 through 2002 in our sample. The calculations assume that a student stays in the same school district over the whole 13 years.

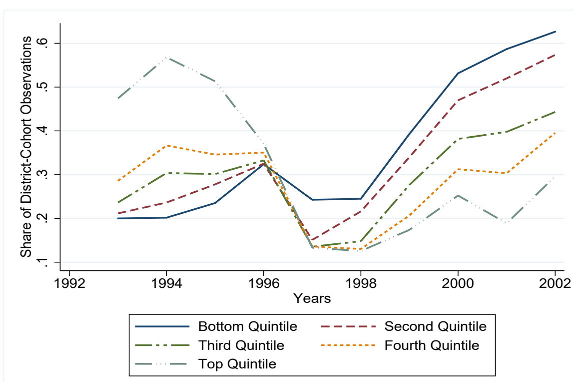
Figure 3: Distribution of Changes in Spending by Cohort Over Time (Based on 1992 Income Quintiles)



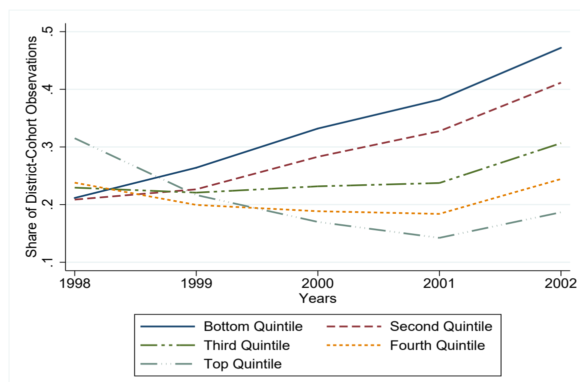
(a) Share of Cohorts Receiving Less Spending than Previous Cohort



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



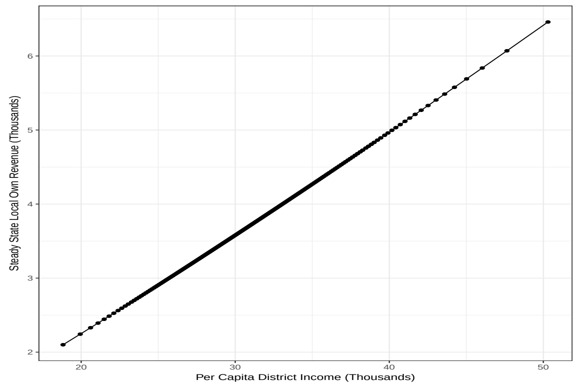
(c) Share of Cohorts for which Spending Grows More Slowly than Income over 1 year



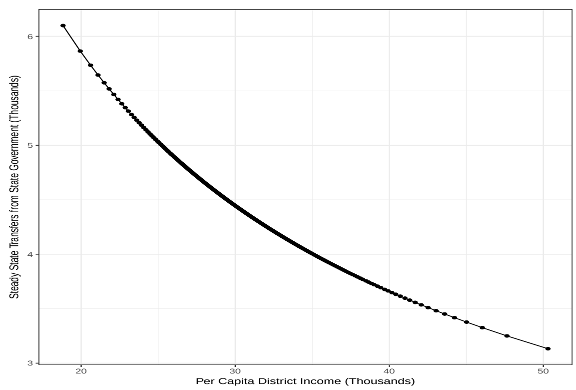
(d) Share of Cohorts for Which Spending Grows More Slowly than Income over 5 years

Notes: Each panel in the figure reports a different summary statistic for total spending per student in a cohort covering all of primary and secondary education, according to which income quintile that student's school district was in at the beginning of our sample period (1992). Complete education career resources are available for cohorts entering kindergarten in 1992 through 2002 in our sample. The calculations assume that a student stays in the same school district over the whole 13 years.

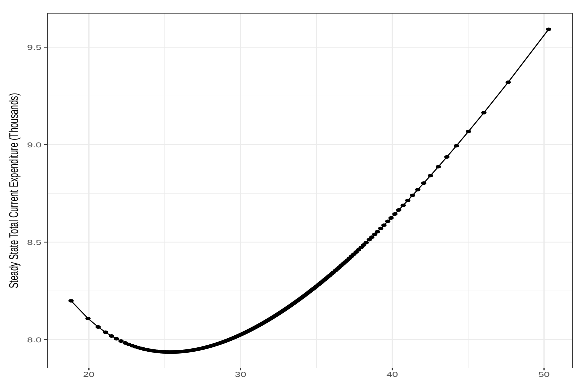
Figure 4: Model-Implied Steady State Distributions



(a) Locally Raised Revenue per Student



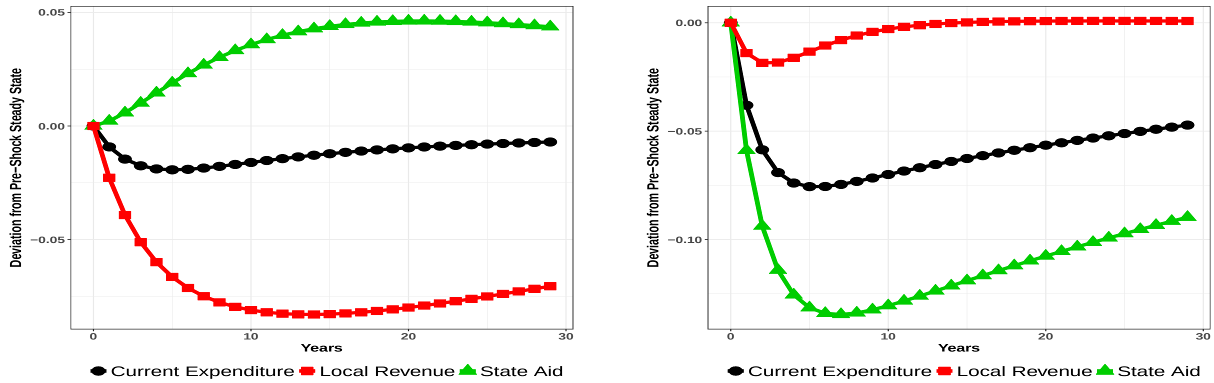
(b) State Transfers per Student



(c) Total Current Expenditure per Student

Notes: The figure shows the steady state distribution implied by the theoretical model for the 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 of the model using the pooled sample.

Figure 5: School Finance Variables: Impulse-Response Functions

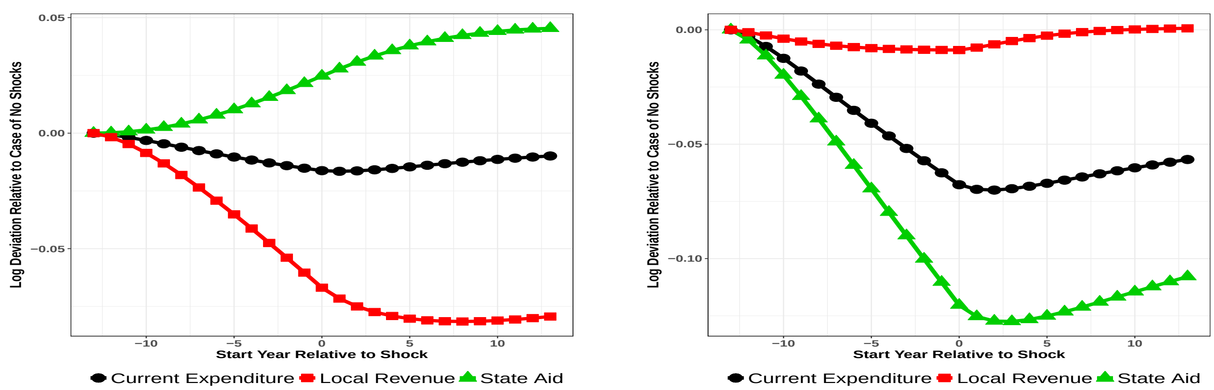


(a) Middle Income District: Idiosyncratic Shock

(b) Middle Income District: State-Level Shock

Notes: The figure shows 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. The left-hand figure (a) offers model-implied responses conditional on an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and the right-hand figure (b) offers model-implied responses in the 50th income percentile conditional on a statewide income shock.

