Tastes for Education or Tastes for Equity: What Motivates State Goverment Aid for K-12?

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Abstract

We ask whether state government aid for K-12 education is motivated by preferences for education or preferences for equalization, by building a model of state government choices for distributing aid to school districts, allowing for interactions with higher education and low-income assistance spendings. We establish systematic correlations between how governments allocate funding to programs aimed at education production or closing resource gaps, across states and over time within states. Using our model, we estimate an income elasticity of equalizing aid of 2.44, and argue that 30 percent of the motivation for education aid is derived from the goal of achieving equalization. JEL: I22, H72, H77

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1 Introduction

State government aid for funding K-12 education in the United States is a quantitatively significant component of overall spending in the United States, averaging close to 2 percent of overall GDP over the years from 1992 to 2019. Compared with the overall state government budget, spending on K-12 education has averaged around 31 percent over that same period, and for all spending on education, the state aid share has averaged around 55 percent. Given these substantial quantities, there is no question as to the importance of understanding what should motivate these spending decisions.

That said, it is not actually obvious what is the predominant preference driver that lays behind all of this spending. In this paper, we propose that there are at least two aims that K-12 education aid is meant to achieve. One, the more straightforward, is the desire to produce education, which leads, in principle, to greater amounts of human capital for residents of each state. The second, however, is an equalization motive. Since the 1976 *Serrano v. Priest* decision in California, there have been concerted efforts in most states to use the state education budget to allocate more resources to students from lower-income school districts in an effort to provide a more equal playing field. Biolsi, Craig, Dhar, and Sørensen (2022) demonstrate that, on average, state aid is distributed in a highly progressive manner, with lower-income school districts receiving much greater amounts on a per-student basis than school districts at the more affluent end of the district income distribution.

In a classic discourse on economic policy making, Tinbergen (1952) proposed that, for every policy aim, there needed to be a separate policy tool. This would imply that, to achieve two aims (educating the population and closing income gaps), the state government would need to have at least two policy levers with which to work. A separate seminal work, this one by Shepsle (1979), argues instead that there are significant interactions among policy tools and goals, and that it is difficult to disentangle them into discrete and independent choice settings. We will present evidence that the ideas in Shepsle (1979) are readily apparent in the state government decision-making process as it relates to K-12 education aid.

Our aim in this paper is to attempt to provide an estimate of the relative importance of state government tastes for equity or for education production in choosing the levels and distribution of state education aid. To do so, we will extend the analytical framework of Biolsi, Craig, Dhar, and Sørensen (2022) so as to allow the state government decision-makers to possibly interact state aid choices with those relating to spending on higher education and low-income assistance. We suppose that the principal motivation behind state government funding for higher education is a desire to produce a more capable workforce in the state (so that it is only associated with the tastes for education). Similarly, we imagine that allotments for low-income assistance (in the form of welfare spending or funding for health care and hospitals) derive mainly from tastes for equity. We use these budget items as proxies that may help us to shed light on what actually determines K-12 funding choices.

Of course, it is not literally the case that the only motivation behind spending on higher education is to produce human capital. A Pew report (Fry and Cilluffo, 2019) notes that students from families in poverty have increased their representation at less selective institutions, such as public two-year colleges, over the course of the sample period that we study, which suggests a role for publicly-funded higher education is improving intergenerational mobility. Still, the majority of students at public universities are from the middle and upper classes, and this suggests that the policy objective that these institutions are aimed at is primarily an educational one. Similarly, one may argue that there are efficiency gains associated with transferring funds from high-income families to families in poverty, who have much higher marginal propensities to consume, via low-income assistance programs. We still take it to be uncontroversial, however, that the main impulse behind such programs is an equity-minded one. For instance, Kolko, Neumark, and Mejia (2013) demonstrate that states spending more on transfer programs rank less highly in indexes of states' business climates that predict faster economic growth.[1]

After deriving optimality conditions in the model, we fit the first-order conditions to data

[1]See also Neumark and Muz (2016).

on 8,512 school districts in 45 states from 1992 through 2019. While most of the overlapping parameter estimates align closely with those found in Biolsi, Craig, Dhar, and Sørensen (2022), we are able to present a set of new findings. Most relevantly, the weighting term on local resources in the state aid distribution decision becomes more negative when the state spends more on higher education per college student in the public university system. This means that when a state offers more generous funding for higher education relative to its own average, it is coincident with a more progressive state aid distribution. The same weighting term becomes less negative when the state allocates more to low-income assistance (such that greater funding for welfare programs associates with a less progressive distribution of K-12 education aid). Most simply, these results would support the Shepsle (1979) view that such policy choices are not made in a vacuum, the policies geared towards the production of education rather interact significantly with those geared towards equity goals.

That notion is also supported by evidence of meaningful cross-state correlations between tastes for equity and tastes for education production. We show that states that spend more on K-12 aid overall also spend more on higher education and low-income assistance. Further, states spending more on these budget items also appear to systematically engage in less resource equalization among school districts.

We then use our model to simulate how state governments alter their allocation decisions in response to a resource shock. Unsurprisingly and consistent with the results in Biolsi, Craig, Dhar, and Sørensen (2022), the total amount of funding for K-12 aid declines sharply, and, interestingly, moreso than does that available for higher education and low-income assistance, which can each help to pursue some policy goal that K-12 aid may be aimed at. One of our main findings, though, is that, as hinted at above, the modest declines in higher education and low-income assistance spending alter the degree of progressivity of the K-12 aid distribution to school districts. In fact, we are able to estimate an income elasticity of equalizing K-12 aid of 2.44, implying that equalizing aid may be considered a sort of luxury good and that even modest resource decline can have serious implications for the attempts at using the state aid budget to address resource disparities. What is more, our model allows us to conduct counterfactual exercises in which we can "shut down" the influence of either higher education spending or low-income assistance (or both) on the preferences for equalizing aid. Doing so, we produce an estimate that, at the margin, about 30 percent of the state aid budget is motivated by equalization tastes and the balance derives from tastes for the production of education.

When assessing underlying motivations behind state government aid for K-12 education, one can assess the magnitudes allocated and their distribution, or one can evaluate their elasticities with respect to resource shocks. We undertake both efforts in this paper. A third approach, which we do not follow, would involve examining the effectiveness of the various spending programs at achieving their supposed aims, such as in actually producing human capital or improving intergenerational mobility. These are worthy research goals, which have been pursued extensively in the literature (Silva and Sonstelie, 1995, Murray, Evans, and Schwab, 1998, Hoxby, 1998, 2001, Card and Payne, 2002, Downes and Shah, 2006, Jackson, Johnson, and Persico, 2016, Lafortune, Rothstein, and Schanzenbach, 2018, Zheng and Graham, 2022), and we do not consider such questions here, focusing instead on what preference parameters might be said to have the greatest influences on the inputs into the production functions of policy.

2 Data

Our main unit of study is state governments in the United States, and we collect information on a number of budgetary variables at that level. We use the Annual Survey of State Government Finances to obtain data on state government spending on higher education, welfare, health, and hospitals for 1992 to 2019. We transform these figures into constant dollar terms using the national-level GDP deflator. Spending on welfare, health, and hospitals are combined into one category, which we term "Low-Income Assistance."

