Is Education Finance Driven by Tastes for Equity or Tastes for Education? Both.

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Abstract

This paper analyzes the state government preferences that motivate aid for K-12 education, as well as its distribution across school districts, via the lens of political equilibrium. We bulid a model of state government choices for distributing aid to school districts, allowing for interactions with higher education and low-income assistance funding. The optimizing equations are then fit to data for 45 states and 8,512 school districts over 1992 to 2019. We find that across states, there is a positive correlation between tendencies to spend on K-12 education aid, higher education, and low-income assistance. We also find that states spending more on these items appear to have reduced tastes for the equality of the state aid distribution across school districts. Within a given state, spending more on higher education actually makes the distribution of K-12 aid more progressive, while spending more on K-12 aid makes it less progressive. Using simulation evidence, we illustrate how these preferences actually magnify the vulnerability of lower-income school districts to aggregate-level business cycle shocks. Overall, we argue that K-12 education aid largely reflects a taste for production of education in steady state, but that it may be used to achieve equalization ends when the primary equalizing tools are constrained over the business cycle.

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1 Introduction

This paper concerns itself with political equilibria in state governments in the United States. The specific application that we engage in is the political choice of how much a state will spend on K-12 education aid and how to distribute it. We ask whether the motivations that drive these choices are primarily interested in producing education for students or if they are generated by a desire to address resource inequities. We find that the answer is a subtle one, in that, in steady state, education spending largely aims to produce education for students. Away from steady state, however, the state government apparently does employ the K-12 education budget to pursue equalization aims if the main tools for doing so (such as the budgets for welfare and health spending)[1] are constrained because of lower tax revenues.

In the last five decades, there have been sweeping changes to the frameworks governing how state governments allocate aid to school districts providing K-12 education, with many of them having been instigated by court decisions. Often, those changes have been intended to produce a more equitable distribution of education dollars by closing gaps in resources between high- and low-income school districts. More recently, so-called "adequacy" reforms have aimed to ensure that all children have access to some minimal level of education resources.[2] Such changes, however, do not take place in a vacuum. They both influence and are influenced by state government decisions regarding spending on various other government programs. In this paper, we aim to discuss the relationships between the equalization motives in state aid formulas for K-12 and other budget items.

Our approach involves asking how K-12 state aid allocations are influenced by tastes for higher education funding and low-income assistance. Craig and Palumbo (1999) demonstrate that there is systematic variation in how state governments dole out assistance. Specifically,

[1] In this paper, we use the terms "low-income assistance" or the more general "welfare" to refer to spending on welfare programs, health programs, and public hospitals.

[2] For examinations of the educational consequences of equality- and adequacy-based reforms, a non-exhaustive list includes Silva and Sonstelie (1995), Murray, Evans, and Schwab (1998), Hoxby (1998), Hoxby (2001), Card and Payne (2002), Downes and Shah (2006), Jackson, Johnson, and Persico (2016), Lafortune, Rothstein, and Schanzenbach (2018), and many others.

they show that states appear to treat unemployment insurance and Aid for Families with Dependent Children (two cash assistance programs) as substitutes, but that unemployment insurance and in-kind assistance programs (such as Medicaid) were more like complements. We draw inspiration from Craig and Palumbo (1999) in examining the possible existence of systematic correlations between funding for education and an equalization objective, using the preference specification of Biolsi, Craig, Dhar, and Sørensen (forthcoming).

Our study imagines that policy makers in the state government may have tastes for education production at all levels (K-12 and tertiary), but also that they may have tastes for equalizing resource disparities between people and/or places. Preferences for producing education could possibly be generated by a belief that greater funding for education improves the productivity of the state workforce, or it may simply be to win the favor of constituencies of teachers or parents.[3] Other policy makers, on the other hand, may favor equalization of incomes (thus favoring low-income assistance), and for a given amount of K-12 aid, may be more inclined to allocate it in a more progressive fashion (i.e., send more to poorer school districts), which might possibly close future income disparities. Choices as to how to distribute limited state government resources, therefore, may bring equalization-minded policy makers into conflict with those favoring greater expenditures on education. Education programs, however, provide a possible outlet for compromise in that greater spending on K-12 may be combined with more forceful direction of that spending towards the lower end of the income distribution. In this paper, our aim to shed light on how these preferences interact with each other and to characterize the set of political equilibria that result.

In our preference model, an extension of that introduced in Biolsi, Craig, Dhar, and Sørensen (forthcoming), we assume that state governments form preferences over spending on total funding for K-12, higher education spending, low-income assistance, and "other" uses (which may just include returning money to taxpayers in the form of lower taxes). We further propose that states have preferences over the distribution of K-12 aid according to

[3]We take no stance on why exactly policy makers may want to produce education.

the amount of revenue raised in heterogeneous local school districts. Over the course of the business cycle, these distributional preferences are allowed to be influenced by the amounts allocated to higher education or funding for low-income assistance programs.

We estimate our preference model with the use of data that covers 45 states and about 8500 school districts over the years from 1992 to 2019. First, based on parameter estimates that measure the behavior of the "average" state, we can illustrate the role of higher education or low-income assistance spending in the dynamic propagation of state-level income shocks and, in particular, what their ramifications are for allocations of state aid across the school district income distribution. Then, we can take heterogeneity across states more seriously in order to potentially tease out systematic preference correlations among total K-12 aid, higher education, and low-income assistance.

Our econometric estimates allow us to draw certain conclusions with respect to the steady state preferences of the states in our sample. Following the methodological approach of Craig and Palumbo (1999), we first note that states exhibit statistically significant positive correlations in their spending on total amounts of K-12 aid, higher education, and low-income assistance. Specifically, the state fixed effects for log spending on K-12 per student have a significantly positive correlation with those for log spending on higher education per student of 0.36. The analogous figures for K-12 aid with low-income assistance and for higher education with low-income assistance are 0.37 and 0.32, respectively. Thus, we can establish that states spending more on primary, secondary, and tertiary education also tend to spend more on income equalization programs, implying that such programs are complements in the state government's preference framework.

Then, we can compare how spending on these budget items compares with the progressivity of state education aid for school districts. We define "progressivity" of state aid as how negatively education grants from the state to school districts covary with revenue raised locally.[4] Our estimates suggest that spending on total state aid, higher education, and low-

[4] Our preference framework allows for both the state and school districts to behave strategically in choosing aid (in the former case) and local revenue (in the latter).

income assistance all correlate in a significantly positive manner with the gradient of state aid with respect to local revenue. This means that states spending more on those programs also have a *less* progressive distribution of state education aid. The implication of this appears to be that states spending greater amounts on total state aid, higher education, and low-income assistance also pay less attention to reducing within-state resource disparities for K-12 students. Thus, education-minded policy makers are able to secure larger budgets for both K-12 and higher education, but must also allow for more spending on low-income assistance (and less on, say, tax cuts). In this steady state political equilibrium, those policy makers who favor equalization, having successfully argued for more aid for the lower-income residents of the state, are more willing to forego a more progressive distribution of state aid at the school district level.

In steady state then, the overall pattern suggests that K-12 education aid largely acts towards the efficient production of education within the state. Were it aimed at equalization, we might expect that higher spending on state aid would be distributed more progressively. Further, we might expect that states devoting relatively large shares of their budgets to low-income assistance would also be allocating education aid in a more progressive fashion. Neither of these patterns manifest in the data. That said, there is evidence that away from steady state, the K-12 budget is put towards equalizing ends. When a negative income shock hits the state, the low-income assistance budget declines because of lower tax revenues. State governments apparently respond by, holding everything else equal, re-orienting the K-12 budget towards the lowest-income school districts. Similarly, any shock that causes funding for higher education to rise from its steady state level also leads to a more progressive K-12 aid distribution. Out of steady state then, states do apparently turn to state education aid to assist in achieving their equalization priorities.

In our model, we can simulate how these state-level preference differences might imply differing degrees of dynamic inequality among school districts within a state in response to income shocks. Further, we examine how these differences might relate to state-level features such as the average level of income in the state or the prevalence of private universities, which may have some bearing on the interaction of public higher education spending with other items in the state government.

The rest of this paper proceeds as follow. Section 2 describes the data that we use to estimate our preference model, which is specified in Section 3. Then, Section 4 reports the parameter estimates and discusses the steady state implications that the model has for the "average" state. We also illustrate the dynamic ramifications of a business cycle shock to income in the "average" state, employing simulation evidence. Next, we look across states to divine what systematic preference patterns with respect to the role of education spending might exist in the cross-section, before concluding in Section 6.

2 Data

We collect data on school district finances from the Annual Survey of School System Finances, collected by the U.S. Census Bureau, and we apply the same filters as in Biolsi, Craig, Dhar, and Sørensen (forthcoming). Our data cover the years from 1992 to 2019, and draws from the 45 different states that have at least some number of independent school districts, which have some degree of autonomy over local property tax rates, the distribution of funds to the various schools within the district, and other matters.[5] For the purposes of our study, we are most interested in information on state transfers, local revenue, current expenditure, and enrollment, and we ignore aid from the federal government (which tends to be for specialized functions, like free lunch) or any spending on capital. We also drop any especially small school districts. In the final reckoning of the data, we have a balanced panel of 8,512 school districts.[6]

The school district data is merged with information on personal income at both the state

[5] As in Biolsi, Craig, Dhar, and Sørensen (forthcoming), we do not include any school districts in Alaska, Hawaii, the District of Columbia, Maryland, North Carolina, or Virginia, as none of these are denoted in the Census Bureau data as being "independent."

[6] See Biolsi, Craig, Dhar, and Sørensen (forthcoming) for further details on the data, to include summary statistics.

and the county levels, collected from the Bureau of Economic Analysis. The use of income as a measure of economic conditions is motivated in some respects by convenience, since it is available at the level of the county for each year for which we have school district information, but Hoxby (1998) also shows that income levels are a significant predictor of school spending even after controllling for other factors, like property valuations, so we argue that it is the best available measure to use in this analysis.