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

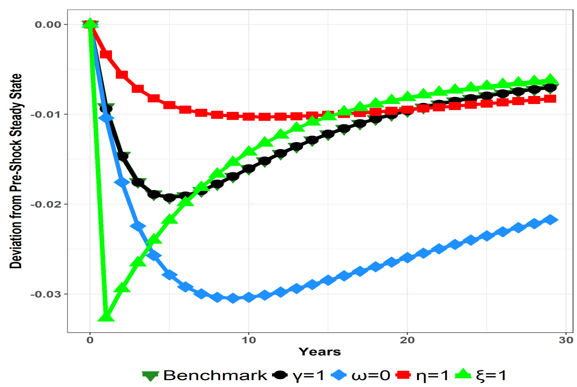


(a) Middle Income District: Idiosyncratic Shock

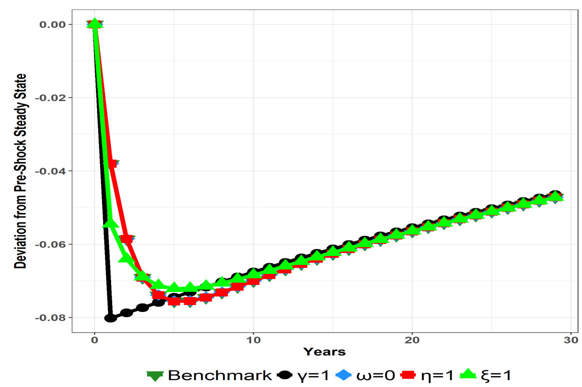
(b) Middle Income District: State-Level Shock

Notes: The figure depicts the total education resources received by a cohort of students 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 left-hand figure (a) offers model-implied responses conditional on an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and the right-hand figure (b) offers model-implied responses in the 50th income percentile conditional on a statewide income shock.

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



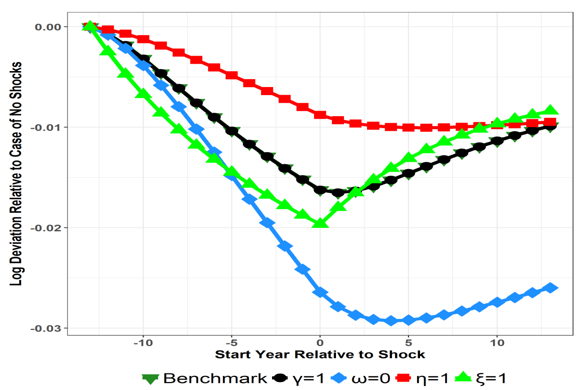
(a) Middle Income District: Idiosyncratic Shock



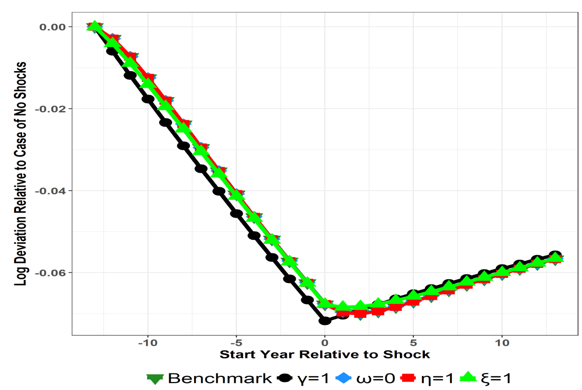
(b) Middle Income District: State-Level Shock

Notes: The figure shows 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 state governments do not exhibit unequal caring across school districts, i.e. setting $\omega = 0$, or adjust allocations immediately in response to shocks and do not have inequality aversion with respect to state aid, i.e. setting $\eta = 1$. The baseline response is included for comparison purposes. The left-hand figure (a) offers model-implied responses to an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and the right-hand figure (b) offers model-implied responses in the 50th income percentile conditional on a statewide income shock.

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 the total education resources received by a cohort of students 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 left-hand figure (a) offers model-implied responses conditional on an idiosyncratic income shock to a district at the 50th percentile of the state income distribution, and the right-hand figure (b) offers model-implied responses in the 50th income percentile conditional on a statewide income shock, assuming state governments do not exhibit unequal caring across school districts, i.e. setting $\omega = 0$, or adjust allocations immediately in response to shocks and do not have inequality aversion with respect to state aid, i.e. setting $\eta = 1$. The baseline response is included for comparison purposes.

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 aggregate 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:

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

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,[23] 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.

[23] Each 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 Table A3 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 in the model 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 $\eta = 1$.[24] 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

[24]Note 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.

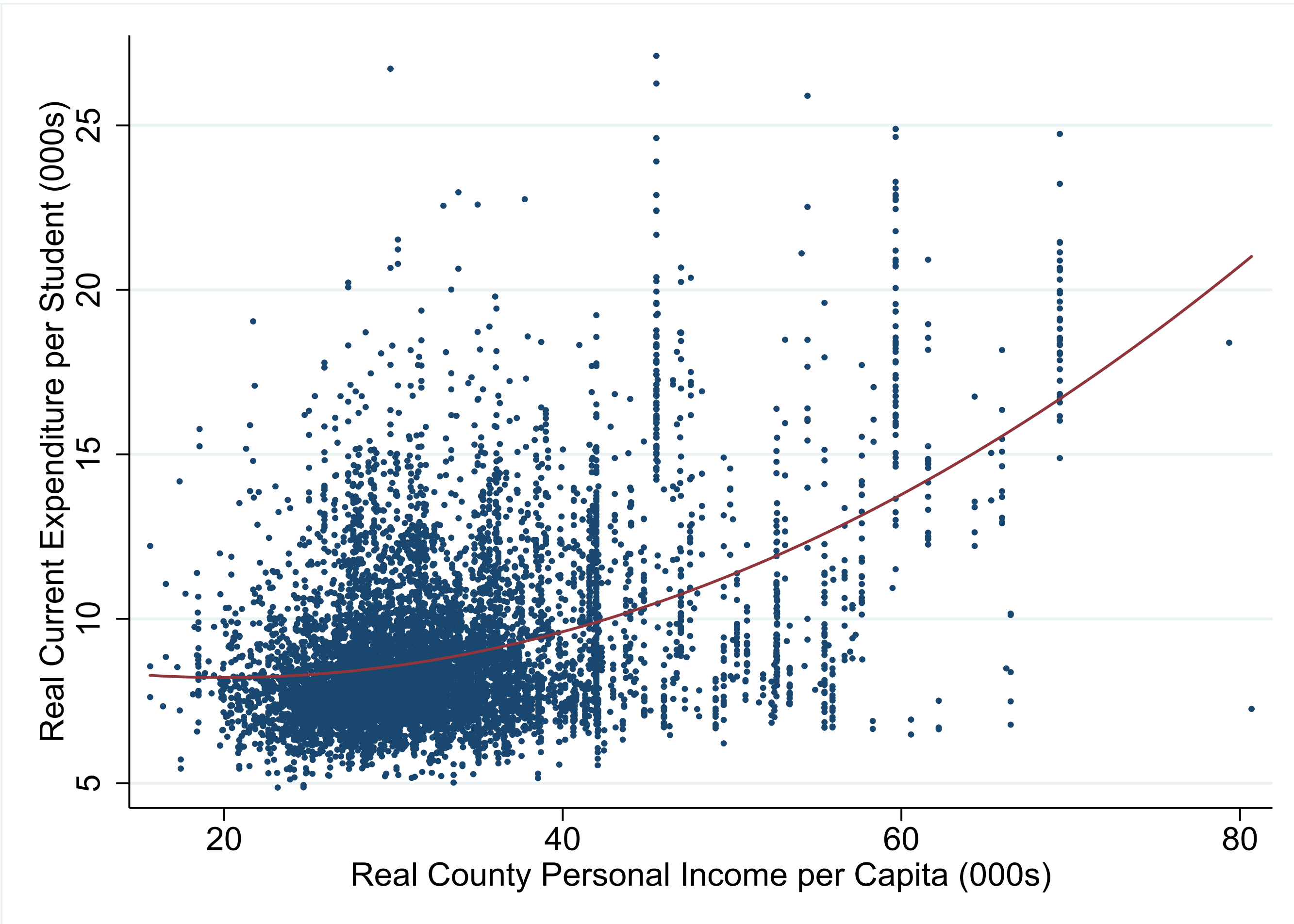
then might imply that slow adjustment of local governments to shocks is a more important determinant of cross-sectional variation than slow adjustment of the state government to the same shocks.

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.

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.