Because we are not only interested in the level of K-12 education aid, but also its distribution, we need information on school district finances for the years 1992 to 2019, obtained from the Annual Survey of School System Finances, conducted by the U.S. Census Bureau. We follow the analysis in Biolsi, Craig, Dhar, and Sørensen (2022) as far as filtering out unsuitable school districts as follows. We limit our study to 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.[2] 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.

These two datasets are then merged with information on personal income at both the state 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.

Finally, we collect information on fall semester enrollment at public and private colleges and universities 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. Table 1 summarizes many of the key variables in our analysis.

[2]As in Biolsi, Craig, Dhar, and Sørensen (2022), 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."

Table 1: Summary Statistics for Key Variables: Total Sample

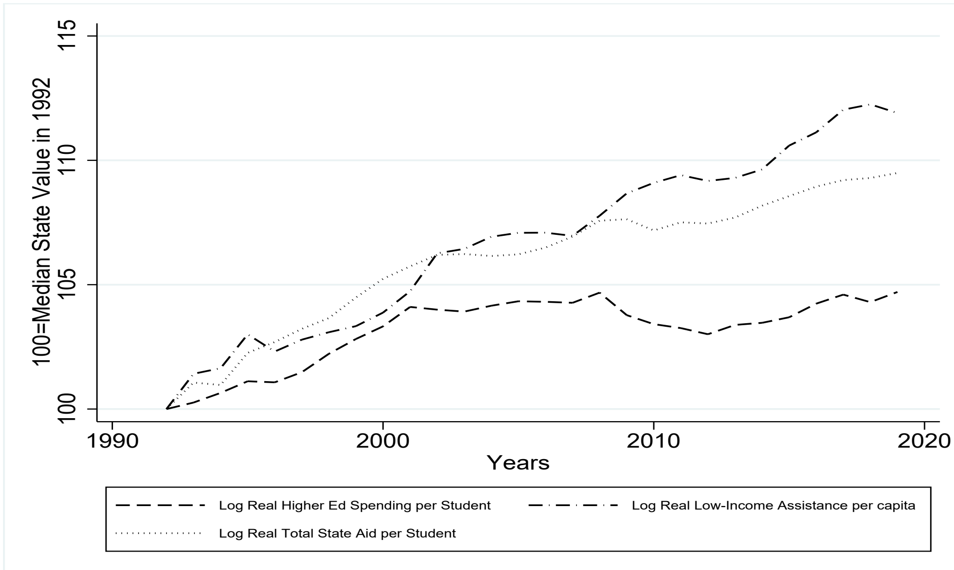
Variable	Mean	Std Dev 1 (across districts/states within years)	Std Dev 2 (across years within districts/states)
State Level Variables (000s of 2012 dollars)			
Total K-12 Aid Per Student	8.98	6.99	3.99
Higher Education Spending per Public Enrollment	11.62	3.09	1.59
Low-Income Assistance per Capita	1.73	0.44	0.42
School District Variables (000s of 2012 dollars per Student)			
Total Revenue	11.75	4.28	2.41
State Aid (District-Level)	5.56	2.52	1.38
Local Revenue	5.38	4.32	1.35
School Spending (District-Level)	9.87	3.16	1.82

Notes: The table reports summary statistics of the different types of revenue and income for the sample of 8,512 independent school districts in the United States for the period 1992 to 2019 (238,336 district-year observations). Values for levels are expressed in thousands of 2012 dollars per student (for the education variables) or 2012 dollars per capita (for the other spending variables). "Std Dev 1" is defined as the average across years of $[(1/D)\sum_d (X_{d,t} - \bar{X}_t)^2]^{1/2}$. "Std Dev 2" is defined as the cross sectional average of $[(1/T)\sum_t (X_{d,t} - \bar{X}_d)^2]^{1/2}$.

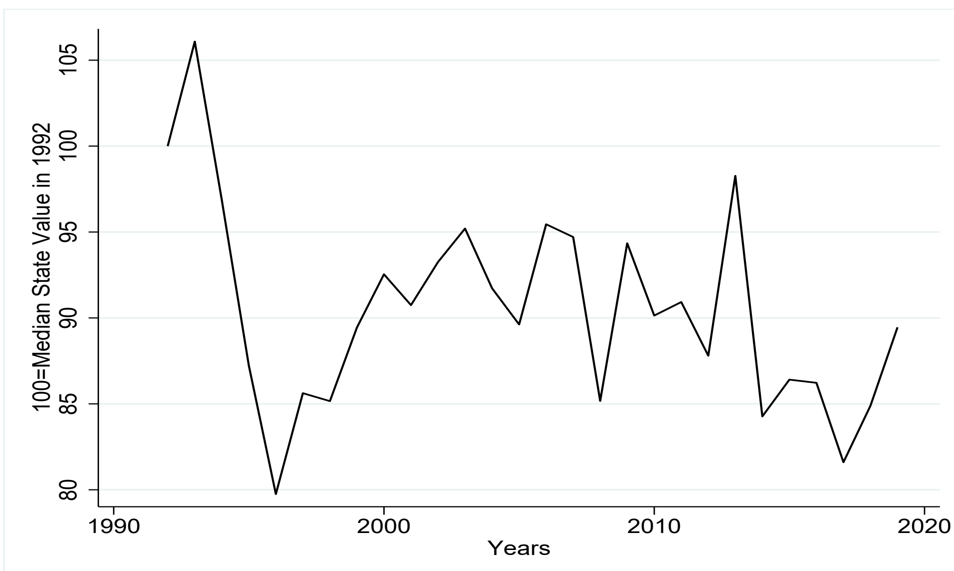
In Figure 1, we depict the evolution over our sample period of state funding for overall state aid per total state enrollment to school districts for K-12 education, higher education per college student, and low-income assistance per capita in the median state in each year, scaled by the value for the median state in 1992 to make the time series dynamics easier to observe. A number of things stand out from this figure. First, real per-student higher education spending in the median state has stagnated since around the year 2000, and it suffers a sustained drop in the wake of the Great Recession. Total per-student state aid also declines during the Great Recession. Low-income assistance does not, although it is important to remember that this includes spending on health care, which was boosted by large federal grant increases in this period associated with the American Recovery and Reinvestment Act (see Chodorow-Reich, Feiveson, Liscow, and Woolston, 2012).

The bottom panel of Figure 1 illustrates the time series behavior of the median state's cross-school district standard deviation of per-student state aid. This metric exhibits far

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



(a) Log Per-Person or Per-Student Spending



(b) Cross-School District Standard Deviation of Log State Aid per Student

Notes: The top panel of the figure shows the time series behavior of the log of real per-college student spending in the median state (relative to the median state in 1992), the log of real per-capita low-income assistance spending in the median state (relative to the median state in 1992), and the log of real per-student total state aid in the median state (relative to the median state in 1992). The bottom panel reports the time series behavior of the standard deviation across districts of state aid per student in the median state (relative to the median state in 1992).

more noise over the time series than do the various spending variables in the top panel of the figure. Still, one may observe that there is a sharp drop in the standard deviation in the years surrounding the Great Recession. Given the documented progressivity of state aid, a fall in the standard deviation across school districts implies a less progressive aid distribution. Combine this with the fact that low-income school districts are much more dependent on state aid than are high-income districts (Jackson, Wigger, and Xiong, 2018), and the implication is that a more equal state aid distribution generates a less equal cross-district spending distribution.