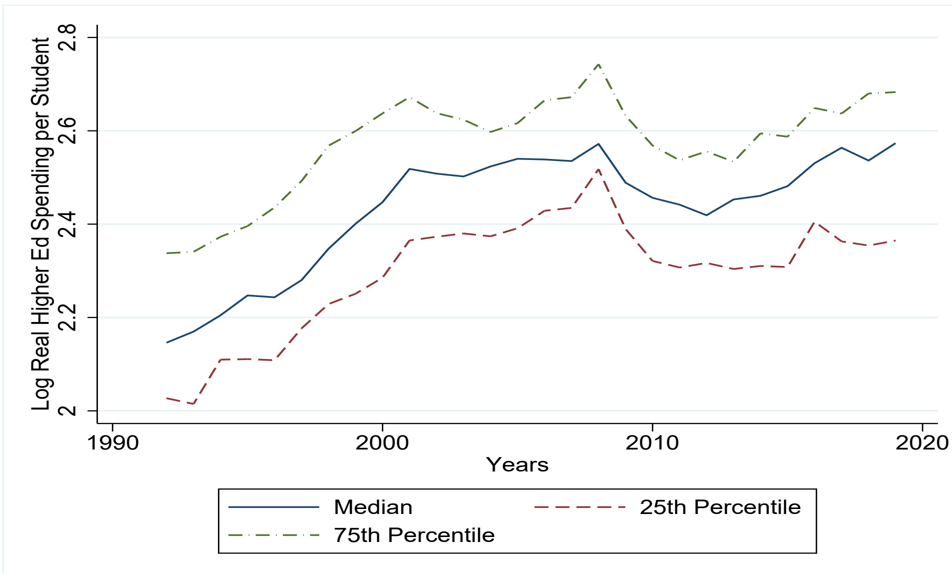
Next, we obtain data on state government spending on higher education, welfare, health, and hospitals for 1992 to 2019 from the Annual Survey of State Government Finances. These variable, in addition to those for school district finances, are deflated using the national GDP deflator. While we consider higher education as its own single spending category, we combine spending on welfare, health, and hospitals into a single item, which we term "Low Income Assistance." Appendix Table A1 contains summary statistics for these two variables.

Finally, we find information on fall semester enrollment at public and private colleges and universities, which comes from the Digest of Education Statistics at the National Center for Education Statistics. Fall semester enrollment lines up better with most states' fiscal years. We use public enrollment as the normalizing variable for state government higher education spending, while private enrollment will serve as an instrument in our system estimation, to be described below.

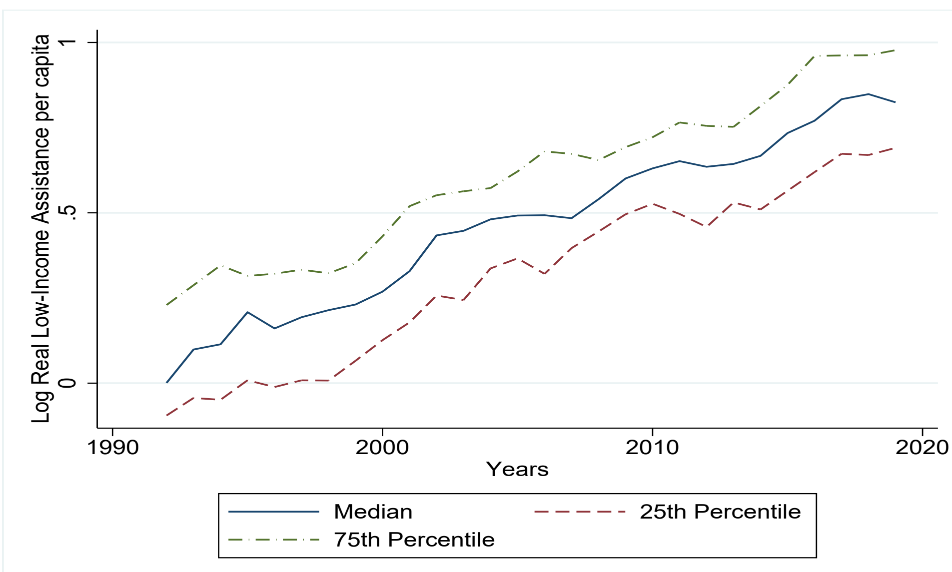
In Figure 1, we depict the evolution over our sample period of both state funding for higher education per college student and low-income assistance per capita. The most salient feature in the time series data is the steep plunge in the level of public funding per college student that took place during the Great Recession. The top panel of Figure 1 shows that this drop occurred across the distribution of states by log real per-student funding. The effects of that recessionary shock are also apparently quite persistent, as spending per student had not generally fully recovered by 2019. The main line of inquiry in this paper is to explore the ramifications this sharp decline might have for other items in the state government budget, and specifically, how states distribute their state amongst their constituent school districts.

The bottom panel of Figure 1 shows that there are also declines in that period of spending on low-income assistance, though they are not quite as sharp or persistent.

Figure 1: Time Series Evolution of State Funding for Higher Education and Low-Income Assistance



(a) Higher Education Spending per College Student



(b) Low-Income Assistance per capita

Notes: This figure shows the time series behavior of the distribution of log real per-college student spending across states and the time series behavior of the distribution of log real per-capita low-income assistance spending.

3 The Preference Model

To aid in our interpretation of the data, we adopt the preference specification framework of Biolsi, Craig, Dhar, and Sørensen (forthcoming) to identify whether and how state government decision makers may dynamically choose allocations of state education aid to school districts, as well as how such choices may interact with choices to fund public higher education or state welfare programs.[7] We assume that the state government maximizes the following objective function:

$$\max_{\{R^S_{d,t}\}^D_{d=1}, HE^S_t, LIA^S_t} \Sigma_d \left(R^L_{d,t}\right)^{(\omega_0+\omega_1 \ln HE^S_t+\omega_2 \ln LIA^S_t)} \frac{1}{1-\eta}\left[\left(\frac{R^S_{d,t}}{R^S_t}\right)/\left(\frac{\widetilde{R^S_{d,t}}}{R^S_t}\right)\right]^{1-\eta} + \frac{1}{1-\gamma}\left(\frac{R^S_t}{\widetilde{R}^S_t}\right)^{1-\gamma}$$
$$+ \frac{1}{1-\nu}\left(\frac{HE^S_t}{\widetilde{HE}^S_t}\right)^{1-\nu} + \frac{1}{1-\psi}\left(\frac{LIA^S_t}{\widetilde{LIA}^S_t}\right)^{1-\psi}$$
$$+ \frac{1}{1-\kappa}(Y^S_t - R^S_t - HE^S_t - LIA_t)^{1-\kappa}, \tag{1}$$

$\log R^S_{d,t}$ is aid from the state government to district d at time t, $\log R^S_t = \sum_{d=1}^D R^S_{d,t}$ is the sum of state aid to all districts, $\log R^L_{d,t}$ is local own revenue in district d, HE^S_t is state government funding for higher education, LIA^S_t is the sum of state funding for low-income assistance such as welfare, health, and hospitals (we simply use the term "welfare" for this category going forward), and the last term captures spending on all other functions, to include private sector spending. All of the choice variables are expressed with respect to a "reference" level (denoted with tildes), that is a linear function in logs of the previous observation of that variable. Formally, we formulate the reference levelfor each of the three state-level spending items in the following ways:

$$\log \widetilde{R}^S_t = \varrho^R + \log R^S_{t-1} \tag{2}$$

$$\log \widetilde{HE}^S_t = \varrho^{HE} + \alpha_1 \log HE^S_{t-1} \tag{3}$$

[7] For the purposes of this section, we define welfare programs as comprising social safety net payments, health care, and hospitals.

$$\log \widetilde{LIA}_t^S = \varrho^{LIA} + \alpha_2 \log LIA_{t-1}^S \ , \tag{4}$$

while that for the shares of total state aid sent to school districts is similarly written as:

$$\frac{\widetilde{R_{d,t}^S}}{R_t^S} = \varrho^{R_d} + \log \frac{R_{d,t-1}^S}{R_{t-1}^S} \tag{5}$$

These reference-level expressions parsimoniously capture a form of habit formation that appears to be empirically important, given the persistent dynamics observed in the data. For habits relating to K-12 finance (Equations 2 and 5), we follow Biolsi, Craig, Dhar, and Sørensen (forthcoming) in assuming a coefficient of unity on the lagged terms, but we allow that coefficient in Equation 3 and 4 to potentially differ from unity. This is without loss of generality as it does not alter the reduced-form dynamics that we study, but it does aid us in the interpretation of the ν and ψ parameters. The parameters η, γ, ν, ψ, and κ all measure the willingness of the state government to change funding on various spending items over time. A higher value of any of these parameters means that changes in their respective spending item are more persistent.

Finally, the weight on local revenue raised in district d is weighted by the term $\omega_0 + \omega_1 \ln HE_t^S + \omega_2 \ln LIA_t^S$. ω_1 is the baseline "unequal caring" parameter (using the terminology in Behrman and Craig, 1987) that describes the extent to which state government education committees wish to provide more aid to lower-income school districts. We allow this unequal caring to be influenced by spending on higher education and welfare. That is, for $\omega_1 < 0$, the implication is that states spending more than their state-specific average (which we will interpret as their steady state) on higher education also have a more unequal distribution of state aid (which leads to a more equal distribution of spending per student). On the other hand, $\omega_1 > 0$ gives a less unequal distribution of state aid and a more unequal spending distribution. There is an analogous interpretation for ω_2 with respect to welfare spending.

At the local level, the various school districts within the state optimize:

$$\max_{R^L_{d,t}} (R^S_{d,t})^{\phi} \frac{1}{1-\xi} (\frac{R^L_{d,t}}{\tilde{R}^L_{d,t}})^{1-\xi} + \frac{1}{1-\theta} (Y^L_{d,t} - R^L_{d,t})^{1-\theta} \ , \tag{6}$$

which we take directly from Biolsi, Craig, Dhar, and Sørensen (forthcoming) without modification.

In solving the model, we assume that the state government decides first how much to spend on state education aid in total, higher education, and welfare. Then, taking these items as given, state education finance committees turn to the allocation of aid to the various independent school districts in the state. We assume that the state is myopic with respect to how these choices affect future preferences (so that they are not internalizing their own habit formation when choosing how much to spend on any of the programs), and, importantly, that they are also myopic with respect to how their top-level decisions on higher education and low-income assistance influence the preferences with respect to the distribution of state aid over school districts. Taking first-order conditions, incorporating the specification of the reference value of the relevant variables, taking logs, replacing constant terms with state and year fixed effects, and rearranging delivers the following estimating equations:

$$\ln R^S_t = \delta_{s,1} + \delta_{t,1} + \frac{\gamma - 1}{\gamma} \ln R^S_{t-1} + \frac{\kappa}{\gamma} \ln(Y^S_t - R^S_t - \alpha_1 HE^S_t - \alpha_2 LIA^S_t) + \varepsilon_{1,s,t} \tag{7}$$

$$\ln HE^S_t = \delta_{s,2} + \delta_{t,2} + \frac{\nu - 1}{\nu} \alpha_1 \ln HE^S_{t-1} + \frac{\kappa}{\nu} \ln(Y^S_t - R^S_t - HE^S_t - LIA^S_t) + \varepsilon_{2,s,t} \tag{8}$$

$$\ln LIA^S_t = \delta_{s,3} + \delta_{t,3} + \frac{\psi - 1}{\psi} \alpha_2 \ln LIA^S_{t-1} + \frac{\kappa}{\psi} \ln(Y^S_t - R^S_t - HE^S_t - LIA^S_t) + \varepsilon_{3,s,t} \tag{9}$$

As far as estimating this system, there is a complication in that the three dependent variables all appear on the right-hand side of each equation (within the budget constraint), generating mechanical correlation with the error term in each estimating equation. We instrument for the budget constraint variable with the log of real state income per capita (specifically its contemporaneous value and four lags). We also include the log of private university enrollment as an instrument for log state public education financing per student. The equations are estimated simultaneously using three-stage least squares (3SLS).