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)

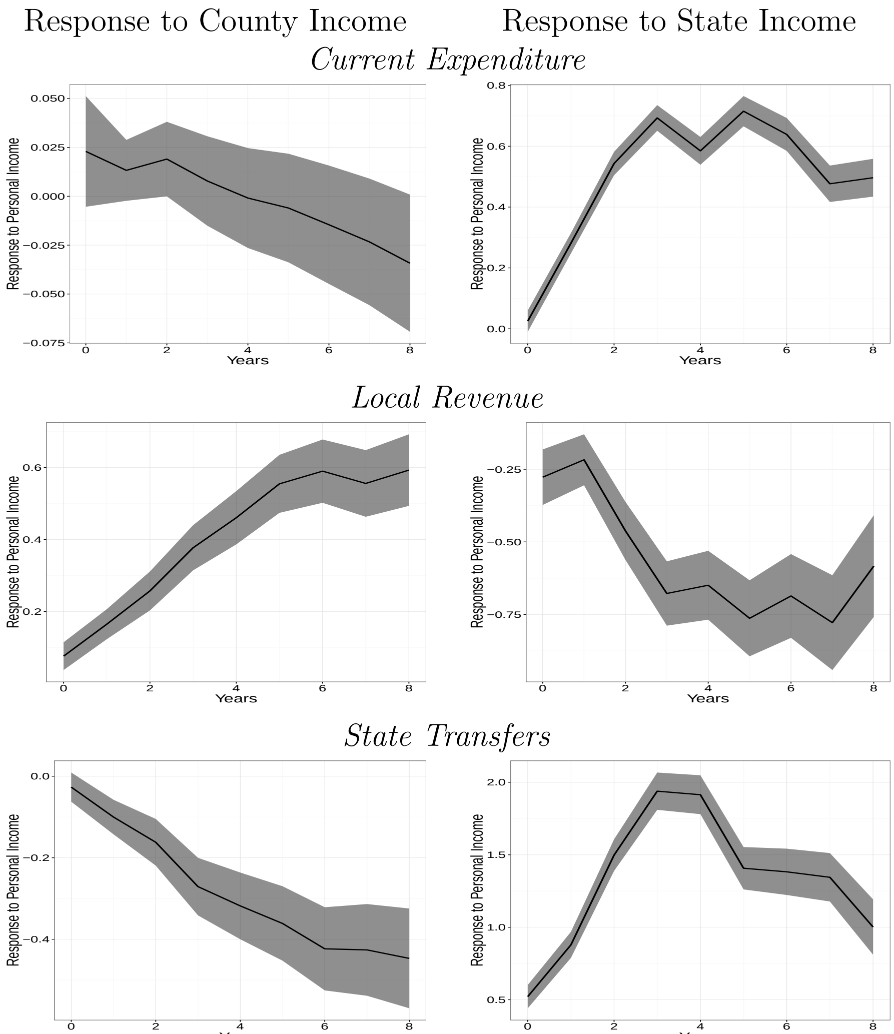
Notes: The table reports estimates from the equations $\log R_t^S = \mu_s + \zeta_t + a_1 \log R_{t-1}^S + a_2 \log(Y_t^S - R_t^S) + \epsilon_{1,s,t}$ (state total education spending), $\log R_{d,t}^S = \mu_{s,t} + b_1 \log R_{d,t}^L + b_2 \log R_{d,t-1}^S + \epsilon_{2,d,t}$ (state aid to districts), 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 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 the county in which school district d is located. Estimation includes year fixed effects, county and/or state dummies as appropriate. $^{***},^{**},^{*}$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors (in parentheses) are clustered by state for results in top panel and clustered by school district for results in bottom two panels.

Table A3: Model Simulation Results: Variation in Expenditure per Student

Specification	Cross-Sectional Standard Deviation		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

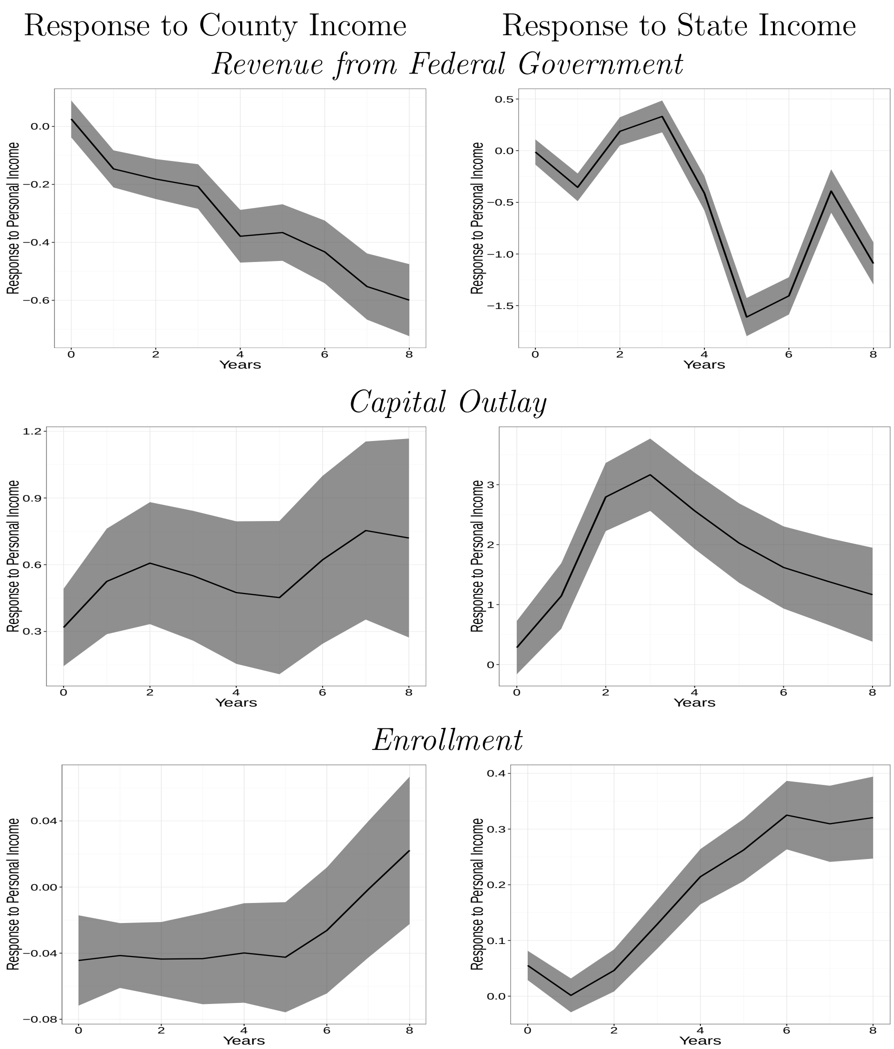
Notes: The table reports the standard deviations of per student expenditure in the steady state and averaged over 500 simulation sequences. For reference, the average cross-sectional standard deviation in 1,035 state-year cells is about 0.15. The average within-district standard deviation across 8.676 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 A2: Responses to Income Innovations



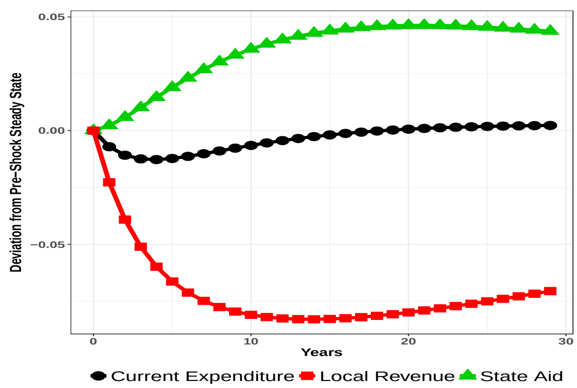
Notes: This figure displays the results from estimating $\Delta Z_{d,c,s,t} = \mu + \sum_{p=0}^{8} \alpha_p^L \Delta Y_{c,s,t-p} + \sum_{p=0}^{8} \alpha_p^S \Delta Y_{s,t-p} + \sum_{p=0}^{8} \gamma_{1,p} \Delta pop_{c,s,t-p} + \sum_{p=0}^{8} \gamma_{2,p} \Delta pop_{s,t-p} + \delta_t + \varepsilon_{d,c,s,t}$, 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. $\Delta Y_{c,s,t}$ denotes the change in the log of real personal income in county c 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

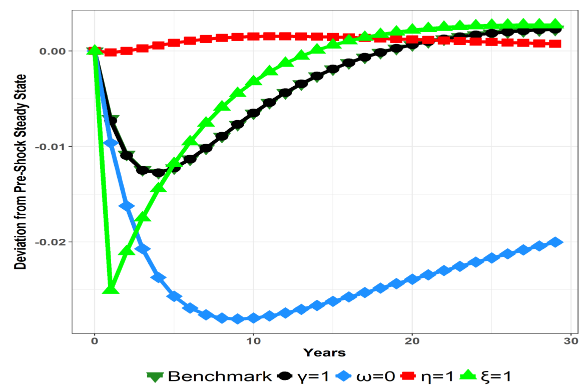


Notes: This figure displays the results from estimating $\Delta Z_{d,c,s,t} = \mu + \sum_{p=0}^{8} \alpha_p^L \Delta Y_{c,s,t-p} + \sum_{p=0}^{8} \alpha_p^S \Delta Y_{s,t-p} + \sum_{p=0}^{8} \gamma_{1,p} \Delta pop_{c,s,t-p} + \sum_{p=0}^{8} \gamma_{2,p} \Delta pop_{s,t-p} + \delta_t + \varepsilon_{d,c,s,t}$, 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. $\Delta Y_{c,s,t}$ denotes the change in the log of real personal income in county c 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.

