

# Educational Policy and Intergenerational Mobility

Tomoaki Kotera and Ananth Seshadri\*

Department of Economics, University of Wisconsin-Madison

## Abstract

In the United States, there is considerable variation in intergenerational mobility across states. We argue that the distribution of public school spending across school districts under public school finance systems affects intergenerational mobility within the United States. We build a dynamic model in which school districts vote over public school spending per pupil taking the finance system as given. We embed this model with median voting at the district level within a fairly standard Ben-Porath model of human capital accumulation later in life. Our model can replicate the relationship between the distribution of public school spending and intergenerational mobility observed in data. Furthermore, three counterfactual simulations suggest that i) the correlation between parental human capital and a child's learning ability plays a significant role in explaining the cross-state variation in intergenerational mobility, ii) a more equal distribution of public school spending under a foundation program by relaxing a borrowing constraint improves intergenerational mobility, especially when a child's learning ability is not highly dependent on parental human capital, and iii) switching to a full state funding program improves intergenerational mobility, but not enormously. This is because full state funding limits public school spending, which hinders intergenerational mobility.

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\*We thank seminar participants at the HCEO conference on Human Capital and Inequality as well as Marco Bassetto, Dean Corbae, Mariacristina DeNardi, James Heckman, Lance Lochner, Chris Taber and particularly, our discussant Elizabeth Caucutt for very helpful comments. Kotera acknowledges the financial support from the Nakajima Foundation.

# 1 Introduction

Intergenerational mobility is an important issue in the United States. Evidence suggests that the United States is one of the least mobile countries in the world.<sup>1</sup> There is also considerable variation in intergenerational mobility at the state level. According to our calculations based on data from Chetty et al. (2014), the most and least mobile states are Hawaii and Mississippi, respectively. In Hawaii, rank-rank slope, a measure of relative mobility, is 0.236, whereas the corresponding value in Mississippi is 0.414. These slopes mean that if the difference in income ranks of two parents is 100, the difference in their child’s income rank will fall to 24 in Hawaii and 41 in Mississippi. Therefore, where a family resides affects a child’s future outcomes significantly.

A natural question is: what factors generate this variation across states? Chetty et al. (2014) argue that segregation, income inequality, school quality, social capital and family structure are highly correlated with the variation in intergenerational mobility. However, since all of these variables are endogenous, more work is needed to better understand the underlying causal factors.

We take the stand that public school spending is an important determinant of intergenerational mobility. Recent evidence suggests that early childhood investments are critical in improving child’s status and consequently, intergenerational mobility (Cunha and Heckman (2007), and Caucutt and Lochner (2012)). Therefore, spending on public schools potentially plays an important role.

The focus of our paper is on the distribution of public school spending across school districts within a state, which, in practice, is measured as the estimated coefficient of school district income on public schooling spending per pupil (henceforth, the ‘slope coefficient’).<sup>2</sup> We find a substantial variation in the distribution of public school spending across states. For example, rich school districts in Illinois tend to spend more on public schools than poor school districts, whereas public school spending is more equally distributed in California. More importantly, we find a positive correlation between the distribution of public school spending and rank-rank slope across states. That is, a more equal distribution of public school spending is associated with lower rank-rank slope. This suggests that the cross-state variation in the distribution of public school spending is a potential contributor to the variation in intergenerational mobility.

We explore the relation between public school spending and intergenerational mobility by taking into account the public school finance systems. In the U.S, there are four public school finance

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<sup>1</sup>For example, Corak (2013) shows that the intergenerational income elasticity (introduced in the next section) in the United States is close to 0.5. This number is the highest among the OECD countries.