At the local district level, our estimating equations are:

$$\begin{aligned} \log R^S_{d,t} = \delta_{s,t} + \frac{\omega_0}{\eta} \log R^L_{d,t} + \frac{\omega_1}{\eta} (\log HE_t \times \log R^L_{d,t}) \\ + \frac{\omega_2}{\eta} (\log LIA_t \times \log R^L_{d,t}) + \frac{\eta - 1}{\eta} \log R^S_{d,t-1} + \varepsilon_{4,d,t} \ . \end{aligned} \tag{10}$$

$$\log R^L_{d,t} = \delta_s + \delta_t + \frac{\xi - 1}{\xi} \log R^L_{d,t-1} + \frac{\phi}{\xi} \log R^S_{d,t} + \frac{\theta}{\xi} \log(Y^L_{d,t} - R^L_{d,t}) + \varepsilon_{5,d,t} \ . \tag{11}$$

The interaction terms are expressed in deviations from their unit-specific means (states for HE^S_t and LIA^S_t, districts for $R^L_{d,t}$), which is consistent with the recommendations in Balli and Sørensen (2013). For each of these, we use the contemporaneous value and four lags each of the log of real state income per capita and the log of real county income per capita as instruments.

4 Parameter Estimates and Steady State Implications

The results of estimating the preference system are presented in Table 1.[8] We report the parameter estimates from the 3SLS specification with delta method standard errors clustered at state or school district level, depending on which equation estimates each parameter.

The values for κ and γ are quite similar to those reported in Biolsi, Craig, Dhar, and Sørensen (forthcoming). Of interest are the values found for ν and ψ, which are quite close in magnitude, implying coefficients of relative risk aversion in the range of 10.6 to 10.9. States appear to exhibit a much weaker willingness to allow intertemporal spending fluctuations on higher education or welfare relative to K-12 education aid or other (including "private")

[8] Biolsi, Craig, Dhar, and Sørensen (forthcoming) demonstrate that the results are quite robust to different specifications of the empirical model, such as using district income or county house prices instead of county income, or to using different instrumental variable techniques. To avoid duplication of the work in that paper, we omit such analysis here.

Table 1: Objective Function Parameter Estimates

γ	3.88^{***}	ω_0	-0.52^{***}
	(0.77)		(0.04)
κ	1.66^{***}	ω_1	-2.90^{***}
	(0.24)		(1.11)
ν	10.66^{**}	ω_2	1.30^{***}
	(4.42)		(0.32)
ψ	10.88^{*}	ξ	5.53^{***}
	(5.69)		(0.55)
α_1	0.61^{***}	θ	0.91^{***}
	(0.19)		(0.03)
α_2	0.61^{*}	ϕ	-0.39^{***}
	(0.31)		(0.03)
η	5.68^{***}		
	(0.34)		

Notes: The table contains parameter estimates derived from estimation of $\ln R_t^S = \delta_{s,1} + \delta_{t,1} + \frac{\gamma-1}{\gamma} \ln R_{t-1}^S + \frac{\kappa}{\gamma} \ln(Y_t^S - R_t^S - \alpha_1 HE_t^S - \alpha_2 LIA_t^S) + \varepsilon_{1,s,t}$, $\ln HE_t^S = \delta_{s,2} + \delta_{t,2} + \frac{\nu-1}{\nu} \ln HE_{t-1}^S + \frac{\alpha_1\kappa}{\nu} \ln(Y_t^S - R_t^S - \alpha_1 HE_t^S - \alpha_2 LIA_t^S) + \varepsilon_{2,s,t}$, $\ln LIA_t^S = \delta_{s,3} + \delta_{t,3} + \frac{\psi-1}{\psi} \ln LIA_{t-1}^S + \frac{\alpha_2\kappa}{\psi} \ln(Y_t^S - R_t^S - \alpha_1 HE_t^S - \alpha_2 LIA_t^S) + \varepsilon_{3,s,t}$, $\log R_{d,t}^S = \delta_{s,t} + \frac{\omega_0}{\eta} \log R_{d,t}^L + \frac{\omega_1}{\eta} (\log HE_t \times \log R_{d,t}^L) + \frac{\omega_2}{\eta} (\log LIA_t \times \log R_{d,t}^L) + \frac{\eta-1}{\eta} \log R_{d,t-1}^S + \varepsilon_{4,d,t}$, and $\log R_{d,t}^L = \delta_s + \delta_t + \frac{\xi-1}{\xi} \log R_{d,t-1}^L + \frac{\phi}{\xi} \log R_{d,t}^S + \frac{\theta}{\xi} \log(Y_{d,t}^L - R_{d,t}^L) + \varepsilon_{5,d,t}$. R_t^S represents state aid to school districts per student at time t, Y_t^S represents state income per person at time t, HE_t^S represents higher education funding from the state per college student, LIA_t^S represents per-person low-income assistance, $R_{d,t}^S$ is state aid per student to district d, and $R_{d,t}^L$ is per-student revenue raised locally in district d. In the cases of the three-stage least squares estimation, we use as excluded instruments the lagged values of log per-capita state income (as well as the contemporaneous value, in the first column) and the log of private university enrollment. We compute standard errors for the parameters via the delta method, reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively.

uses.

Considering the allocation of state aid across independent school districts, we see that the baseline value for ω_0 is -0.52, which illustrates the fact that state governments shift more aid to school districts with lower revenue-raising capacity of their own, speaking to the now familiar desire to equalize spending per student across school districts. What may be of greater interest are the values found for ω_1 and ω_2. An $\omega_1 = -2.90$, as reported in Table 1, suggests that when states spend more than is usual on higher education, this leads to a more negative weight on local district revenue when allocating state education aid. For example, spending 1 percent more on higher education than normal reduces ω from its mean value of -0.52 to nearly -0.55. This means that, holding total state aid constant, a state spending more on higher education will shift more of the resources available to K-12 aid to poorer districts, making the overall aid distribution steeper with respect to local income. If one thinks of the marginal dollar spent on higher education as being done so efficiently, then states are more concerned with equity for younger students.

The opposite is the case for welfare spending. An extra 1 percent spent on welfare relative to the state-specific mean reduces the weight on local revenue in the allocation function by 0.013 (increasing the baseline ω from -0.52 to -0.507). Thus, welfare spending serves as a substitute for state education aid as far as a state government's equalization motives are concerned. Rather than spending on poor places, the state spends more on poor people.

The local objective function parameters, ξ, θ, and ϕ, are all roughly in the same range as found in Biolsi, Craig, Dhar, and Sørensen (forthcoming), and we do not discuss them further here. In this paper, their main function is to describe the endogenous reactions of school districts to state aid, which we need for our simulation exercises in Section 4.1.

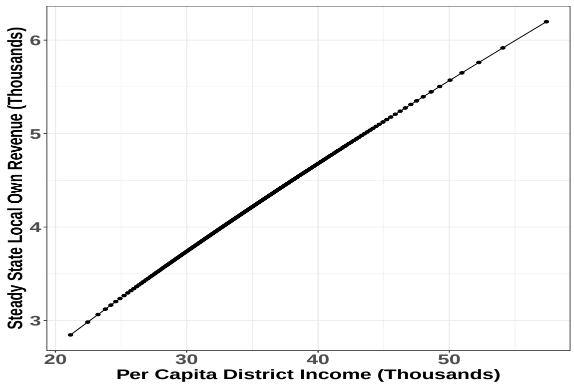
4.1 Dynamic Ramifications of the Estimated Preferences

Our next task is to illustrate how the model's main mechanisms operate in response to a business cycle shock. Doing so for the "average" state's parameters may be helpful when we study cross-state heterogeneity, giving a sense of the dynamic implications of the parameter values. For this exercise, we follow the simulation approach adopted in Biolsi, Craig, Dhar, and Sørensen (forthcoming), in which we simulate the model to assess the implications of the estimated preferences for spending on higher education, as well as for the total amount of state aid doled out and its distribution across a heterogeneous set of school districts. Our hypothetical state comprises 200 school districts (approximately the average in the data), and their steady state income distribution is assumed to be log normal with mean and standard deviation matching the average across state-year cells in our dataset. Specifically, we assume that log mean per capita income in a school district d is distributed $N(3.55, 0.18)$. We assume that there is one K-12 student and one college student per school district. K-12 students attend a school in their school district, while all college students attend the one state university. Given the income distribution, we solve for steady state outcomes at the state level (total state aid R_t^S, higher education funding HE_t^S, and low-income assistance spending LIA_t^S). Conditional on total state aid and the income distribution, we then solve the static game played by the state and each of the 200 school districts that determines state aid and local revenue (and thus total spending, since we abstract from federal aid). The steady state distributions are found in Figure 2. For the purposes of this study, we note that local revenue per student relates strongly positively with local per-person income, and state aid per student has a negative correlation with income. When summed together, we find that spending per student rises sharply with local income. Biolsi, Craig, Dhar, and Sørensen (forthcoming) demonstrate that these patterns closely match what is observed in the data.

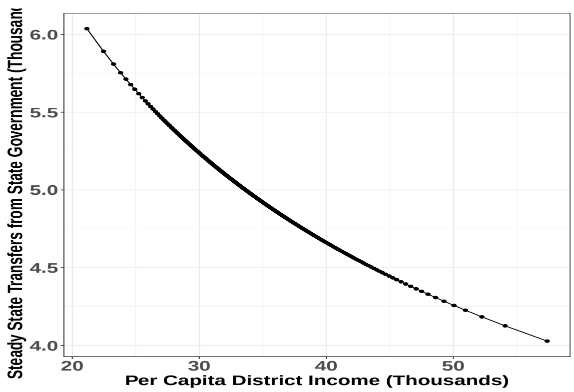
With the steady state allocations in hand, we then turn to our quantitative experiment. Specifically, we shock the state with a loss of per-capita income equal to 4.4 percent of steady state income.[9] Each district within the state experiences the same 4.4 percent per-capita income reduction. Figure 3 illustrates the responses of the main state-level variables of interest to this shock.

[9] This is the average per-capita income loss across the states in our sample during the 2007-2009 financial crisis.