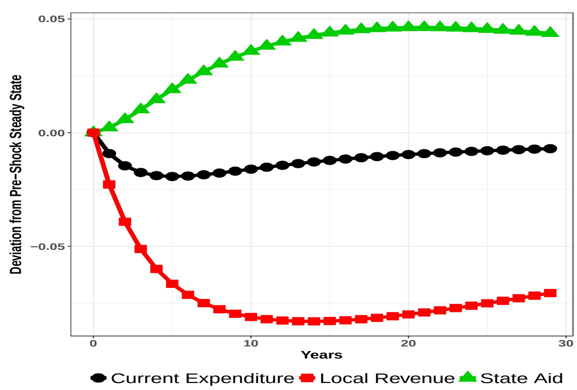
Figure A4: Model-Implied Responses to a Transitory Local Income Shock in a Single District



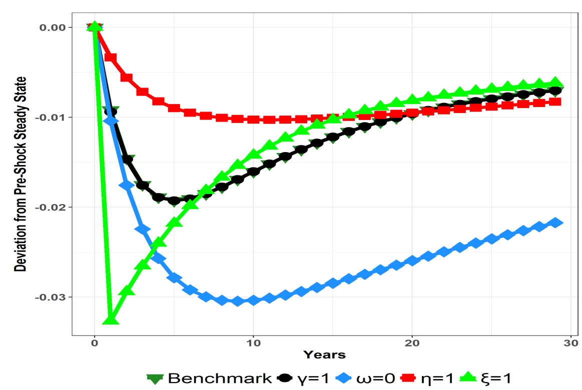
(a) Poor District: Benchmark Parameters



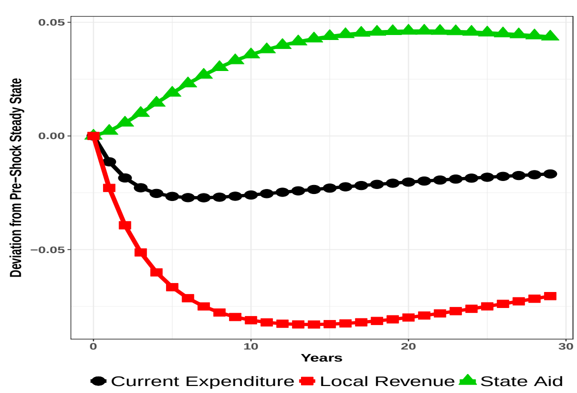
(b) Poor District: Alternative Parameters



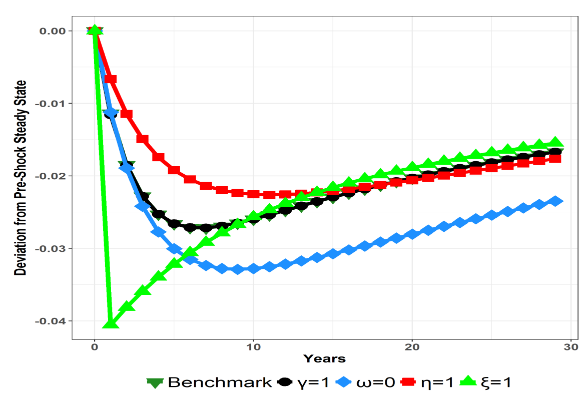
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



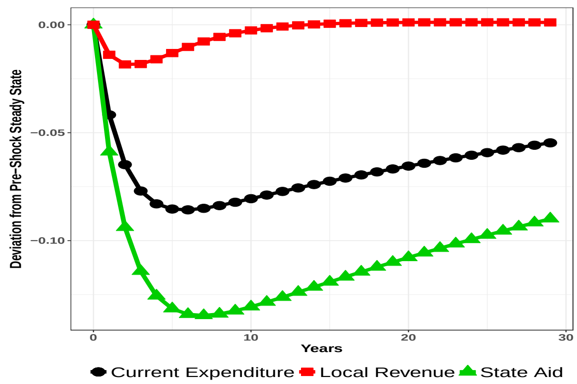
(e) Rich District: Benchmark Parameters



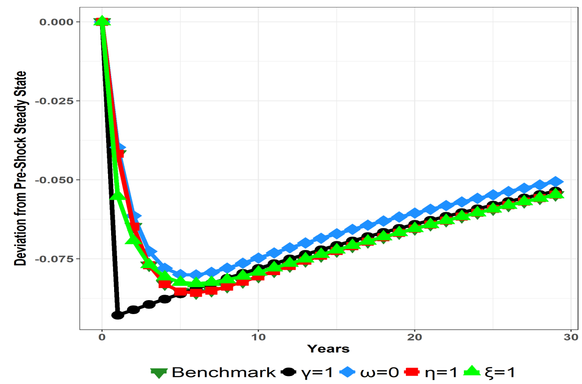
(f) Rich District: Alternative Parameters

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 transitory negative income shock of 10 percent of steady state local income. 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 $\eta = 1$.

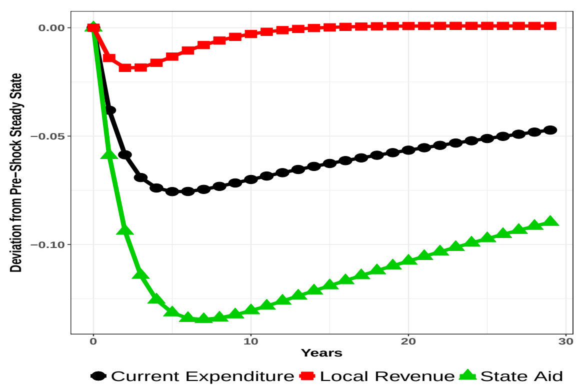
Figure A5: Model-Implied Responses to a Transitory Income Shock in All Districts



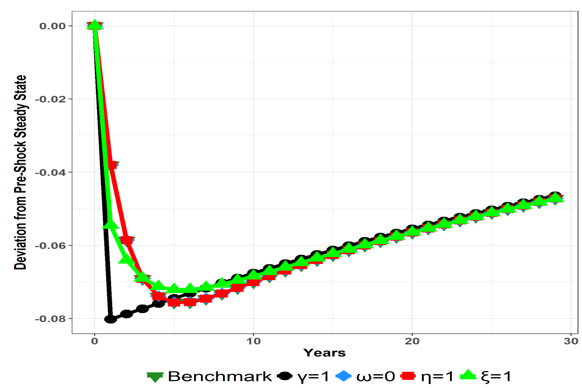
(a) Poor District: Benchmark Parameters



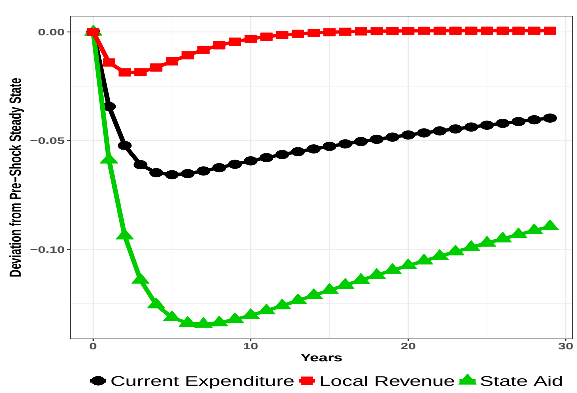
(b) Poor District: Alternative Parameters