In the preference model that we introduce in Section 3, we will tie these dynamics together and offer an argument for what they may reveal about the goals of K-12 finance.

3 The Preference Model

To aid in our interpretation of the data, we adopt the preference specification framework of Biolsi, Craig, Dhar, and Sørensen (2022) to identify how state government decision makers may dynamically choose both the levels and the district-level allocations of state education aid. We also allow K-12 aid choices to interact with decisions relating to funding public higher education or state welfare programs, which we take to proxy for the state's desire to engage in education or human capital production or equalization-minded initiatives.[3] We assume that, in period t, the state government (that comprises a total of D school districts) maximizes the following objective function:

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

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

$R^S_{d,t}$ is aid from the state government to district d at time t, $R^S_t = \sum_{d=1}^{D} R^S_{d,t}$ is the sum of state aid to all districts, $R^L_{d,t}$ 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 (which we simply describe as "low-income assistance" going forward), and the last term captures spending on all other functions, to include private sector spending. We express the three main aggregate choice variables 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 level for each of the three state-level spending items in the following ways:

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

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

$$\ln \widetilde{LIA}^S_t = \varrho^{LIA} + \alpha_2 \ln LIA^S_{t-1} \ , \tag{4}$$

We adopt the same reference specification for the shares of total state aid sent to school districts:

$$\frac{\widetilde{R^S_{d,t}}}{R^S_t} = \varrho^{R_d} + \log \frac{R^S_{d,t-1}}{R^S_{t-1}} \tag{5}$$

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 (2022) 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 in the budget from year to year. A higher value of any of these parameters makes for more persistent changes in the relevant spending category.

Y_t^S represents state-level income, and we assume it to be exogenous. While aggregate income could, in the very long run, be influenced by the state population's human capital, we impose in this model that there is no effect at business cycle frequencies. Thus, shocks to income are the sole propagators of the model's mechanisms.

Finally, the 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. A negative value of ω_0 produces a progressive state aid distribution, with lower-income districts receiving more than do higher-income districts. Importantly, we allow this unequal caring preference to be influenced by spending on higher education (proxying tastes for the production of education) and low-income assistance (proxying tastes for equity). That is, $\omega_1 < 0$, implies 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 spending on low-income assistance.

In order to close the model, we also must account for possible endogenous reactions by the school districts themselves. 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 (2022) without modification. School districts choose how much to raise locally via taxes (most often property taxes), subject to the same kind of habit formation that we specify at the state level and to the budget constraint incorporated in the second term. The parameter ξ captures stickiness in locally-raised revenue over time (with a higher value implying less willingness to change the amount raised from year to year), and ϕ acts as a sort of "flypaper" parameter that measures the degree to which school districts reduce funds raised locally when they experience an increase in aid coming from the state government. In the same way that we take state income as being exogenous with respect to state-level decisions at business cycle frequencies, we assert that local (county) income is exogenous with respect to school district decisions.[4]

In solving the model, we assume that the state government decides first how much to spend on the three aggregate budget items: state education aid in total, higher education, and low-income assistance. Then, taking these decisions 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. We derive first-order conditions, incorporate the specification of the reference value of the relevant variables, take logs of the main variables, and replace constant terms with state and

[4]We use county income as a measure of school district economic dynamics. American Community Survey reports household income at the school district level, but it has a much shorter time dimension than the county-level series. Biolsi, Craig, Dhar, and Sørensen (2022) demonstrate that the estimation results are not sensitive to the use of either county-level or school district-level income data, so we opt to make use of the series with the longer time series.

year fixed effects. Rearranging delivers the following estimating equations, which we will take to the data:

$$\ln R_t^S = \delta_{s,1} + \delta_{t,1} + \frac{\gamma - 1}{\gamma} \ln R_{t-1}^S + \frac{\kappa}{\gamma} \ln(Y_t^S - R_t^S - HE_t^S - LIA_t^S) + \varepsilon_{1,s,t} \tag{7}$$

$$\ln HE_t^S = \delta_{s,2} + \delta_{t,2} + \frac{\nu - 1}{\nu} \alpha_1 \ln HE_{t-1}^S + \frac{\kappa}{\nu} \ln(Y_t^S - R_t^S - HE_t^S - LIA_t^S) + \varepsilon_{2,s,t} \tag{8}$$

$$\ln LIA_t^S = \delta_{s,3} + \delta_{t,3} + \frac{\psi - 1}{\psi} \alpha_2 \ln LIA_{t-1}^S + \frac{\kappa}{\psi} \ln(Y_t^S - R_t^S - HE_t^S - LIA_t^S) + \varepsilon_{3,s,t} \tag{9}$$

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 are operating under the assumption that current state business cycle conditions are not influenced in any meaningful way by state government funding for education (a supposition bolstered by the very small share in state income that we document when we calibrate our preference model). We also include the log of private university enrollment as an instrument for log state public education financing per student. This should capture demand for higher education on the part of students, but it is unlikely to influence state government funding. We also consider specifications in which we include federal aid to states (sometimes excluding aid for health and welfare programs) as an instrument for low-income assitance programs. The equations are estimated simultaneously using three-stage least squares (3SLS), which is necessary in order to obtain inference on the taste parameters, which involve cross-equation algebraic manipulations.

Note that in this three-equation system, excluding the state and year fixed effects, there are six right-hand side reduced-form coefficients that we estimate, and there are six preference parameters that we aim to identify (γ, κ, ν, ψ, α_1, α_2). There is then an exact one-to-one mapping from estimated coefficients to taste parameters which we undertake with simple algebraic manipulations of the 3SLS coefficients.

At the local district level, our estimating equations are:

$$\ln R_{d,t}^S = \delta_{s,t} + \frac{\omega_0}{\eta} \ln R_{d,t}^L + \frac{\omega_1}{\eta} (\ln HE_t \times \ln R_{d,t}^L) \\ + \frac{\omega_2}{\eta} (\ln LIA_t \times \ln R_{d,t}^L) + \frac{\eta - 1}{\eta} \ln R_{d,t-1}^S + \varepsilon_{4,d,t} \ . \tag{10}$$

$$\ln R_{d,t}^L = \delta_s + \delta_t + \frac{\xi - 1}{\xi} \ln R_{d,t-1}^L + \frac{\phi}{\xi} \ln R_{d,t}^S + \frac{\theta}{\xi} \ln(Y_{d,t}^L - R_{d,t}^L) + \varepsilon_{5,d,t} \ . \tag{11}$$

The interaction terms are expressed in deviations from their unit-specific means (states for HE_t^S and LIA_t^S, districts for $R_{d,t}^L$), 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, as in Biolsi, Craig, Dhar, and Sørensen (2022).