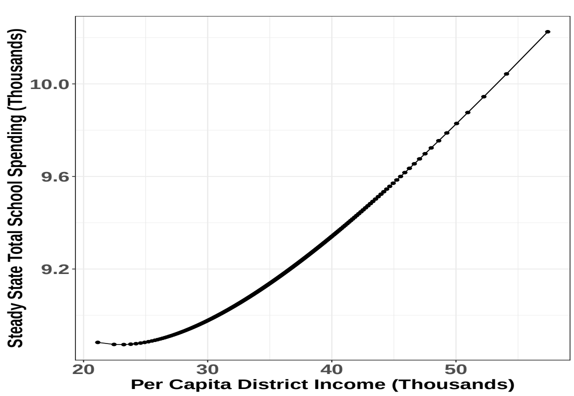
Figure 2: Model-Implied Steady State Distributions



(a) LocalRevenue per Student



(b) State Aid per Student



(c) School Spending per Student

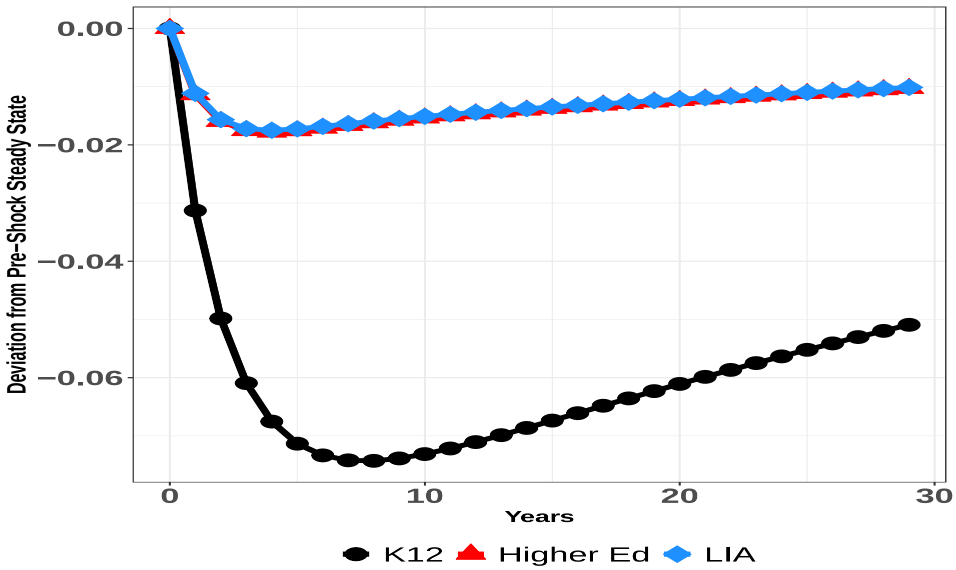
Notes: The figure shows the steady state distribution implied by the theoretical model for local revenue, state aid, and school spending (all in per student terms), conditional on an income distribution with mean and standard deviation taken from the pooled data. Model parameters are based on the estimated preferences using the pooled sample, reported in Table 1.

Following the shock, the state government reduces total state aid to be distributed to all school districts sharply and to an economically meaningful degree. At the trough of the response, total state aid has fallen by more than 7 percent eight years after impact. State aid then begins to rise back to its steady state value, but only at a very gradual pace. Higher education spending and spending on welfare also fall and by similar amounts to each other. In the case of higher education spending, the decline is quite similar to what we observe in the data around the time of the Great Recession, if not quite as dramatic. It appears that low-income assistance falls more than in the data, although it is important to keep in mind that, as part of the American Recovery and Reinvestment Act, there were substantial transfers to state governments from the federal government for these kinds of items (in particular, Medicaid; see Chodorow-Reich, Feiveson, Liscow, and Woolston, 2012). They trough earlier than state aid, but they also only return to their steady state values very slowly. These dynamics are a consequence of the strong desire to smooth expenditures on these programs, encapsulated by the very high degrees of relative risk aversion (above 10).

Next, we analyze the effects of state-level shocks on education finance variables at the level of school districts, as well as how these effects are influenced by the estimated interactions with higher education and low-income assistance spending. We start with a high-level examination of the distribution of state aid. Figure 4 illustrates how the distribution changes over the years that follow the state-level income shock.[10] Slowly, but surely, in the years following the shock, the shape of the distribution becomes flatter, "tilting" (so to speak) on its axis in favor of higher-income districts and against lower-income districts. This tilting distribution of aid relates to the sharp decline in spending on higher education, because, given the magnitudes of ω_1 and ω_2, the interaction with higher education influences the state aid distribution to a greater degree than does that interaction with low-income assistance.

[10] We note that the actual state aid distribution shifts downward as a whole following the shock, but in these figures, we re-center the distribution to call attention to the changing gradient of the distribution with respect to steady-state local income.

Figure 3: Impulse Responses of State-Level Variables to State Income Shock

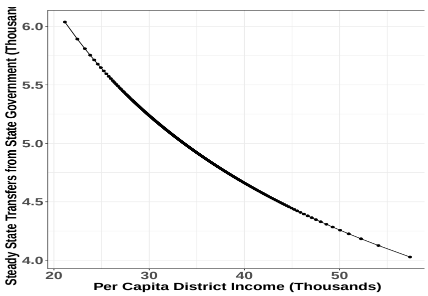


Notes: The figure shows the impulse responses of total state aid to all school districts, higher education spending, and spending on welfare, health, and hospitals with respect to a negative shock to state income equal to 4.4 percent of steady state income.

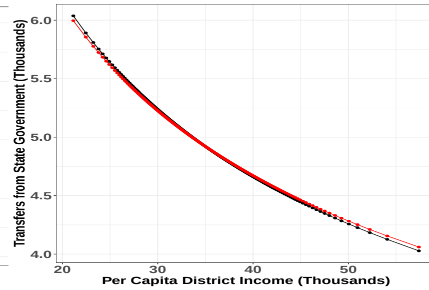
We noted in Table 1 that the weight on aid to school districts becomes more negative when more funds are put towards higher education. This means that greater spending on higher education associates with a more progressive distribution of K-12 aid. After a state-wide income shock, spending on all items, including higher education, falls. This fall in higher education funding helps make the weight that state governments place on local district income in their state aid objective function less negative, so that the overall state aid distribution tilts less in favor of low-income districts. Of course, this effect is mitigated by the simultaneous decline in spending on low-income assistance, which has an offsetting (if quantitatively smaller) effect on the distribution of state aid.

The left-hand panel of Figure 5 offers a different perspective on the changing distribution of state aid. The black line with circles reports the impulse response of the within-year standard deviation of state aid to the school districts. In our benchmark model, the standard deviation of state aid declines on impact and continues to fall for several years after the initial

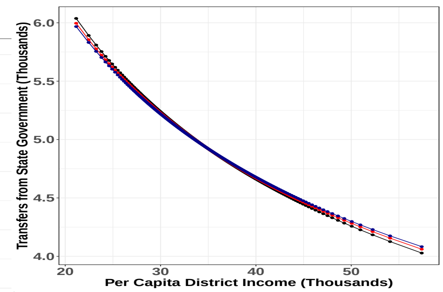
Figure 4: Changing Distribution of State Aid Following State Income Shock



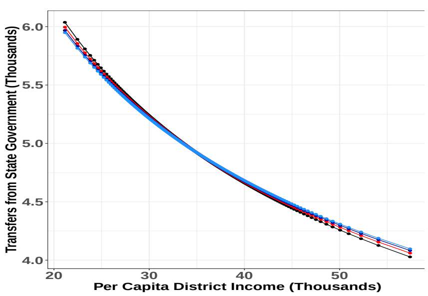
(a) Steady State Distribution of State Aid to School Districts



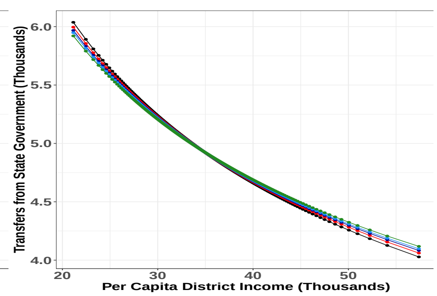
(b) Distribution of State Aid in Year of Income Shock



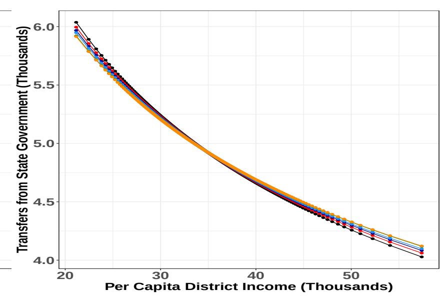
(c) Distribution of State Aid One Year After Income Shock



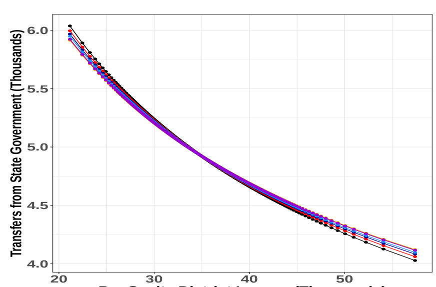
(d) Distribution of State Aid Two Years After Income Shock



(e) Distribution of State Aid Five Years After Income Shock



(f) Distribution of State Aid Ten Years After Income Shock

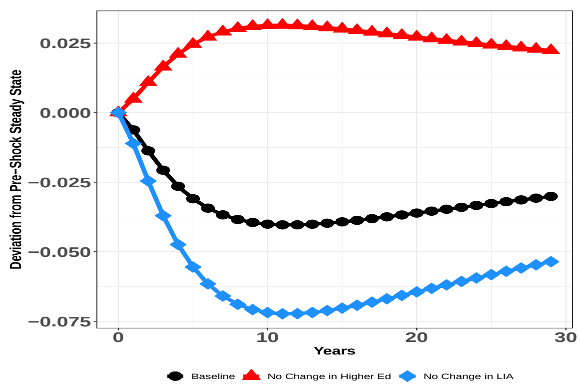


(g) Distribution of State Aid Fifteen Years After Income Shock

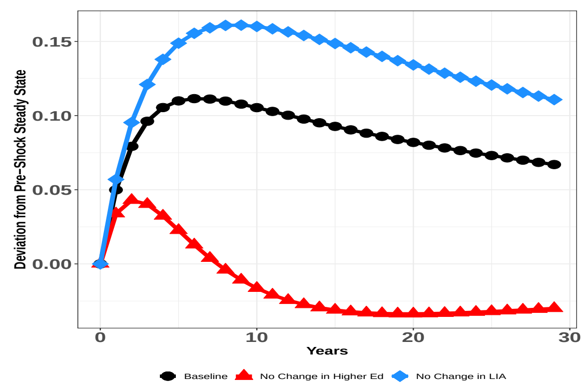
Notes: The figure shows the evolution of the distribution of state aid to school districts as it relates to each district's steady state per-capita income in the years following a state-wide income shock. The first panel (in the top left) shows the steady state distribution of state aid, and each panel shows how the distribution changes as the stated number of years pass. For years following the income shock, the actual distribution of state aid shifts downward as a whole, but we re-center the distribution so as to highlight the change in the slope of the distribution.

income shock. At the trough, the standard deviation has fallen by around 4 percent of the standard deviation in steady state. Keep in mind that a more unequal distribution of aid implies a more equal distribution of current expenditure per student (because state aid tends to favor low-income districts, partly offsetting their inability to raise funds locally). Therefore, the reduced standard deviation following the shock helps contribute to a less equal distribution of spending on students.