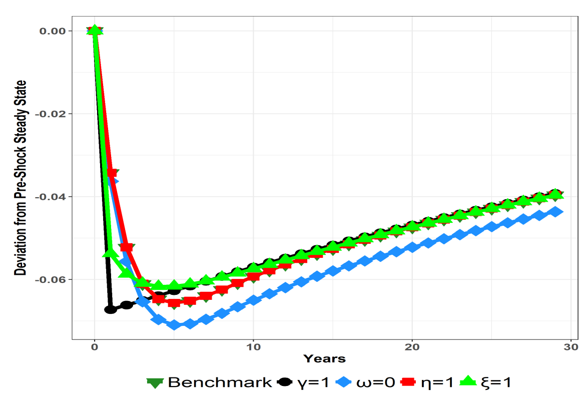
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



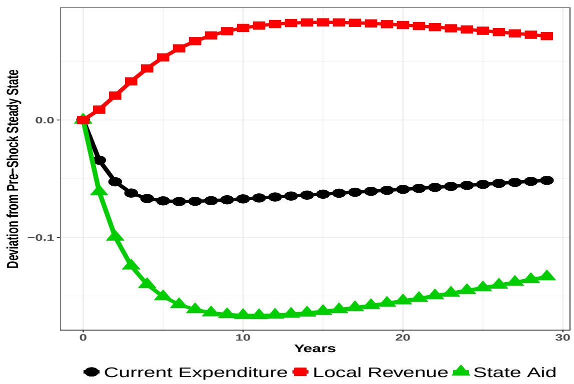
(e) Rich District: Benchmark Parameters



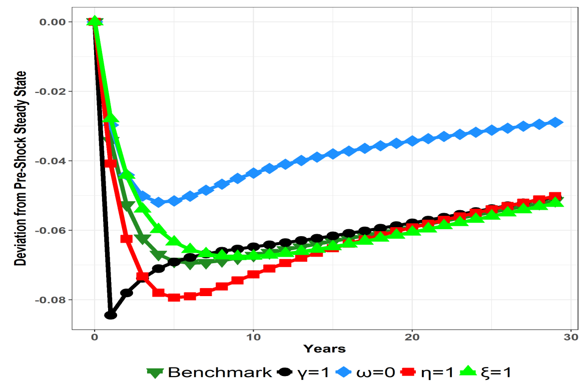
(f) Rich District: Alternative Parameters

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 transitory negative income shock of 10 percent of steady state local income that simultaneously affects all school districts. 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 $\eta = 1$.

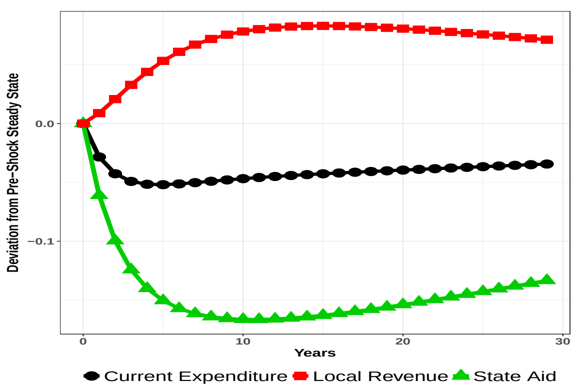
Figure A6: Model-Implied Responses to Transitory Income Shocks in All Other Districts



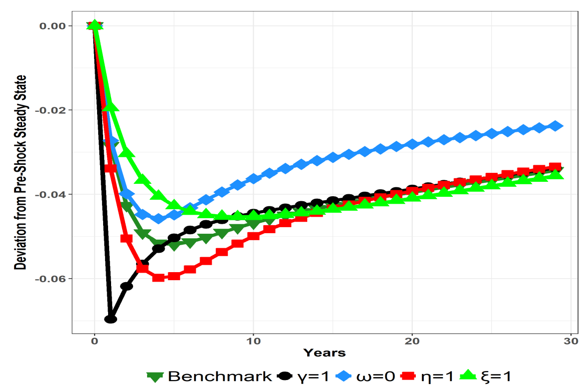
(a) Poor District: Benchmark Parameters



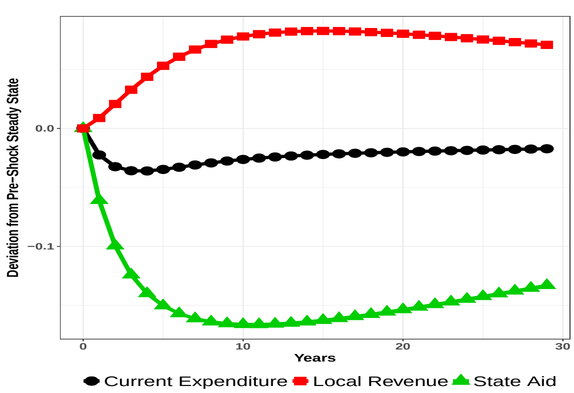
(b) Poor District: Alternative Parameters



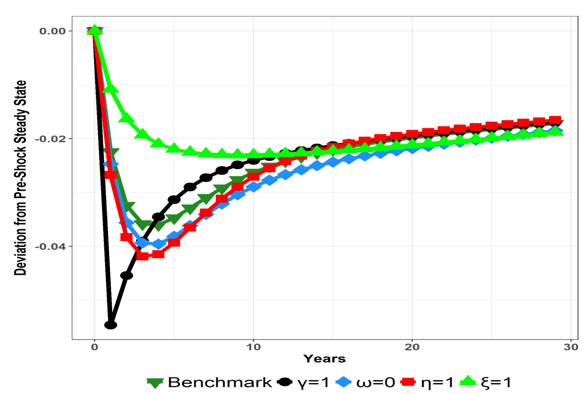
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



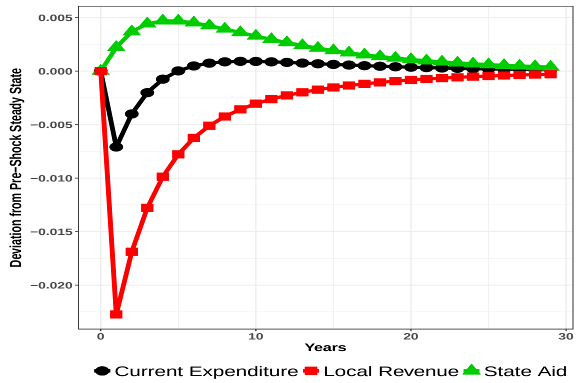
(e) Rich District: Benchmark Parameters



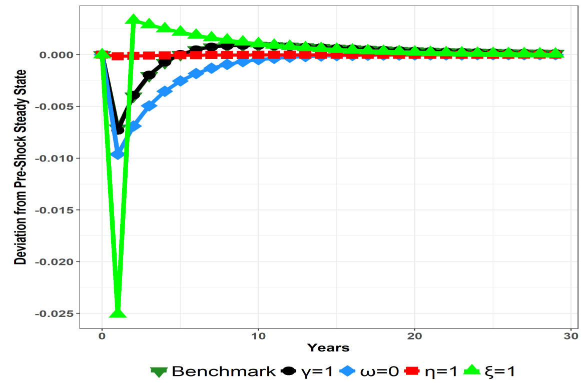
(f) Rich District: Alternative Parameters

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 transitory negative income shock of 10 percent of steady state local income that simultaneously affects all school districts, except for the one depicted. 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 $\eta = 1$.

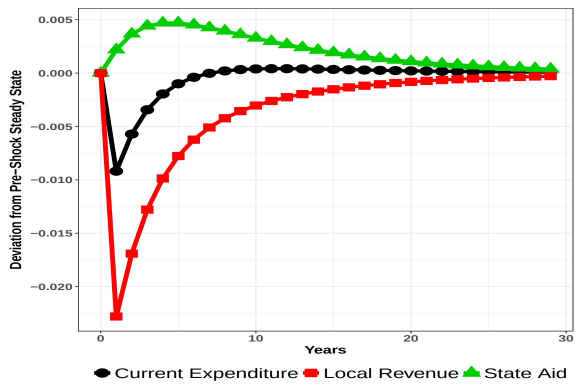
Figure A7: Model-Implied Responses to a White Noise Local Income Shock in a Single District