4 Empirical Results

Our next task is to estimate the set of equations derived in Section 3 and assess some of the steady state implications of our results. Before reporting the specific results, we address a number of operational issues. We express all state aid variables (at the district level and aggregated to the state level) in per-student terms, with enrollment of K-12 pupils the denominator. For higher education spending, we use public university fall semester enrollment as the denominator. Finally, low-income assistance is calculated in per-capita terms, as is the income variable that appears on the right-hand side of Equations 7 through 9. Given that we are relying heavily on instrumental variable-type strategies, we begin our discussion of the results with first-stage estimates.

4.1 First-Stage Results

Table 2 reports first-stage F-statistics for the instruments for variables that appear in the 3SLS system, namely the log of total state aid for K-12 per enrollee, the log of low-income assistance per capita, the log of higher education funding per college student, the lag of each of the above-named variables, and the residual income term. In each instrumental variables specification, we include as instruments the contemporaneous value and four lags of the log of per-capita state income, in addition to the contemporaneous log of private university enrollment. In the first column of Table 2, these are the only insruments included. Each of the next three columns adds a different extra instrument to this set, which is the contemporaneous log of federal aid to the state (second column), the contemporaneous log of federal aid to the state excluding aid for health and welfare programs (third column), and the contemporaneous value of federal aid for health and welfare programs only (fourth column).

Table 2: First-Stage F-Statistics: 3SLS System

	State-Level Regression (1)	State-Level Regression (2)	State-Level Regression (3)	State-Level Regression (4)
$\ln R_t^S$	64.54	63.82	63.95	63.64
$\ln LIA_t^S$	149.05	191.76	147.20	213.36
$\ln HE_t^S$	152.06	151.00	150.33	151.43
$\ln R_{t-1}^S$	58.08	57.47	57.45	57.35
$\ln LIA_{t-1}^S$	150.69	175.21	148.61	185.38
$\ln HE_{t-1}^S$	164.27	163.09	162.65	164.41
$\ln(Y_t^S - R_t^S - HE_t^S - LIA_t^S)$	15980.13	20082.81	15797.65	21285.48

Notes: The table reports first-stage F-statistics for the endogenous variables in the 3SLS system represented by Equations 7 through 9. Each column represents a different instrumental variables specification. In each column, we include as instruments the contemporaneous value and four lags of the log of state income per person and the contemporaneous log of private university enrollment. The second column adds to this set the contemporaneous value of the log of federal government aid to the state. The third column instead adds the contemporaneous value of the log of federal aid to the state excluding aid for health and welfare programs. The fourth column instead adds only the contemporaneous log of federal aid for health and welfare programs.

No matter which instrumental variables specification we employ, we find strong instrument relevance for our state-level estimation system. All of the first-stage F-statistics easily clear weak instruments hurdles, such as exceeding the rule-of-thumb value of 10 recommended by Staiger and Stock (1997). Next, we turn to our local-level regression estimations, which include the state aid allocation in Equation 10 and the local revenue raising expression in Equation 11. These first-stage F-statistics are found in Table 3.

Table 3: First-Stage F-Statistics: Local Level Regressions

	State Aid Allocation Regression (Equation 10)	Local Revenue Regression (Equation 11)
$\ln R^L_{d,t}$	313.33	
$\ln HE_t \times \ln R^L_{d,t}$	199.39	
$\ln LIA_t \times \ln R^L_{d,t}$	256.76	
$\ln R^L_{d,t-1}$		312.90
$\ln R^S_{d,t}$		369.95
$\ln(Y^L_{d,t} - R^L_{d,t})$		$9.5e05$

Notes: The table reports first-stage F-statistics for the endogenous variables in Equations 10 and 11. For Equation 10, the instruments include the contempraneous value and four lags of the log of per-capita county income as well as the interaction of the log of per-student local revenue with the log of private university enrollment. For Equation 11, the instruments include the contemporaneous value and four lags of both log per-capita county and log per-capita state income.

In the case of the local-level regressions, we again find strong instrument relevance. Confident that our approach is free from any sort of weak instrument concerns, we next turn to discussing our parameter estimates.

4.2 Parameter Estimates

We report our estimates of the various taste parameters in our preference model in Table 4. In the case of the state-level regressions dealing with the choices on total state aid per student, higher education funding, and low-income assistance, we report the results from the models with the different instrumental variables specifications, but in the case of the two local-level regressions, we have only the one specification, which we report. All of the state-level regressions cluster standard errors by state. For the two local-level regressions, we cluster standard errors by school district.

Table 4: Objective Function Parameter Estimates

	(1)	(2)	(3)	(4)
γ	3.88***	4.04***	4.09***	3.88***
	(0.77)	(0.81)	(0.84)	(0.76)
κ	1.66***	1.66***	1.68***	1.66***
	(0.24)	(0.25)	(0.26)	(0.24)
ν	10.66**	16.69**	12.41**	15.53**
	(4.42)	(7.97)	(5.14)	(6.45)
ψ	10.88*	109.27	13.97*	148.15
	(5.69)	(379.77)	(8.24)	(706.56)
α_1	0.61***	0.81***	0.69***	0.79***
	(0.19)	(0.13)	(0.15)	(0.11)
α_2	0.61*	1.24***	0.76***	1.26***
	(0.31)	(0.07)	(0.26)	(0.06)
η	5.68***			
	(0.34)			
ω_0	−0.52***			
	(0.04)			
ω_1	−2.89***			
	(1.11)			
ω_2	1.30***			
	(0.32)			
ξ	5.53***			
	(0.55)			
θ	0.91***			
	(0.03)			
ϕ	−0.39***			
	(0.03)			

Notes: Each column reports parameter estimates from the estimation of the 3SLS system in Equations 7 through 9, with each column representing a different specification of the instrumental variable approach. In each column, we include as instruments the contemporaneous value and four lags of the log of state income per person and the contemporaneous log of private university enrollment. The second column adds to this set the contemporaneous value of the log of federal government aid to the state. The third column instead adds the contemporaneous value of the log of federal aid to the state excluding aid for health and welfare programs. The fourth column instead adds only the contemporaneous log of federal aid for health and welfare programs. The first column also includes estimation of Equations 10 and 11. Appropriately clustered standard errors are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

Looking across the columns of Table 4. we note that, in most cases, the parameter estimates are not particularly sensitive to the set of instruments that we use in the analysis. The possible exceptions would include ψ (measuring how unwilling states are to change spending on low-income assistance programs from year to year) and α_2, which measures the persistence of the reference utility for low-income assistance spending. Specifically, the estimates for ψ become very imprecise and the values for α_2 become very high when federal aid for health and welfare programs is included among the instruments. Even so, the qualitative implications are the same in all cases (spending on low-income assistance is an extremely persistent process). In what follows, we proceed using the estimates from our benchmark specification listed in the first column.

The first observation that stands out to us is that, for the parameters that are common across our model and the previous framework introduced in Biolsi, Craig, Dhar, and Sørensen (2022), the estimates are extremely similar, even though we have added five additional years of data (an increase of more than 20 percent). This leads us to believe that the taste parameters that we estimate are quite stable over time, boosting our instincts to interpret these as capturing something fundamental about the preferences of state and local government policymakers.