Figure 5: Impulse Responses of Aid and Spending Distributions to State Income Shock



(a) Response of State Aid Standard Deviation



(b) Response of Spending Standard Deviation

Notes: The figure shows the impulse responses of the standard deviations of state aid and current expenditure across all school districts with respect to a negative shock to state income equal to 4.4 percent of steady state income. The units on the y-axis are percent deviations relative to the steady-state standard deviation. The black line with circles depicts the response for our baseline model. The red line with triangles depicts the response when we shut down the influence of higher education spending on the state aid distribution.

On the right-hand side, we can observe what the implications are for the distribution of per-student current expenditure. The baseline estimates are represented by the black lines. Following the income shock, the variation in per-student spending increases by more than 11 percent of its steady state value, meaning an even more unequal allocation of spending in favor of high-income students relative to low-income students, compared with the already substantial inequities observed in steady state.

In Figure 5, we also show specifically how the dynamic influence of higher education spending and low-income assistance spending manifest in the distribution of aid and current

K-12 education expenditures. We can do this by "shutting down" the effect of either higher education or low-income assistance funding on the weight on local revenue in the objective function (i.e., setting ω_1 or ω_2 to zero), and the impulse responses for such an exercise are depicted in the red lines with triangles (when higher education declines are shut down) or in the blue lines with diamonds (when welfare declines are eliminated). In these counterfactual scenarios, we get very different results. For the case of shutting down the influence of higher education spending, the standard deviation of the state aid distribution actually rises (by over 3 percent of its steady state value), and that of spending falls, albeit with a lag, bya little over 3 percent. The reason for these dynamics is that, while we have shut down the interaction with higher education funding, we have maintained the interaction with spending on low-income assistance. If, however, the influence of low-income assistance funding is shut down while maintaining that of higher education funding, the the state aid standard deviation drops by over 7 percent, leading to an increase in the standard deviation of K-12 expenditures across school districts of around 16 percent.

The intuition is as follows. Greater spending on state colleges and universities will associate with a steeper tilt of the state aid distribution towards lower-income districts. This might make for a more complete risk-sharing mechanism with respect to idiosyncratic local shocks, of the kind discussed in Biolsi, Craig, Dhar, and Sørensen (forthcoming). This does, however, enhance the vulnerability of low-income districts to aggregate shocks, which cannot be insured against. State-wide shocks lead to an overall decline in the state aid budget, and the simultaneous drop in spending on higher education generates a less progresssive tilt of the distribution of state aid to school districts. Shutting down this state aid influence, however, would have the opposite effect on the distributional consequences at least. Declining funding for low-income assistance may induce state policy-makers to alter their state aid formulas. The intuition could be that, being less able to provide state transfers to low-income *people* via welfare programs, the state may instead push more of the remaining state aid budget to low-income *places*.

Combined, these results suggest that education finance does serve two purposes: one aimed at an "efficient" educational motive and one aimed at an "equalizing" motive. If one assumes that higher education (which tends to benefit individuals that are, at least in expectation, to be in the higher parts of the income distribution) is focused solely on efficient provision of academics, then its decline may induce states to replace it by shifting more of the scarce K-12 budget towards students in high-income areas who might otherwise have been expected to benefit from higher education spending.[11] Alternatively, losing the ability to fund low-income assistance programs may compel states to compenstate by shifting the state aid budget further towards low-income districts where there is a greater concentration of children who would otherwise have been beneficiaries of those programs. In this sense, K-12 education serves as an equalizing program, at least in those circumstances when other equalization programs are constrained.

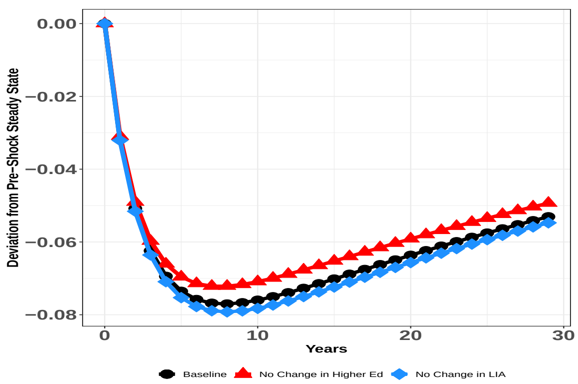
In a sense, away from steady state one might view state aid for K-12 education as a sort of compromise tool. When the higher education budget declines from its steady state, education-minded policy makers might be mollified by having more of the state aid budget devoted to higher-income districts, which produce more college students. If the welfare budget declines, the K-12 budget tilts more towards low-income districts where beneficiaries of low-income assistance programs are more likely to live.

Next, to be a little more concrete, we zoom in to examine the responses for two specific school districts, namely a "poor" school district (with per-capita income at the 15^{th} percentile of the state income distribution) and a "rich" school district (the 85^{th} percentile of the distribution). Figure 6 contains the impulse responses of log state aid per student and log total spending per student for each one. In each figure, we report three impulse responses. The first is for the benchmark model (black lines with filled circles). The second response shuts down the interaction between higher education spending and state aid

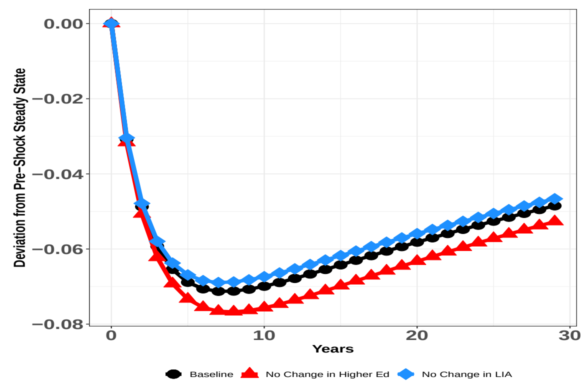
[11]Given the persistent effects of income shocks, students in grades K-12 in the year of the shock may still experience lower funding for colleges and universities relative to the case of no shocks at the time that they finally enroll.

allocation decisions (red lines with filled triangles), and the third shuts down the interaction between low-income assistance funding and the state aid allocation (blue lines with filled diamonds).

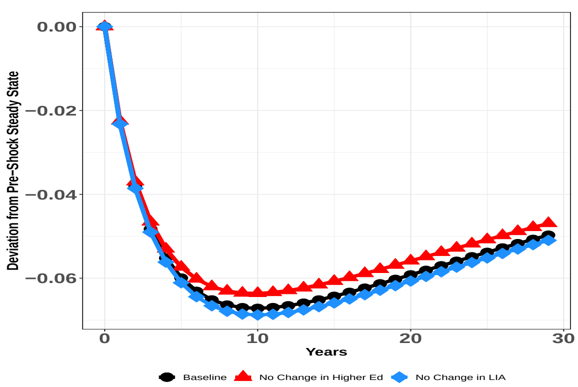
Figure 6: Impulse Responses of Local-Level Variables to State Income Shock



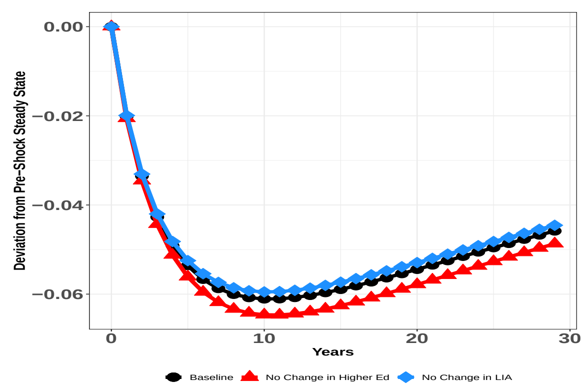
(a) Response of State Aid to Poor District



(b) Response of State Aid to Rich District



(c) Response of School Spending in Poor District



(d) Response of School Spending in Rich District

Notes: The figure shows the impulse responses of state aid per student (top row) and school spending per student (bottom row) in a poor school district (left column) and a rich school district (right column), with respect to a state-level income shock of 4.4 percent of steady state income.

Our first observation is that, in the benchmark model where state aid allocations interact with both higher education and spending on low-income assistance, state aid to a poor district falls by almost 8 percent at the trough following the state-level shock, whereas it falls by just over 7 percent for a rich district. This is especially challenging for the poor district, since it depends more on state aid than does the rich district, so spending per student declines more there than in the rich district, as can be seen in the bottom row of the figure. This is the same sort of dynamic that was analyzed in Biolsi, Craig, Dhar, and Sørensen (forthcoming). Perhaps the more interesting finding in these figures, however, is how the dependence on allocations to higher education and low-income assistance affects the rich and the poor district differentially. If we shut down the higher education influence, state aid to the poor districts falls by less and aid to the rich district falls by more, consistent with the notion that the decline in higher education spending generates a less progressive state aid distribution. The opposite occurs if we shut down the interaction with welfare spending. Again, these opposing effects speak to the notion that K-12 aid incorporates both an efficiency-minded and, outside of steadys tate, an equalizing motive. The responses of spending per student reflect these state aid differences. Spending in the low-income district falls by more when the weight the state government places on local income is allowed to be influenced by funds sent to universities and colleges than when this mechanism is shut off. The opposite is true in the case of the high-income district.

We further quantify the influence of the higher education and welfare effects on spending for K-12 students, in Table 2. We group each of the simulated school districts in the state into quintiles according to their steady state income. For each quintile, we report the average per-student K-12 spending change induced by the aggregate shock on impact and ten years later. Clearly, there is a negative relationship between steady state income and the magnitude of the spending loss, similar to that observed in Jackson, Wigger, and Xiong (2018). This owes to the fact that poor districts are more dependent on state aid to maintain their education budgets, and thus are more sensitive to any aggregate factor that puts downward pressure on state government spending. More interesting for our purposes is that a little less than three percent of the overall decline on impact and seven percent of the decline ten years later is explained by the dependence of the state aid distribution on higher education spending. In other words, if not for the relationship between higher education funding and the distribution of state aid, spending in the poorest fifth of districts would be seven percent (or about $36) higher per student ten years after the statewide shock.