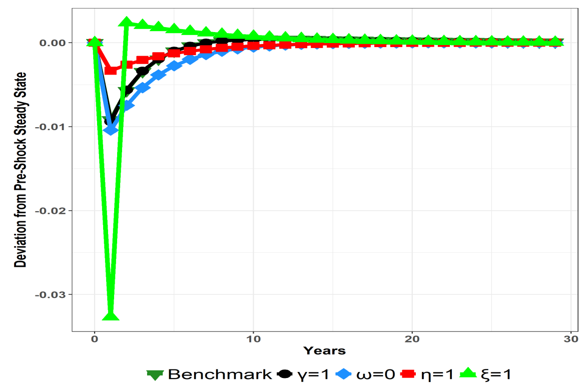
(a) Poor District: Benchmark Parameters



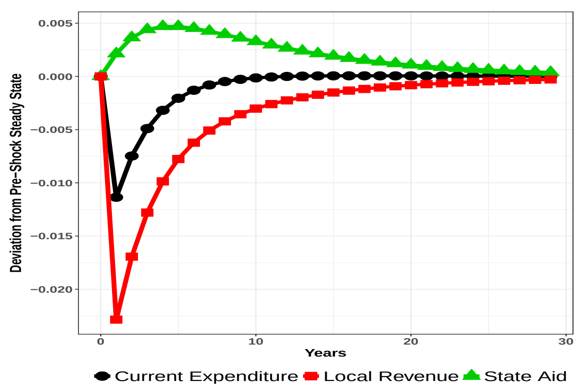
(b) Poor District: Alternative Parameters



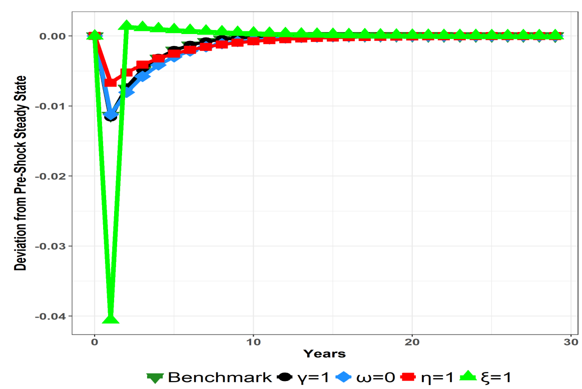
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



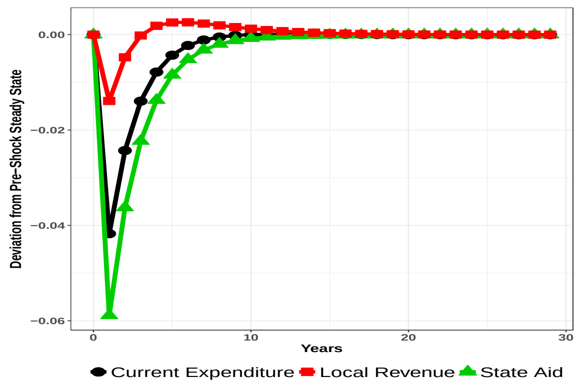
(e) Rich District: Benchmark Parameters



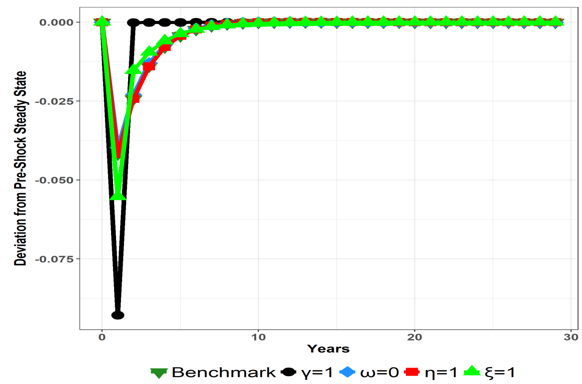
(f) Rich District: Alternative Parameters

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 white noise negative income shock of 10 percent of steady state local income. 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 $\eta = 1$.

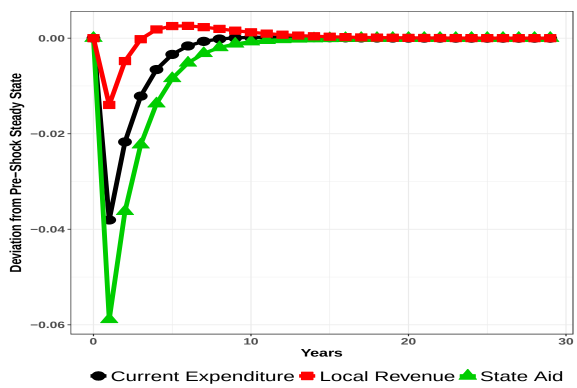
Figure A8: Model-Implied Responses to a White Noise Income Shock in All Districts



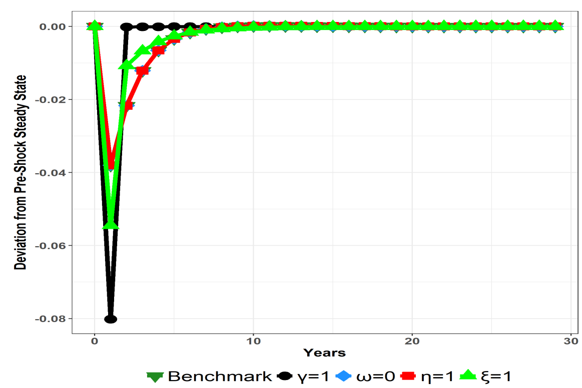
(a) Poor District: Benchmark Parameters



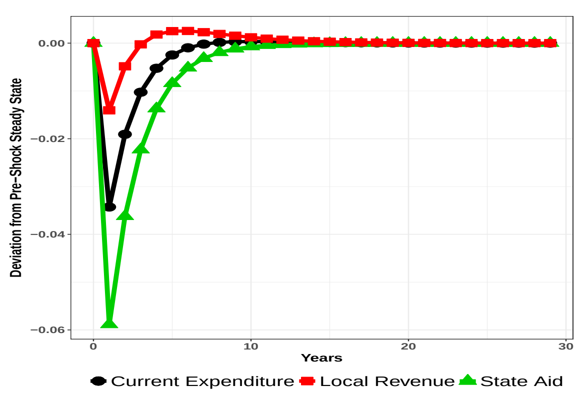
(b) Poor District: Alternative Parameters



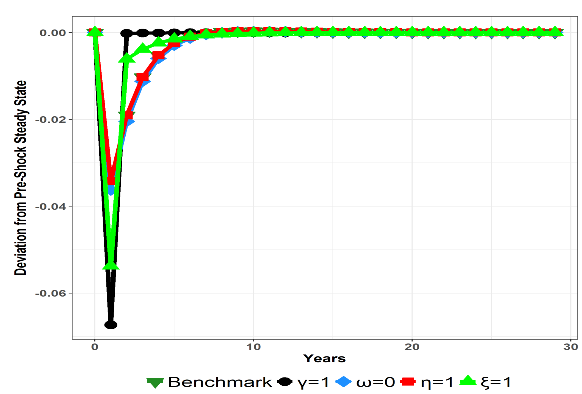
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



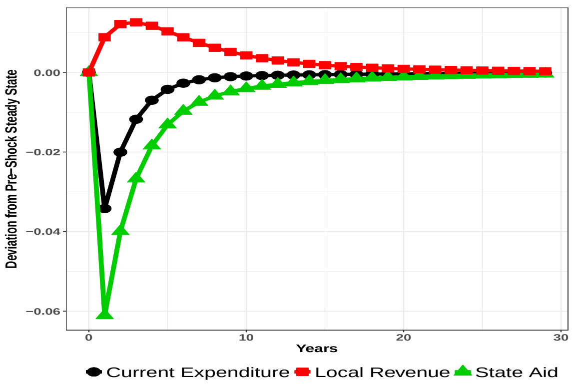
(e) Rich District: Benchmark Parameters



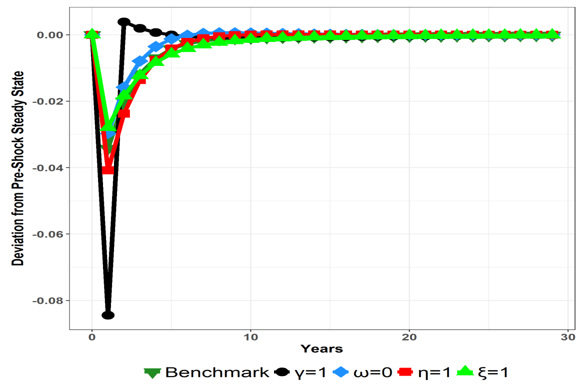
(f) Rich District: Alternative Parameters

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 white noise negative income shock of 10 percent of steady state local income that simultaneously affects all school districts. 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 $\eta = 1$.