Secondly, as it relates to some of the novel parameters we bring into the model, the spendings on higher education and low-income assistance programs apparently are quite persistent over time. Policymakers appear to have little appetite for enduring large fluctuations in either type of spending, especially as compared with spending on K-12 aid.[5] This can be seen from the fact that, in the baseline specification in Column 1, both ν and ψ are above 10, implying very low intertemporal elasticities of substitution.

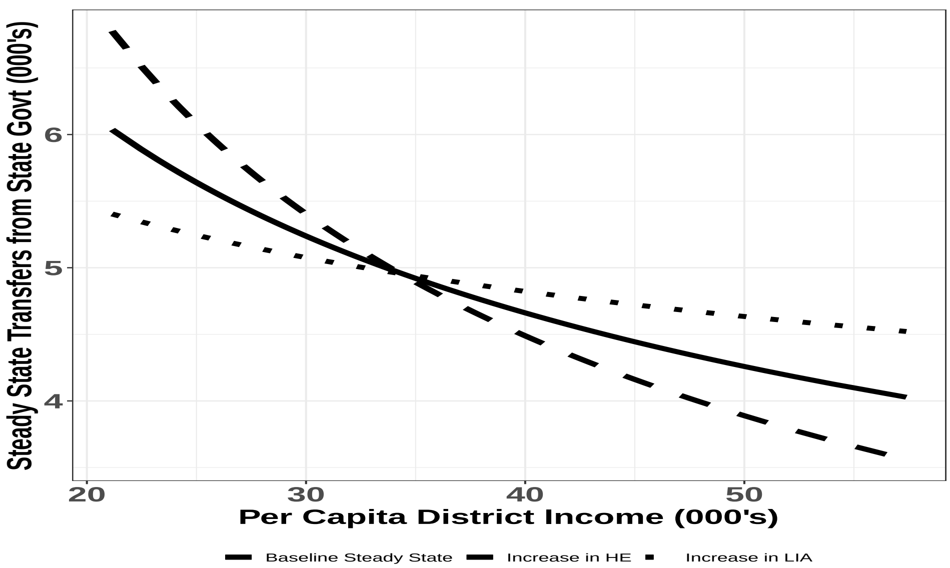
Third, and perhaps most interesting, we consider the estimates of ω_1 and ω_2 to be important findings of our study, with significant implications for the dynamic allocations of state aid. We arrive at a value of $\omega_1 = -2.89$, which implies that as spending on higher education

[5] That said, we cannot statistically reject that γ (the preference term for K-12 aid) is equal to either ν (p-value of 0.12) or ψ (p-value of 0.22).

per student rises above its state-specific average, the allocation of state aid to K-12 districts becomes more progressive. For example, the standard deviation of demeaned (by state) log per-student higher education spending is 0.14. Then, a one-standard-deviation increase in state funding for public universities (holding spending on low-income assistance constant) would change the "unequal caring" term (Behrman and Craig, 1987) on locally-raised revenue in the state aid allocation equation from -0.52 to $-0.52 - 2.89 \times 0.14 = -0.93$. Our estimation produces an estimate of $\omega_2 = 1.30$, and the positive value implies that an increase in funding for low-income assistance programs above the state-specific average coincides with a less progressive distribution of state aid across school districts. The standard deviation of demeaned (by state) log per-person low-income assistance is 0.24, which means that for a one-standard-deviation increase in such funding (holding higher education funding constant), the unequal caring term on locally-raised revenue changes to $-0.52 + 1.30 \times 0.24 = -0.20$. This makes for a much flatter distribution of aid across districts. Strikingly, these results suggest that states view K-12 aid as being a substitute for low-income assistance in achieving equalization goals.

Figure 2 visually depicts the scale of these influences. We simulate a synthetic state with 200 school districts, and the district income mean and standard deviation is calibrated to match the average of state-year cells in the data. We solve for the steady state of the model and plot simulated state aid per student against per-person income in each district. The solid line shows the baseline steady state of our model, with $\omega_0 = -0.52$. The dashed line and the dotted line show how the distribution changes for exogenous one-standard-deviation increases in the logs of higher education funding per college student and low-income assistance per person, respectively. Note that, for the purposes of this figure, we are imposing exogenous changes in these latter two variables, just to illustrate the quantitative aspect of their influences on the distribution of K-12 aid. Of course, these are endogenous variables, and one would not change without the other also changing. We will return to a more rigorous simulation exercise in Section 5. For now, we use Figure 2 only as an expository device.

Figure 2: State Aid Distribution to School Districts



Notes: The figure plots K-12 aid distributions for a simulated state, with different specifications of the ω weighting term on locally-raised revenue. The solid line in the figure plots average per-student K-12 aid to each simulated district against average per-person income in that same simulated district using the baseline $\omega_0 = -0.52$ parameter estimate. The dashed line exogenously increases per-college student higher education funding by one standard deviation, which changes the weighting term to $\omega_0 + \omega_1 \times 0.14 = -0.93$. The dotted line exogenously increases per-person low-income assitance funding by one standard deviation, which changes the weighting term to $\omega_0 + \omega_2 \times 0.24 = -0.20$.

The aid distribution that assumes an exogenous one-standard-deviation increase in higher education funding is much steeper than is the baseline distribution, which, in turn, is much steeper than the very flat distribution generated by an exogenous one-standard-deviation low-income assistance increase. A student living in a school district at the 15^{th} percentile of the state-specific income distribution receives over $200 more in state aid when there is an increase in higher education funding, compared with the baseline. When the increase is, instead, in funding for low-income assistance, the same student would receive over $200 less. These figures reinforce the notion that states treat K-12 aid as a sort of substitute for other equalization programs. More funding for public universities, on the other hand, associates with a desire to apply a more progressive K-12 aid distribution. We may interpret this as implying that higher education funding and K-12 aid are aimed at different policy objectives. Of course, this analysis has supposed that we can hold one spending on one of these programs equal while imposing exogenous changes on another. In fact, all of these variables are endogenous in our preference model, and changes in one will induce changes in others as well, as we will demonstrate.

4.3 State-wide Analysis

Before turning to a dynamic simulation analysis, it is worthwhile to look across states to establish that there may be a systematic relationship between how much states choose to spend on state aid in total, or higher education, or low-income assistance and how progressively they provide aid to school districts for K-12. To do that, we collect the set of state fixed effects from each equation in the 3SLS system, corresponding to total state aid per student ($\delta_{s,1}$), higher education funding per student ($\delta_{s,2}$), and low-income assistance per capita ($\delta_{s,3}$). By the nature of their estimation, we are supposing that these fixed effects reflect time-variant preferences in each state for each type of spending. Figure 3 plots scatters of these fixed effects and also reports coefficients from ordinary least squares regressions of each set against the others.[6]

For each of pair of fixed effects, we report a strongly positive and statistically significant correlation. The coefficients range between 0.32 and 0.37, and all have p-values below 0.06. This means that states that wish to spend more on state aid for school districts in aggregate also apparently spend more on both higher education and low-income assistance programs. Similarly, spending more on higher education also associates with more generous health and welfare programs on a per-capita basis. The taste parameters for these various budget items, it seems, are not independently drawn from separate distributions. Instead, states appear to have systematic correlated preferences. To spend more on higher education (which we take to be primarily aimed at the production of human capital) or on low-income assistance (aimed at equalization of resources) would, in either case, lead the state to spend more on K-12 aid on average. This supports the view that K-12 aid is motivated by both policy goals, not just one or the other.