In contrast to these effects in the poorest districts, we note that school districts at the higher end of the income distribution see their declines in state aid mitigated by the relationship with higher education funding. For the top quintile, the spending decline is a little less than three percent smaller than it otherwise would be at the time of the shock and over seven percent smaller ten years later. This makes explicit the notion that, in the face of negative aggregate shocks, the relationship between the state aid distribution and spending on colleges and universities dampens the progressivity of K-12 funding programs.

Finally, we note that the influence of welfare spending works in an opposite fashion. The decline in funding for low-income assistance tends to make the state aid distribution more progressive, which partially offsets the effects of higher education spending declines. Ten years after the aggregate income shock, this mitigates overall spending declines in the lowest-income districts (sparing them an amount equivalent to about three percent of the total drop), but it adds about 3.2 percent to the spending drop in the highest-income districts.

Table 2: Average Share of Spending Decline Explained by Higher Ed Decline and by LIA Decline

	Impact Spending Change	Higher Ed %	LIA %	10-year Spending Change	Higher Ed %	LIA %
Poorest Quintile	$156.35	2.8%	−1.2%	$515.16	7.0%	−3.0%
Quintile 2	$151.34	0.9%	−0.4%	$503.59	2.4%	−1.0%
Quintile 3	$148.89	−0.1%	0.1%	$499.24	−0.4%	0.1%
Quintile 4	$146.89	−1.2%	0.5%	$496.82	−3.1%	1.3%
Richest Quintile	$144.75	−2.8%	1.2%	$497.59	−7.3%	3.2%

Notes: This tables reports, for each quintile of districts based on steady state income, the average decline in spending per student on impact and ten years after an aggregate income shock equivalent to 4.4 percent of steady state income. It also reports how much of the simulated spending decline is explained by the dependence of the cross-district distribution of state aid on total spending on higher education on impact and at the 10-year horizons.

5 Cross-State Heterogeneity

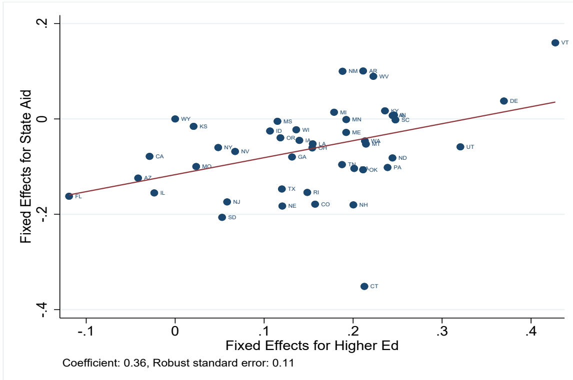
Our next task is to assess how states' preferences over total quantities of state aid, spending on higher education, and low-income assistance expenditures correlate in the cross-section. To do this, we start by collecting the state fixed effects for each budget item from our system estimation of Equations 7, 8, and 9, namely the sets of $\{\delta_{s,1}\}$, $\{\delta_{s,2}\}$, and $\{\delta_{s,3}\}$. This is similar to the approach undertaken in Craig and Palumbo (1999) in their analysis of state spending on unemployment insurance, Medicaid, and welfare (specifically Aid for Families with Dependent Children).[12] The three panels of Figure 7 depict scatter plots of each of the three sets of fixed effects against one of the other sets.

What is immediately apparent from examination of each panel in Figure 7 is that there are strong positive correlations between each pair of fixed effects. States that tend over time to spend more on grants for K-12 education aid also tend to spend more on higher education. The estimated coefficient in a regression of the former on the latter is 0.36 and the heteroskedasticity-robust standard error is 0.11, implying strong degrees of statistical significance. This is consistent with the notion that K-12 spending coincides with tastes for education. Similarly, when regressing state fixed effects for K-12 aid on state fixed effects for low-income assistance, the coefficient is a statistically significant 0.37, and regressing state fixed effects for higher education on those for low-income assistance, we find a coefficient of 0.32 and a robust standard error of 0.16. Clearly, states that spend more on K-12 aid also spend more on both higher education and low-income assistance.

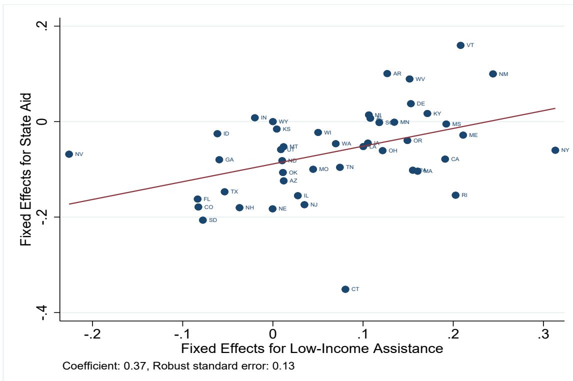
It may be the case that there are some states that are simply more willing to put government funds toward all manner of programs, or, instead, this outcome could be the result of some kind of bargaining among policy makers with different tastes. For example, education-minded policy makers may have to "pay" for greater education funding by appeasing the desires of equity-minded policy makers eager to boost assistance for state residents at the lower ends of the income distribution. We next consider how these estimated state fixed

[12]See also Plotnick (1986) and Moffitt (1990).

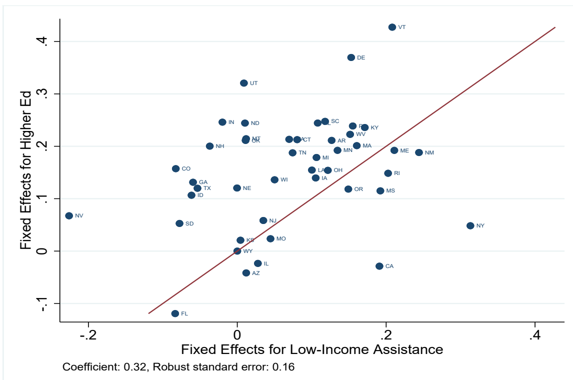
Figure 7: State Fixed Effects from 3SLS Estimation



(a) Fixed Effects for State Aid vs. Higher Ed



(b) Fixed Effects for State Aid vs. LIA



(c) Fixed Effects for Higher Ed vs. LIA

Notes: Each panel plots the correlation of state-level fixed effects estimated for one of total state aid for K-12 from Equation 7, higher education from Equation 8 or low-income assistance from Equation 9 against one of the other two sets. We also draw the linear regression line for each pair and report the coefficient and heteroskedasticity-robust standard error.

effects compare with measures of progressivity of K-12 education aid, which may shed light on this question.

5.1 Cross-State Spending Levels vs. Within-State Distributions

In order to draw firmer conclusions on what drives state spending decisions on K-12 education, we note that the estimated parameter ω_0 from Equation 10 represents a state-level measure of the progressivity of education aid in steady state (when both higher education funding and low-income assistance funding are at their state-specific long-run averages). Recall that a more negative value of ω_0 implies a more progressive aid distribution, as aid falls more sharply with locally-raised revenue. While we have reported estimates for a specification that included all of the states and school districts in our sample, we next estimate the preference framework state-by-state, in order to obtain values of ω_0 for each state. We can compare these state-specific ω_0 values with the set of state fixed effects derived from the the 3SLS estimation.

Table 3: Regression Results for State Aid Fixed Effects

Parameter	OLS	Robust Regression	Weighted	Weighted ex. OK & VT
ω_0	0.02^{***}	0.02^{***}	0.11^{***}	0.12^{***}
	(< 0.01)	(0.01)	(0.03)	(0.03)
ω_1	0.00^{***}	0.00^{**}	-0.00	-0.00
	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
ω_2	-0.00	-0.00	-0.00	-0.00
	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)

Notes: The table reports the results of cross-sectional regressions of $\delta_{s,1} = a_1 + a_2\omega_{s,i} + e_s$, with $i = 0, 1, 2$, or state fixed effects for total state K-12 education aid on state-specific estimates of the progressivity of the distribution of K-12 aid. The first column presents the results from a simple ordinary least squares regression. The second column presents results from so-called "robust regression, " discussed in Li (1985), which is meant to reduce the influence of outliers. The third column weights observations by the inverse of the standard error of the estimate of $\omega_{s,i}$ for each state, and the fourth is a weighted regression that drops outlier observations Oklahoma and Vermont. Heteroskedasticity-robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively.

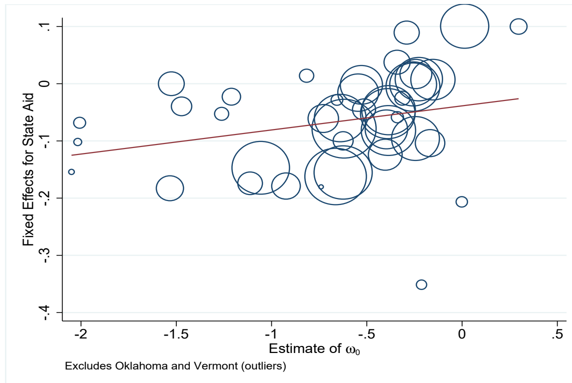
Table 3 offers the results of regressions of the state fixed effects for K-12 education aid against the state-specific estimates of ω_0, as well as those of ω_1 and ω_2[13]. We report results from four specifications. The first is a simple cross-sectional ordinary least squares regression of the state fixed effects from the K-12 regression in Equation 7 against the state-specific estimate of ω_0. The second is a robust regression (see Li, 1985), which is intended to reduce the influence of outlier observations. Third, we consider a weighted regression, where each observation is weighted by the inverse of the standard error of the state-specific ω_0 estimate. The top panel of Figure 8 visually illustrates this weighted regression. The weighted specification is important to consider, because smaller states will have fewer school districts than larger states, and they will thus have noisier preference parameter estimates. Finally, we consider a weighted regression that drops extreme outlier observations Oklahoma and Vermont. Qualitatively, our results are similar across all of these specifications.

Specifically, we find that there is a significant positive correlation between fixed effects for K-12 aid and estimates of ω_0. This means that states spending larger quantities on K-12 aid also have higher values of ω_0, meaning a less progressive distribution of that aid among school districts. Thus, where education-minded policy makers push their arguments most successfully, they have less regard as to the equity dimension for that aid. Such results would indicate that higher K-12 spending by one state relative to another reflects a taste for education production (as opposed to an equalization motive). There is no robust significant relationship between the fixed effect for K-12 spending and the dynamic interaction terms.