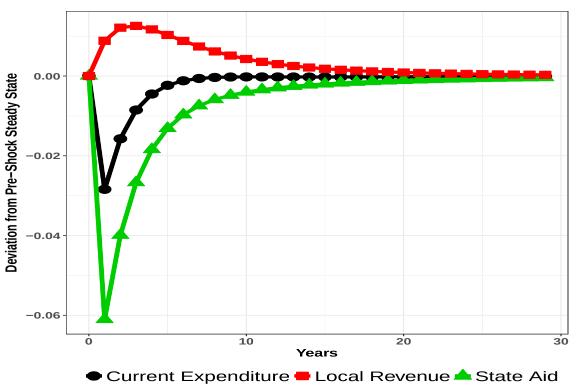
Figure A9: Model-Implied Responses to White Noise Income Shocks in All Other Districts



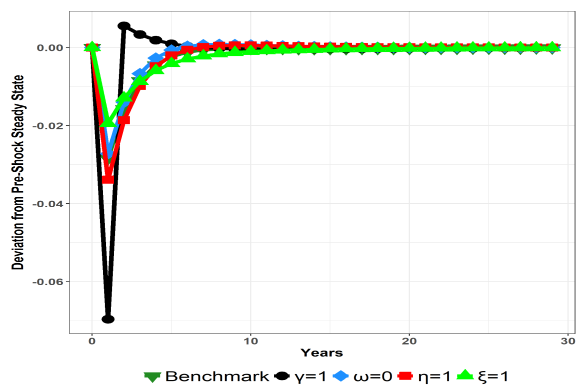
(a) Poor District: Benchmark Parameters



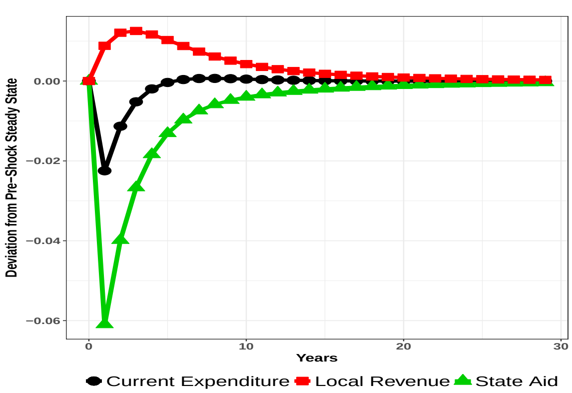
(b) Poor District: Alternative Parameters



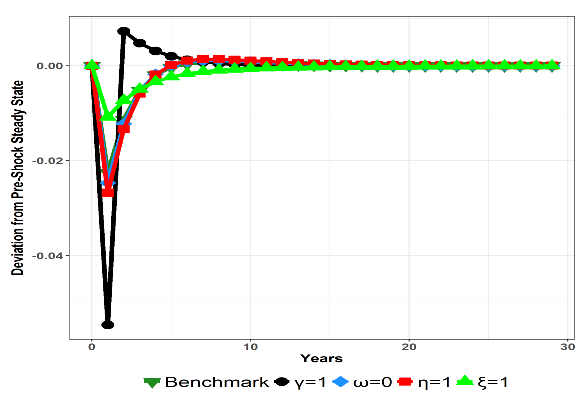
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



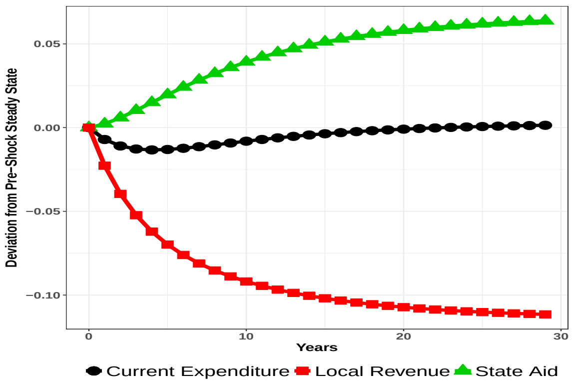
(e) Rich District: Benchmark Parameters



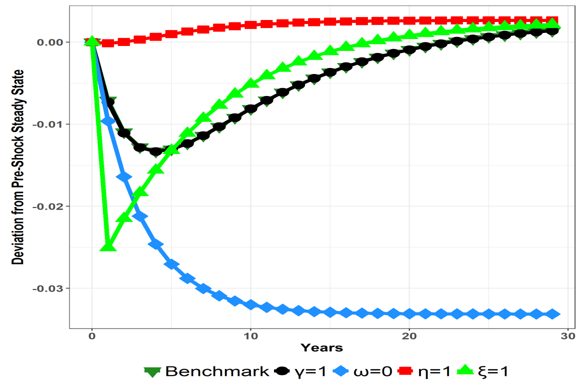
(f) Rich District: Alternative Parameters

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 white noise negative income shock of 10 percent of steady state local income that simultaneously affects all school districts, except for the one depicted. 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 $\eta = 1$.

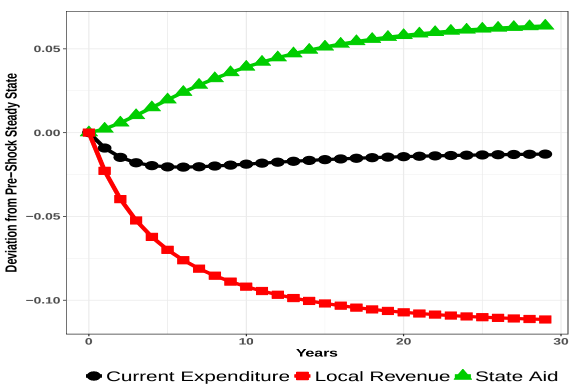
Figure A10: Model-Implied Responses to a Permanent Local Income Shock in a Single District



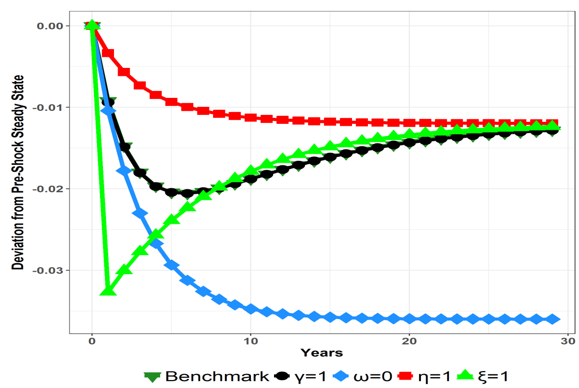
(a) Poor District: Benchmark Parameters



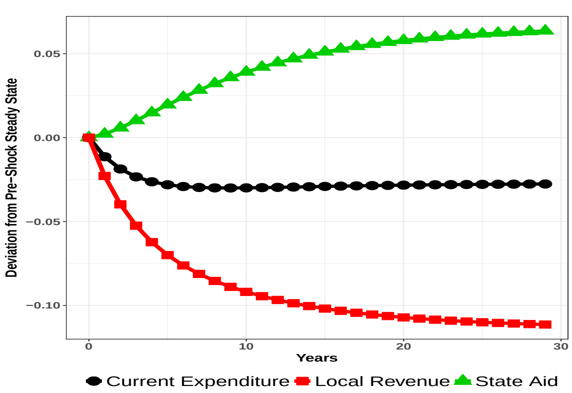
(b) Poor District: Alternative Parameters



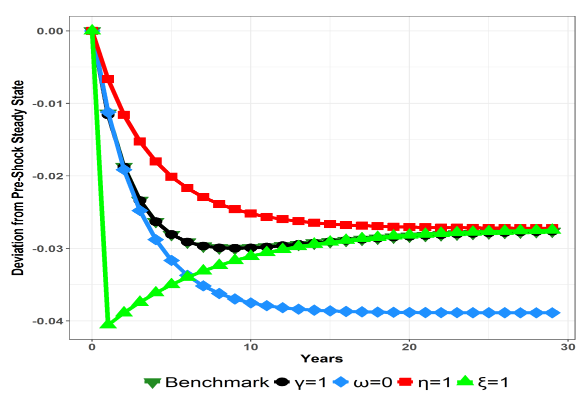
(c) Middle District: Benchmark Parameters