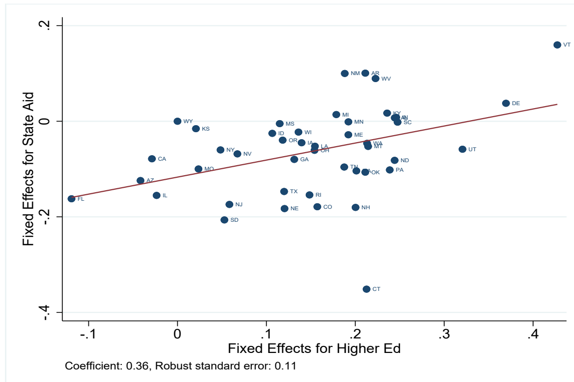
As we have been emphasizing, however, it is not just the amount of K-12 aid in total that matters, but also its distribution across school districts. Therefore, we conduct the following exercise. We estimate Equation 10 separately for each state, in order to obtain state-specific unequal caring parameters ω_i, $i \in 0, 1, 2$. Of course, this imposes some challenges, because some states have a large number of school districts (like Texas), while others (Delaware, for example) have very few. Still, we think it worthwhile to assess the degree to which there may be significant cross-state correlations between the state fixed effects for each aggregate spending function and how progressively (or not) state aid is distributed.

Figure 4 scatters the state fixed effects for each of the aggregate spending categories against the state-specific baseline unequal caring parameters ω_0, obtained from the state-by-state estimations.[7] The figure weights states according to the precision of their ω_0 estimates

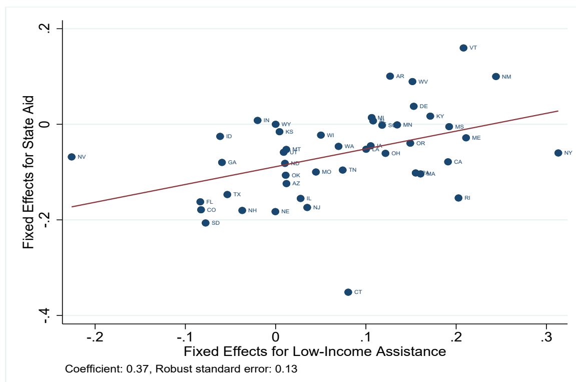
[6]This exercise is similar to that undertaken in Craig and Palumbo (1999). See also Plotnick (1986) and Moffitt (1990).

[7]We also look for relationships between state fixed effects for total state K-12 aid, higher education funding, and low-income assistance and the state-specific ω_1 and ω_2 parameters. We find essentially no correlations at all, but the results are available from the authors upon request.

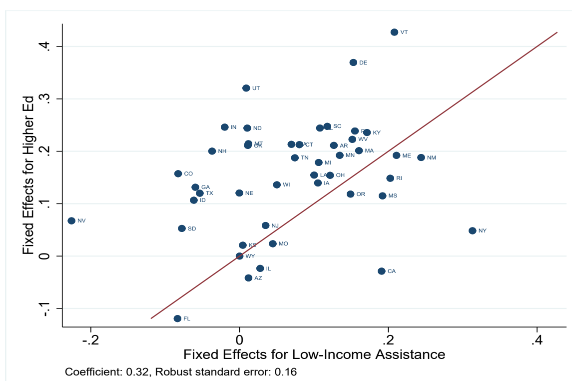
Figure 3: State Fixed Effects Correlations from 3SLS Estimation



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



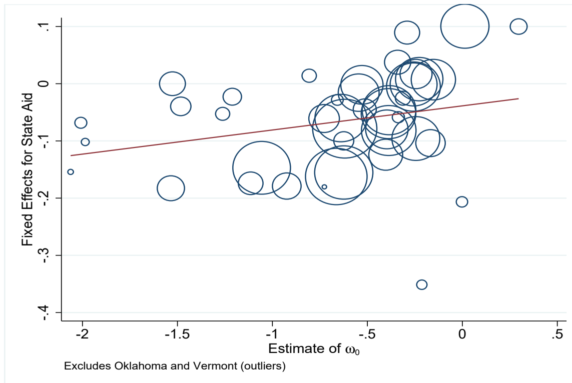
(b) Fixed Effects for State Aid vs. LIA



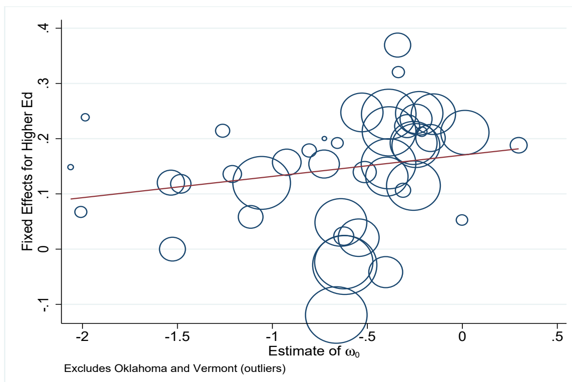
(c) Fixed Effects for Higher Ed vs. LIA

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.

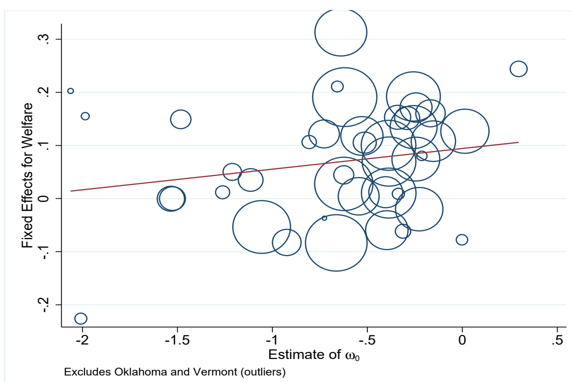
Figure 4: State Fixed Effects vs. State-Specific Unequal Caring Parameters



(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).

(specifically by the inverse of the standard error of ω_0), and larger markers indicate more precisely estimated terms. Each panel in Figure 4 tells a similar story, namely a positive relationship between fixed effects estimated for total state aid per K-12 student, higher education, and low-income assistance with the unequal caring parameter. Table 5 reports regression results that show that these positive relationships are also statistically significant. Thus, states that spend more on average on any of these kinds of programs also, on average, have less progressive aid distributions to school districts.

Table 5: Regression Results for State Aid Fixed Effects vs. Unequal Caring Parameters

Fixed Effect	OLS	Robust Regression	Weighted	Weighted ex. OK & VT
$\ln R^S$	0.02***	0.02***	0.11***	0.12***
	(< 0.01)	(0.01)	(0.03)	(0.03)
$\ln HE$	0.03***	0.03***	0.13***	0.14***
	(< 0.01)	(0.01)	(0.04)	(0.04)
$\ln LIA$	0.01**	0.01	0.09**	0.09**
	(0.01)	(0.01)	(0.04)	(0.04)

Notes: The table reports the results of cross-sectional regressions of $\delta_{s,i} = a_1 + a_2\omega_{s,0} + e_s$, with $i \in 1, 2, 3$, or state fixed effects for total state K-12 education aid, higher education funding, and 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.