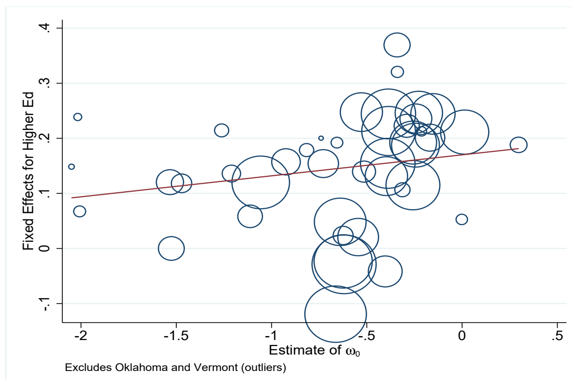
Table 4 offers analogous results for fixed effects for higher education, with the weighted specification depicted in the middle panel of Figure 8. Unsurprisingly, given the strong correlation between fixed effects for total K-12 aid and those for higher education, the results are quite similar. Those states that spend more on higher education on average over time also tend to have less progressive distributions of K-12 aid. Again, where policy makers manage to secure greater funding for education, they are not going to great pains to distribute K-

[13] ω_1 and ω_2 do not correlate significantly with any of the fixed effects, implying that, outside of steady state, the state governments in our sample generally all behave fairly similarly.

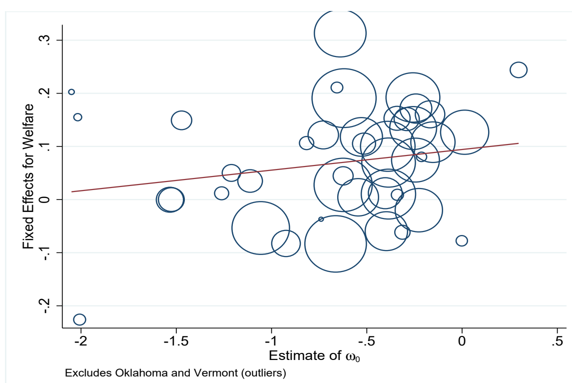
Figure 8: State Fixed Effects from 3SLS Estimation



(a) Fixed Effects for State Aid vs. State-Specific ω_0



(b) Fixed Effects for Higher Ed vs. State-Specific ω_0



(c) Fixed Effects for LIA vs. State-Specific ω_0

Notes: Each panel in the figure plots the correlation of a set of state fixed effects (K-12 education aid in the top panel, higher education in the middle panel, and low-income assistance in the bottom panel) with the state-specific estimates of ω_0 from Equation 10. Larger markers indicate more precise estimates of ω_0 parameters (lower standard errors).

Table 4: Regression Results for Higher Ed Fixed Effects

Parameter	OLS	Robust Regression	Weighted	Weighted ex. OK & VT
ω_0	0.03^{***}	0.03^{***}	0.13^{***}	0.14^{***}
	(< 0.01)	(0.01)	(0.04)	(0.04)
ω_1	-0.00	-0.00	-0.00	-0.00
	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
ω_2	-0.00	0.00	0.01	0.01
	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)

Notes: The table reports the results of cross-sectional regressions of $\delta_{s,2} = a_1 + a_2\omega_{s,i} + e_s$, with $i = 0, 1, 2$, or state fixed effects for higher education aid on state-specific estimates of the progressivity of the distribution of K-12 aid. The first column presents the results from a simple ordinary least squares regression. The second column presents results from so-called "robust regression, " discussed in Li (1985), which is meant to reduce the influence of outliers. The third column weights observations by the inverse of the standard error of the estimate of $\omega_{s,i}$ for each state, and the fourth is a weighted regression that drops outlier observations Oklahoma and Vermont. Heteroskedasticity-robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively.

12 aid disproportionately to low-income school districts, speaking to education tastes as a dominant driver.[14]

Finally, we consider how estimates of ω_0 correlate with fixed effects for low-income assistance, reported in Table 5 and shown in the bottom panel of Figure 8. These are especially interesting in that policy makers favoring a stronger social safety net may also exhibit stronger preferences for a more progressive distribution of state aid. In fact, we find that, in states where more funds are devoted to welfare or health care, the aid distribution is less progressive, as illustrated by a significantly positive relationship between state fixed effects for low-income assistance and ω_0. Thus, we might conclude that these two government programs act like substitutes. Policy makers with a taste for equity can obtain more safey net

[14]It is important to recognize a subtle distinction with respect to the relationship of higher education spending and the progressivity of the state K-12 aid distribution. In the estimation that covers the entire sample, we find that ω_1 is significantly negative. This means that when states spend more on higher education than their own specific average, it also entails a more negative weight on local revenue when deciding on school district aid, or a more progressive distribution of aid. The results in Table 4 speak to a different phenomenon. Cross-sectionally, states that spend more on higher education than others tend to have a less progressive distribution of state education aid. These results, however, do not contradict the notion that spending above their own average will lead to a more progressive distribution.

Table 5: Regression Results for LIA Fixed Effects

Parameter	OLS	Robust Regression	Weighted	Weighted ex. OK & VT
ω_0	0.01**	0.01	0.09**	0.09**
	(0.01)	(0.01)	(0.04)	(0.04)
ω_1	0.00***	0.00	0.00	0.00
	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
ω_2	0.00	0.00	-0.01	-0.01
	(< 0.01)	(< 0.01)	(0.01)	(0.01)

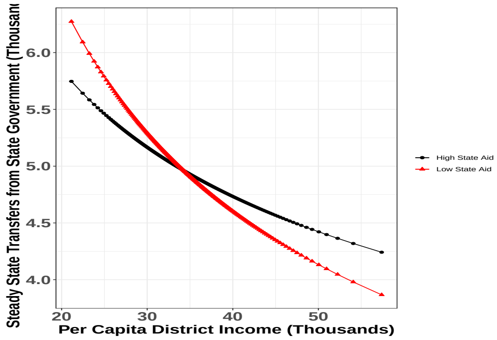
Notes: The table reports the results of cross-sectional regressions of $\delta_{s,3} = a_1 + a_2\omega_{s,i} + e_s$, with $i = 0, 1, 2$, or state fixed effects for low-income assistance on state-specific estimates of the progressivity of the distribution of K-12 aid. The first column presents the results from a simple ordinary least squares regression. The second column presents results from so-called "robust regression, " discussed in Li (1985), which is meant to reduce the influence of outliers. The third column weights observations by the inverse of the standard error of the estimate of $\omega_{s,i}$ for each state, and the fourth is a weighted regression that drops outlier observations Oklahoma and Vermont. Heteroskedasticity-robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively.

funding or get more of the existing K-12 aid budget shifted to poorer areas, but generally not both.

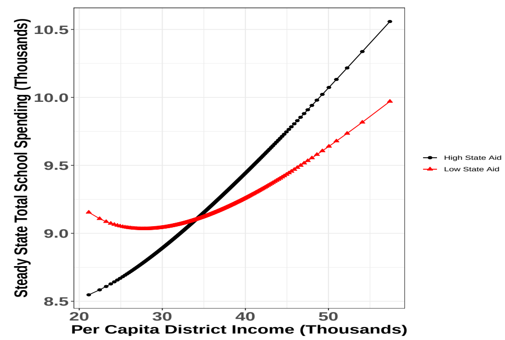
In fact, it is possible to craft a story in which this dynamic plays into the estimates in Tables 3 and 4. It may be that, as policy makers favoring spending on education engage in bargaining with those favoring equity-focused programs, the trade-off for getting more funds for education in all parts of the state (including school districts in more well off areas and for college students, who tend on average to be from higher-income families) is that they also must devote more funds to the very poorest via welfare and health programs.

We can use our model to obtain a sense of the quantitative significance of these estimates. For each set of fixed effects, we identify the states at the 25th and the 75th percentile of the cross-sectional distribution, and we use the estimates in Tables 3, 4, and 5 to compute the implied differences in ω_0 between the two states, holding all other parameters in the model, as well as the data-generating process and the calibration targets, constant. Figure 9 reports the differences in the steady state distributions of both state aid and current expenditure

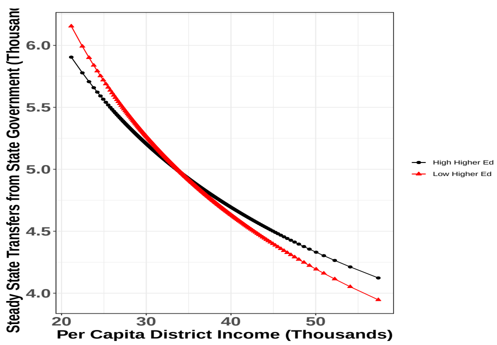
Figure 9: Steady State Distributions for Different ω_0 Values



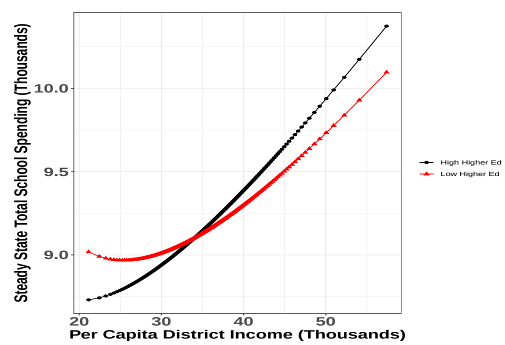
(a) State Aid Distribution: Low vs. High State Aid Fixed Effect



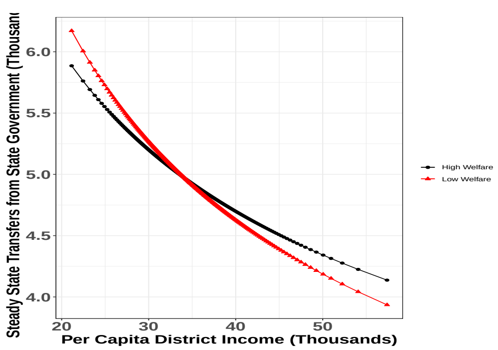
(b) Current Expenditure Distribution: Low vs. High State Aid Fixed Effect



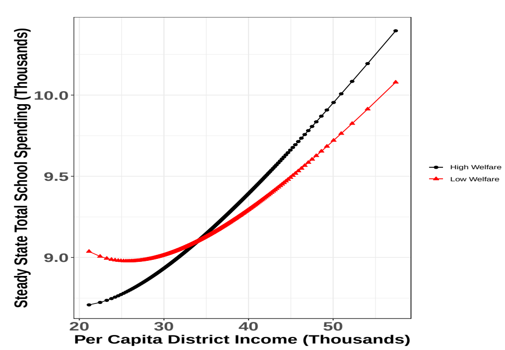
(c) State Aid Distribution: Low vs. High Higher Education Fixed Effect



(d) Current Expenditure Distribution: Low vs. High Higher Education Fixed Effect



(e) State Aid Distribution: Low vs. High LIA Fixed Effect



(f) Current Expenditure Distribution: Low vs. High LIA Fixed Effect

Notes: The left-hand panel of each row plots steady state distributions of state aid, assuming that states are alike in every way except that for one type of state, their ω_0 values are those implied by having total state aid (top row), higher education (middle row), or low-income assistance funding (bottom row) fixed effects at the 75th percentile of the cross-state distribution. The other type of state has ω_0 values implied by having fixed effects at the 25th percentile of the cross-state distribution. The right-hand panel reports analogous distributions for total current expenditure in steady state.

per student across school districts, depending on whether the state has relatively "high" or "low" estimated fixed effect for each of total state aid, higher education, and low-income assistance.