(d) Middle District: Alternative Parameters



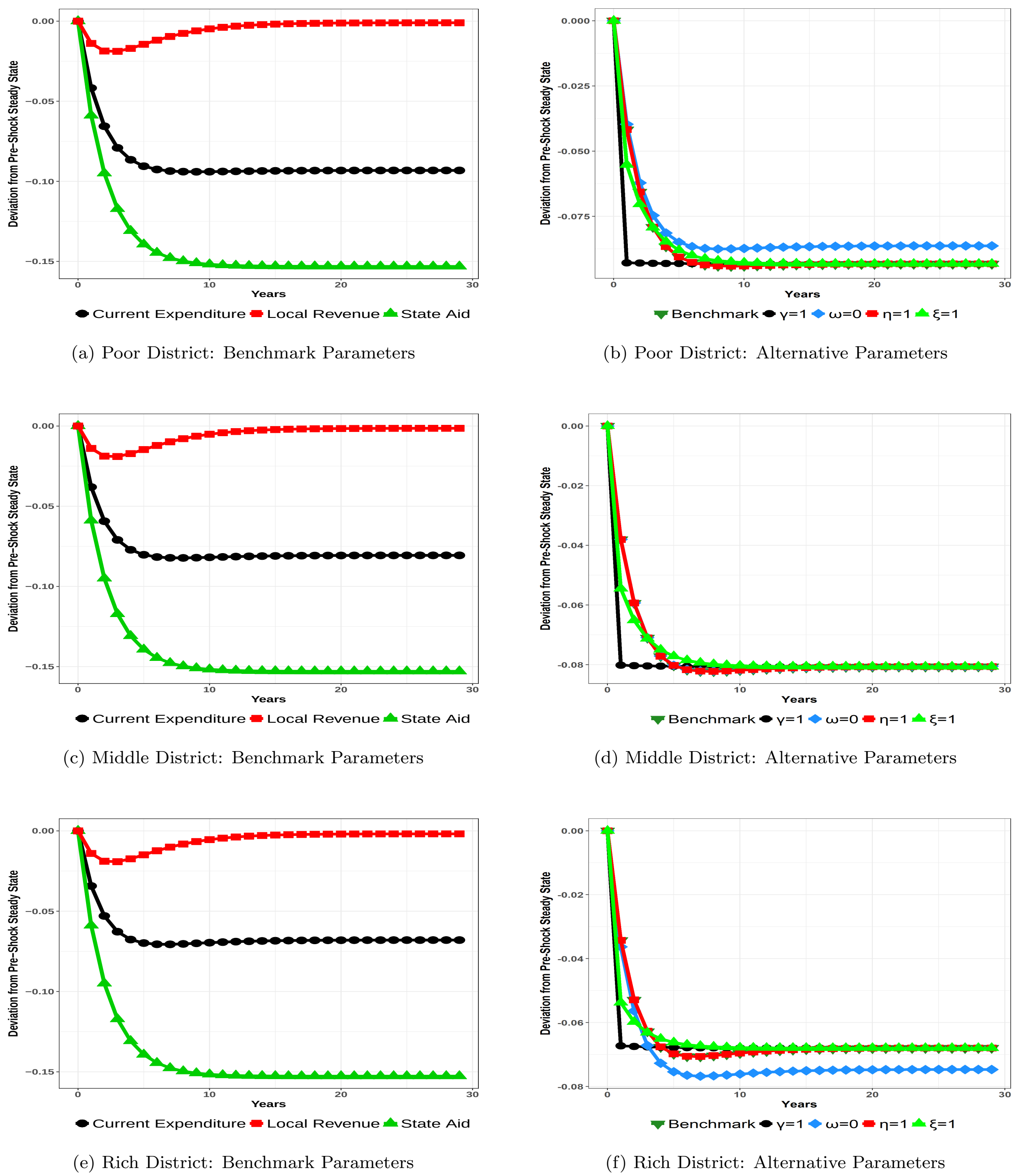
(e) Rich District: Benchmark Parameters



(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 permanent negative income shock of 10 percent of steady state local income. 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 a Permanent Income Shock in All Districts



(a) Poor District: Benchmark Parameters

(b) Poor District: Alternative Parameters

(c) Middle District: Benchmark Parameters

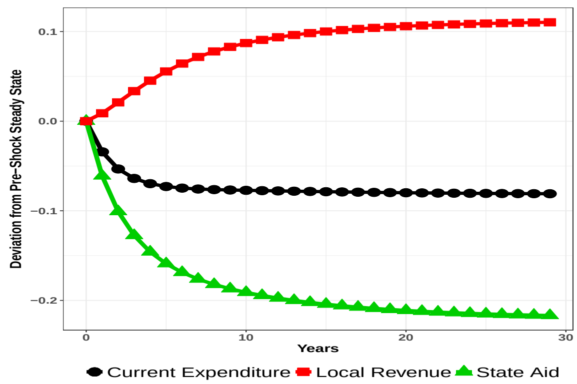
(d) Middle District: Alternative Parameters

(e) Rich District: Benchmark Parameters

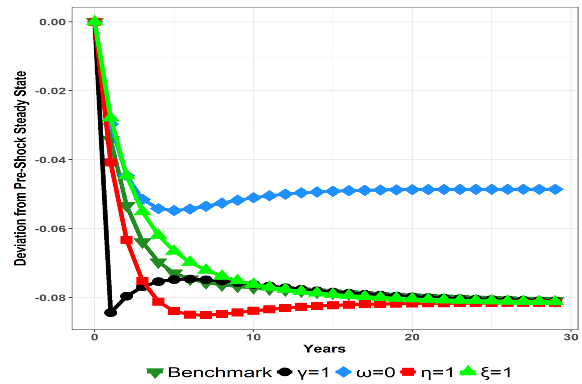
(f) Rich District: Alternative Parameters

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 permanent negative income shock of 10 percent of steady state local income that simultaneously affects all school districts. 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 $\eta = 1$.

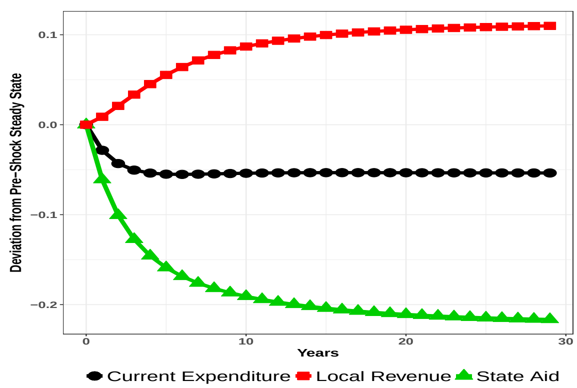
Figure A12: Model-Implied Responses to Permanent Income Shocks in All Other Districts



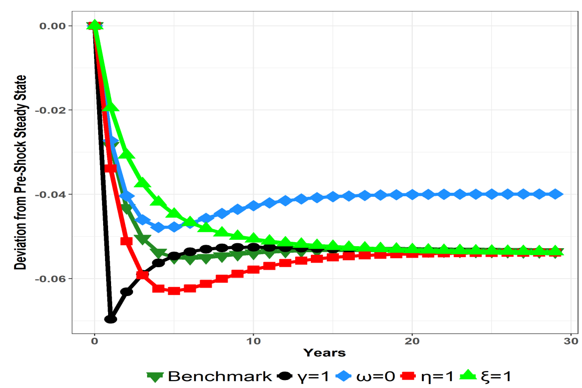
(a) Poor District: Benchmark Parameters



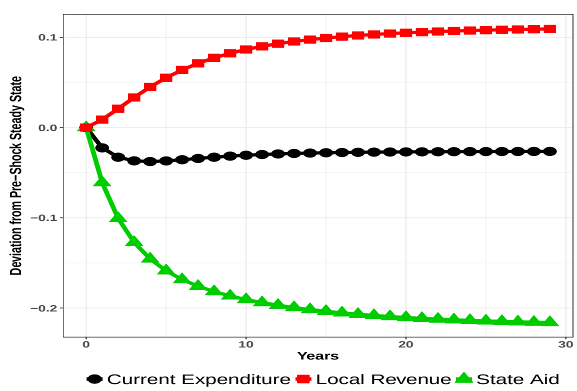
(b) Poor District: Alternative Parameters



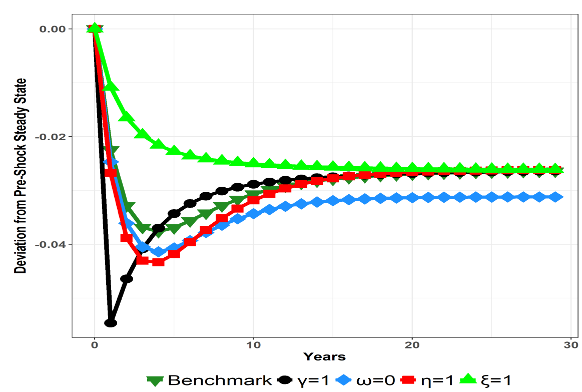
(c) Middle District: Benchmark Parameters



(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 permanent negative income shock of 10 percent of steady state local income that simultaneously affects all school districts, except for the one depicted. 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 $\eta = 1$.