What are the implications of this? The most obvious takeaway is that, consistent with Shepsle (1979), all of these policy choices interact significantly with each other as we look across states. There are systematic relationships between draws of taste parameters. Further, one of the more straightforward interpretations is that we continue to find substitutability between K-12 aid and low-income assistance. States that spend less on various household-level transfer programs tend to have a greater desire to allocate K-12 aid in such a way as to equalize resources among school districts. In other words, where the budget does not allow for generous welfare spending, another means of achieving that policy goal is through a more progressive aid distribution.

The two education spending variables also correlate with less progressive distributions of aid.[8] It is clear here as well that there is a substantial component of K-12 aid that, like spending on universities and colleges, intends to produce more human capital. We can establish then that, as we had conjectured in our introduction, there are two important drivers behind the decision to spend on state education aid, which are a preference for producing more educated workers and a preference to close resource gaps. To try to tease out which preference is the dominant one, we turn to dynamic simulations.

5 Dynamic Simulation Evidence

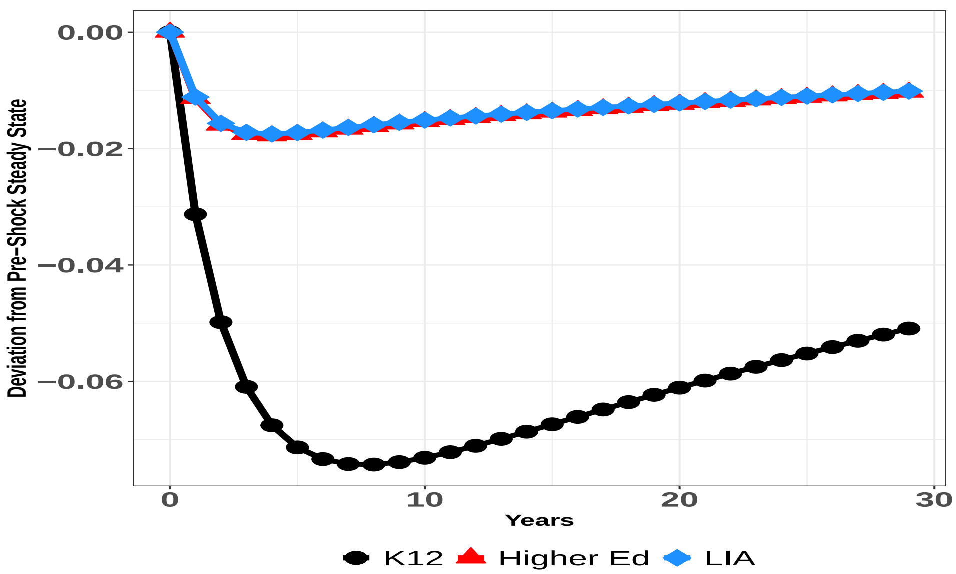
In this section, we put our model to work and draw out the implications for spending on K-12 aid and its distribution, as well as spending on programs aimed largely at education production or equalization of resources, using simulation analysis. We follow the approach adopted in Biolsi, Craig, Dhar, and Sørensen (2022), as briefly spoken to above. 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

[8]This does not contradict our finding that greater funding for higher education makes the unequal caring parameter more negative, as discussed in Section 4.2, as that looks at changes over time within a state, whereas in this section, we are examining cross-state heterogeneity.

revenue (and thus total spending, since we abstract from federal aid).

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, and each one also experiences AR(1) income dynamics with a coefficient on lagged income of 0.98. This means that income shocks are quite persistent, which plays into the dynamics that we simulate. Figure 5 illustrates the responses of the main state-level variables of interest to this shock.

Figure 5: 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.

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 seven years after impact. This implies a dynamic income elasticity of 1.69, so that education aid might be categorized as a

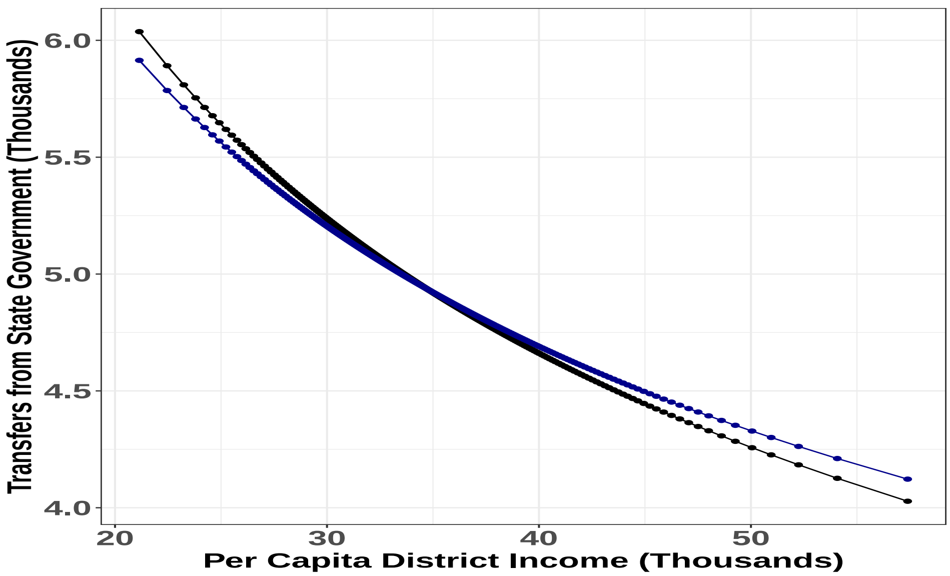
[9]This is the average per-capita income loss across the states in our sample during the 2007-2009 financial crisis.

luxury good. 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. The dynamic income elasticities of both are around 0.40, so that state governments apparently consider these as necessity items. 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 low intertemporal elasticities of substitution (coefficients of relative risk aversion, ν and ψ, above 10).

Not only does state aid fall in total, however, but the changing funding for higher education and low-income assistance also alter the distribution of state aid. Since the declines in higher education and low-income assistance are quantitatively so similar, the fact that ω_1 is greater in absolute value than ω_2 means that over time, state aid will become less progressively distributed and the gradient of state aid with respect to locally-raised revenue will become flatter. The unequal caring parameter, which is -0.52 in steady state, has shifted to -0.49 when the reaction of state aid is at its lowest ebb. This is illustrated in Figure 6, where we observe a substantial flattening of the state aid distribution seven years after the shock at the trough of the total state aid response. Further, given how important state aid is especially to lower-income school districts (Jackson, Wigger, and Xiong, 2018; Biolsi, Craig, Dhar, and Sørensen, 2022), the flatter state aid distribution is associated with a much less equal per-student spending distribution.