It is clear that for states tending to spend more on any of these budget items (so that they have higher fixed effects), their state aid distribution is much less progressive (i.e., much flatter). This results in a much more unequal distribution of spending per student. In the state at the 75th percentile of the total state aid fixed effect distribution, a relatively high-income school district spends 7.8 percent more than a relatively low-income school district per student.[15] A state at the 25th percentile of the state aid fixed effect distribution sees only a 3.1 percent spending difference. For higher education and low-income assistance, the figures are not quite as dramatic, but they tell a similar story. In a state that spends a relatively large amount on higher education, high-income districts spend 6.4 percent more than low-income districts. The difference is 4.1 percent for a state spending relatively little on higher education. Finally, a state that tends to spend large amounts on low-income assistance sees a 6.6 percent difference between per-student spending in high- and low-income school districts, compared with a 4.0 percent difference in a state spending relatively little on welfare.

All of this implies that, in steady state, states do not see education spending primarily as an equalizing program, and that spending on education reflects tastes for education. Where education spending is high, spending on higher education also tends to be high and state aid for K-12 is distributed in such a manner that there are substantial disparities between high- and low-income school districts. Where total spending on K-12 education is high, there is simultaneously a considerable devotion of resources to low-income assistance spending, implying that this is the program that these states rely on to deliver equalization.

This contrasts with our dynamic simulations, where we examined state government preferences outside of steady state. Away from steady state, increases in higher education funding lead to more progressive distributions of state aid, while increases in low-income assistance

[15]Whenever we refer to a high-income school district, we mean a district at the 85th percentile of the steady-state income distribution. A low-income district is one at the 15th percentile of the same distribution.

funding lead to less progressive distributions. Looking across states' long-run averages, however, we observe the opposite result for higher education funding. In and out of steady state, low-income assistance funding appears to be a substitute for more progressive K-12 aid.

5.2 Are States Different Depending on Income or Private University Prevalence?

We next examine the degree to which the preference parameters we analyze are influenced by whether or not a state has high or low average personal income (which may influence how much needs to be allocated towards welfare spending) or whether it has a substantial presence of private universities that may take on some of the burden of educating college students. We split states into high- or low-income groups according to whether average per-person income over the sample period is above or below the cross-sectional median, and we split them into high- or low-private-university groups according to whether the share of private university enrollment in total tertiary enrollment averaged over time is greater than or less than the cross-sectional median. This gives us four basically equally-sized groups: High Income/High Private Enrollment, High Income/Low Private Enrollment, Low Income/High Private Enrollment, Low Income/Low Private Enrollment. Appendix Figure A1 shows which group each state falls into.

For each set of fixed effects and estimates of ω_0, we examine the possibility of differences according to these groupings. Specifically, we regress each set of parameters on dummies indicating which of the four groups the state belongs to, omitting a constant term.

When examining the results in Table 6, we can spy certain patterns. Consider the high-income states in the first two rows in the table. Regardless of their status with respect to private or public university enrollment, both groups of states have relatively low state K-12 aid fixed effects, but the state aid that they do expend is done so fairly progressively, as indicated by their very negative values of ω_0. Neither has average welfare fixed effects that are significantly different from zero. The main difference between these two groups,

Table 6: Preference Differences According to Income and Private University Groupings

Group	State Aid Fixed Effects	Higher Ed Fixed Effects	LIA Fixed Effects	ω_0
High Income/High Private Enrollment	-0.11^{***}	0.04	0.08	-0.59^{***}
	(0.03)	(0.06)	(0.07)	(0.08)
High Income/Low Private Enrollment	-0.09^{***}	0.11^{**}	0.04	-0.70^{***}
	(0.02)	(0.05)	(0.04)	(0.12)
Low Income/High Private Enrollment	-0.05^{**}	0.16^{***}	0.03	-0.37^{***}
	(0.02)	(0.03)	(0.03)	(0.06)
Low Income/Low Private Enrollment	0.01	0.19^{***}	0.14^{***}	-0.31^{***}
	(0.02)	(0.02)	(0.02)	(0.08)

Notes: This table reports the coefficients from a regression of the preference parameters listed in the column headers on the set of dummy variables indicating to which group each state belongs. Outlier states Vermont and Oklahoma are excluded from the regressions. Heteroskedasticity-robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels respectively.

unsurprisingly, is that states with relatively low reliance on private universities tend to spend more on higher education.

For low-income states with a high share of college students in private institutions, we observe that their total amount spent on K-12 aid is greater than the high-income states, but it is allocated less progressively. They also put a substantial amount of funds towards higher education, but do not have significantly higher fixed effects for low-income assistance.

Finally, low-income states with a high dependence on public university systems have high-magnitude fixed effects for higher education, similar to their high-income peers, but they also spend a great deal on low-income assistance. Combine this with the highest relative fixed effects for K-12 aid, allocated in the least progressive manner among the four groups, and it is apparent that these states at least see the two broad programs as achieving two distinct ends. Education spending, whether on K-12 or higher education, is aimed at efficient production of education, while equalization motives are satisfied via the welfare budget.

6 Concluding Remarks

There are a number of possibly conflicting motivating factors that help determine state government decisions about how much to spend on public education and how to distribute it among the school districts that compose the state. Two prominent driving motives are a desire to produce educational attainment and a desire to close resource disparities (both now and in the future). In this paper, we attempt to employ the state government preference frameowrk first introduced in Biolsi, Craig, Dhar, and Sørensen (forthcoming) to tease out the degree to which each of these motives influence actual state government decisions.

We estimate our preference model first for the "average" state, that is, using our entire sample, and we simulate how this average state responds to a business cycle shock calibrated to match that experienced during the Great Recession. As the previous literature has already demonstrated (see, e.g. Jackson, Wigger, and Xiong, 2018 or Biolsi, Craig, Dhar, and Sørensen, forthcoming), an aggregate income shock leads to lower funding for state aid, which disproportionately affects lower-income school districts. Our paper, however, contributes the novel finding that, having been shocked from steady state, the state government allows the distribution of state aid to be influenced by the deviations of higher education and low-income assistance funding. Specifically, lower spending on colleges and universities imparts a stronger desire in policy makers to tilt the state aid distrbution back towards higher-income districts, where students more likely to benefit from college spending reside. This speaks to the idea that education production is the main reason to spend taxpayer dollars on K-12 aid. At the same time, however, declines in low-income assistance program funding leads to more of the scarce K-12 aid budget being shifted towards low-income districts. Being unable to spend progressively on individuals, the state spends more progressively on schools. Away from steady state, then, we can infer that both education production and equalization motives drive funding decisions.

In steady state, it is clearer that education production is the more important influencer in state government decisions regarding K-12 aid. We find significant positive correlations of tendencies to spend on higher education, low-income assistance, and state education aid for districts across all states. Even more convincing, these tendencies also correlate significantly with less progressive distributions of state aid. The steady state political equilibrium thus involves education-minded policy makers putting more funds towards higher education and total state aid, with that state aid distributed in such a manner as to benefit high-income districts more in a relative sense. Equity-minded policy makers, in turn, procure more funds for low-income assistance programs. Alternatively, for low-income assistance funding to be less generous, K-12 aid would be distributed more in favor of low-income districts.

Our analysis therefore supports the idea that education funding serves at least two purposes for state government decision makers. In steady state, depending on how low-income assistance and higher education budgets are settled, it may be used to attain either education production or equity goals. Away from steady state, this may also be true, especially if the budget for low-income assistance is relatively constrained.

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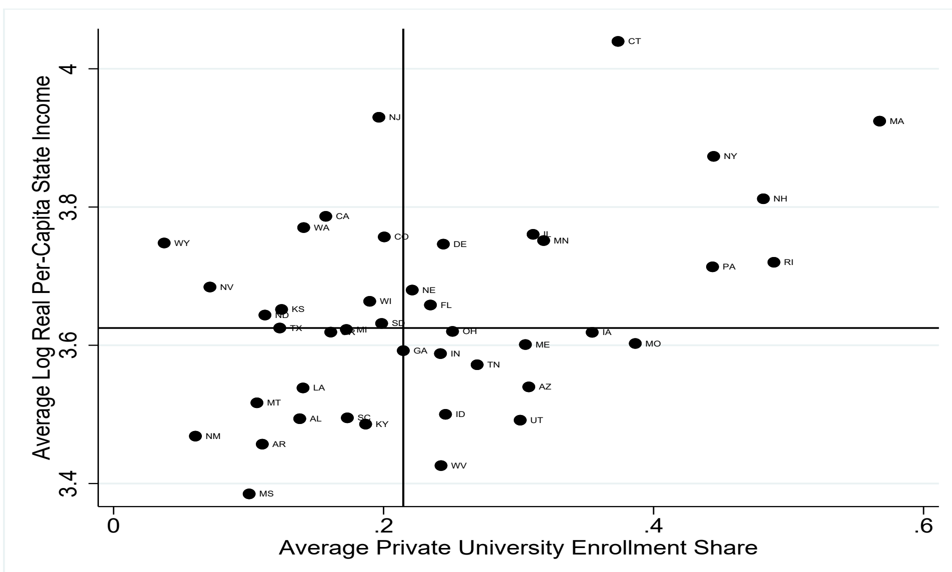
A Appendix Tables and Figures

Table A1: Summary Statistics for Key State-Level Variables

Variable	Mean	Std Dev 1 (across states within years)	Std Dev 2 (across years within states)
Real Higher Education Spending per Student (thousands of 2012 dollars)	\$11.619	\$3.09	\$1.60
Real Low-Income Assistance per capita (thousands of 2012 dollars)	\$1.73	\$0.44	\$0.42

Notes: This table reports summary statistics for real higher education spending per public college student by the state government and real low-income assistance per capita (both expressed in 2012 dollars). "Std Dev 1" is defined as the average across years of $[(1/D)\sum_d (X_{d,t} - \bar{X}_t)^2]^{1/2}$. "Std Dev 2" is defined as the cross sectional average of $[(1/T)\sum_t (X_{d,t} - \bar{X}_d)^2]^{1/2}$.

Figure A1: Average Income vs. Average Private Enrollment



Notes: The figure plots average per-person income over the sample period for each state against the average share (over the sample period for each state) of private university enrollment in total university enrollment.