Our simulation analysis allows us to estimate a key statistic, which is the dynamic income

Figure 6: Changing Distribution of State Aid Following State Income Shock: Steady State vs. 7 Years Later



*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 black line shows the steady state distribution of state aid, and the blue line shows how the distribution changes after seven 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.

elasticity of equalization aid. As a summary measure of the state's attempts to provide progressive K-12 aid, we look at the differences between aid provided to the school district at the 85^{th} percentile of the steady state income distribution (which we term the "high-income" district) and that at the 15^{th} percentile (the "low-income" district). Table 6 contains the relevant figures that we utilize in our calculations.

Table 6: State Aid Levels (000's)

	15^{th} Pct.	85^{th} Pct.	Difference	Elasticity
Steady State	\$5.326	\$4.577	\$0.749	−−
At trough (7 years after income shock)				
Baseline Model (Both Influences)	\$4.931	\$4.262	\$0.668	2.44
Only LIA Influence	\$4.955	\$4.239	\$0.716	0.99
Only HE Influence	\$4.920	\$4.273	\$0.647	3.08
Neither LIA nor HE influence	\$4.944	\$4.249	\$0.695	1.62
$\lambda \equiv$ Equity Share of Motivation for K-12 Aid $= \frac{\$0.716-\$0.695}{\$0.716-\$0.647} = 0.30$				

Notes: The table reports simulations of state aid values provided to a school district at the 15^{th} percentile of the steady state and the 85^{th} percentile of the distribution in thousands of dollars per student. The first line contains steady state values, while the subsequent lines report simulation results for different specifications of our preference model.

In steady state (before any shocks have occurred), the low-income district receives \$5,326 per student in aid from the state government, which compares with \$4,577 that the high-income district receives. The per-student difference between the two is \$749. After the state receives its Great Recession-like income shock, total aid falls across the board and, as discussed above, becomes less progressive, owing to the influences of the declines in higher education funding and spending on low-income assistance programs, flattening the aid distribution. When total state aid reaches its nadir seven years after the initial shock to income, state aid for the low-income district has fallen to \$4,931 per student and that for the high-income district has fallen by over \$300 per student to \$4,262. Clearly, however, the low-income district lost more in the way of state aid so that the difference between the two districts narrowed to \$668 per student, a 10.8 percent decline. Comparing this decrease with the income shock seven years earlier of 4.4 percent, and we compute an income elasticity of equalizing aid of 2.44. The equalization of between-district resource disparities would appear to be a strong luxury good. This is, to our knowledge, an entirely novel result in the literature.

While the dynamic income elasticity of 2.44 is an interesting finding in itself, our model affords us the ability to evaluate counterfactual scenarios that may help us to obtain insights into the motivations behind K-12 aid. Recall that we argue that the main policy goal behind funding for low-income assistance is a desire to promote greater equity among residents of the state. In our model, we can perform an experiment in which we shut down the influence of higher education spending on the K-12 aid distribution (by setting $\omega_1 = 0$), thereby ensuring that, as it relates to away-from-steady-state changes, only the equalization motive for K-12 aid remains. The decline in low-income assistance causes the unequal caring term to become more negative, at about -0.54 when total state aid reaches its trough. With less to spend on helping low-income residents, the state now attempts to address resource disparities by distributing the existing state aid budget more progressively than it otherwise would. Of course, while the aid budget is being distributed more progressively on a proportional basis (the low-income district is getting a greater share of the aid budget than it did in steady state), the overall amount to spend is still declining fairly dramatically. Seven years after the shock, then, state aid for K-12 to the low-income district has fallen to \$4,955 per student while that for the high-income district has fallen to \$4,239, giving a difference of \$716 per student. This implies a dynamic income elasticity of 0.99, making equalization a (barely) necessity good. When the influence from the objective of producing human capital is limited, states are more protective of the progressivity of state aid.

We can perform a similar exercise by shutting down the influence of low-income assistance changes on the unequal caring parameter, setting $\omega_2 = 0$, leaving the education production motive to operate largely on its own. The analogous dynamic elasticity that we calculate in this case is 3.08. Unsurprisingly, when we shut down the equalization motive behind K-12 aid, the equalizing aspect of aid becomes much more of a luxury in the eyes of state policymakers, so that cross-district differences fall substantially in the face of statewide income shocks. When we set both terms to zero (thus replicating the analysis in Biolsi, Craig, Dhar, and Sørensen, 2022) so that the unequal caring parameter stays the same over time, we get a dynamic income elasticity of 1.62. All of these calculations are detailed in Table 6.

Now, we turn to the main question of our study, which is what share of the motivation behind K-12 aid can be assigned to the preference for equalization versus what share may be assigned to the preference for producing human capital. To do so, we make use of our dynamic elasticity estimates. Compared with a situation in which neither influence operates, the difference between the high- and low-income districts is \$21 greater when only the equalization motive is in effect. Similarly, when only the education production objective plays a role, the difference is \$48 lower. Between the two extreme cases then, there is a \$69 gap, of which the equalization motive explains $\frac{\$21}{\$69} = 30$ percent, leaving the other 70 percent to the education production motivation. This leads to our conclusion that, at the margin, about 30 percent of the driving force behind state government for K-12 aid stems from a policy preference for equalizing resource disparities. Such a result can be easily seen from the fact that dynamic income elasticity from the baseline model (2.44) is much closer to the one that results from allowing only the education production motivation (3.08) than it is to the one where only the equalization motivation is allowed (0.99).

6 Conclusion

Our study uses a conceptually simple preference model to establish what motivates state government funding for K-12 aid. Our empirical results establish that, in fact, state government spending choices relating to the production of human capital via education (as proxied by funding for higher education and K-12 education aid to school districts) and to equalization of resources (captured by low-income assistance programs, as well as K-12 aid) are systematically related. We show that, looking across states, there are positive correlations between funding for each of these items.

We also report that there are links between how much states spend on higher education or low-income assistance and how progressively they distribute state aid to school districts. Our results speak to this effect both in the cross-sectional steady state (states that spend more on either of those two programs on average also appear to have less progressive distributions of aid, with less negative unequal caring parameters) and dynamically, within a state. Specifically, we show that when a state spends more than its average level on public universities (holding funding for health and welfare programs constant), they also appear to make their aid distributions more progressive. The opposite happens when they spend more on low-income assistance programs, holding higher education spending constant. Thus, it seems that states treat low-income assistance and equalizing aid to school districts as substitutes in achieving the same policy end.

Simulating our preference model, we calculate a dynamic income elasticity of equalizing aid of 2.44, which exceeds the analogous elasticities computed for the entire state aid budget, higher education spending, or low-income assistance. This implies that states see equalizing aid as a significant luxury good, especially when compared with other uses of state resources. By turning to counterfactual analyses where we turn off the influences of, sequentially, the education production motivation, the equalization motivation, or both, we find that about 30 percent of the overall motivation for state government aid to districts for K-12 at the margin comes from a desire to address resource disparities. This leaves 70 percent to the production of human capital.

On the whole, our results accord with the views expressed in Shepsle (1979). Policy choices are not made in a vacuum, and there can be many policies aimed at a certain objective, as well as many objectives satisfied by a single policy tool. In the case of K-12 aid, we find compelling evidence that it is aimed at two different goals of state governments. At times of income shocks, moreover, states must decide which of these goals to forego in order accommodate the others.

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