<sup>2</sup>As explained later, we use median household income as a measure of school district income. Parent income and school district income are used interchangeably in this paper.

systems: a flat grant program, a full state funding program, a foundation program, and an equalization program. We model a foundation program, the most popular one, and a full state funding program, the ideal one if the goal is to reduce inequality in public school spending. A full state funding program is ideal in terms of equal spending because public school spending is financed only by statewide taxes and local governments cannot impose taxes for additional spending. In contrast, in a foundation program, a minimum amount of public school spending is guaranteed in all school districts by the state government, but local governments can raise spending through a local tax. A foundation program was employed in 39 states in the early 1990s, the period we consider in this paper. Revisiting the relation between public school spending and rank-rank slope by school finance system, we find two salient patterns in data: (1) Among states using a foundation program, there is considerable variation in both the distribution of public school spending and rank-rank slope, and a positive correlation between them still holds; (2) Relative to states with a foundation program, states with a full state funding program have a more equal distribution of public school spending and lower rank-rank slope.

We model the connection between public school spending and intergenerational mobility by extending the framework in Fernandez and Rogerson (2003). In particular, we extend their static model to a dynamic setting with three periods where a child can accumulate human capital both in school and at work. More importantly, human capital accumulation in school depends not only on public resources from the state and local government, but also on private resources from parents and a child's own learning ability. Public school spending from the state government is determined through majority voting under either a foundation program or a full state funding program. Furthermore, parents can make a nonnegative transfer to their children when the children become independent after schooling.

We estimate the model state by state using various data sets. In the estimation, we assume that a child's own learning ability is correlated with parental human capital. Our estimated model fits some aspects of the data reasonably well. In particular, our model generates a positive correlation between the distribution of public school spending and intergenerational mobility across states. However, the set of targeted states is limited in our estimation highlighting a failure of our model. We drop the states in which the slope coefficient is negative. In our model, in order to generate a negative slope coefficient, the correlation between parental human capital and a child's learning ability needs to be negative. This leads to a negative rank-rank slope which is inconsistent with data.<sup>3</sup> With the

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<sup>3</sup>A sceptic might view negative empirical relationship between district funding and income with suspicion and

estimated model, we conduct three counterfactual simulations to understand the determinants of intergenerational mobility. The first simulation shows that the correlation between parental human capital and a child’s learning ability plays an important role in explaining intergenerational mobility. The second simulation shows that allowing parents to borrow against their children’s future income and using it to invest in their children leads to a more equal distribution of public school spending. The effect on rank-rank slope, however, depends negatively on the correlation between parental human capital and a child’s learning ability. With a smaller correlation, allowing parents to borrow against their children’s future income improves intergenerational mobility significantly. In the third simulation, we find that switching to a full state funding program also improves intergenerational mobility. However, when we compare results on rank-rank slope across simulations, we find that the degree to which intergenerational mobility improves in a full state funding program is not dramatic. This result arises from two competing forces prevalent in a full state funding program. On the one hand, a full state funding program leads to a uniform distribution of public school spending across school districts. On the other hand, it restricts the level of public spending. Therefore, poor and middle-income school districts gain little benefit by full state funding. In our exercise, the restriction on public school spending impedes intergenerational mobility in a full state funding program.

To the best of our knowledge, we are the first to model the effect of the distribution of public school spending on intergenerational mobility within a country taking a structural approach. There is now an extensive literature on intergenerational mobility (e.g., Becker and Tomes (1979, 1986), Solon (1992), Restuccia and Urrutia (2004), Mazumder (2005), and Lee and Seshadri (2014)), but these papers consider income mobility of the U.S. at the aggregate level.<sup>4</sup> Another strand of literature compares mobility across countries (Corak (2013), Holter (2015), and Abbott and Gallipoli (2014)). Chetty et al. (2014) offer a first look at intergenerational mobility at a finer division (county level) and propose possible explanations. There is also a large literature on public spending on primary and secondary education. The effect of school finance reform on equality of spending across districts has been discussed extensively. Hoxby (2001) and Card and Payne (2002) examine the short-run effect of school finance equalization using drop-out rates (Hoxby (2001)), and SAT scores (Card and Payne (2002)). Some recent papers discuss the long-run impact of educational

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this may well be a failure of the way in which we look at this relationship empirically (i.e. just the raw correlation). We tried several controls including urban/rural dummy and racial dummies but the negative coefficient persists. Interestingly, Biasi (2015), also finds a negative coefficient. She regresses median per-capita household income in district on per-pupil expenditure in district for each community zone. Her result shows that the slope coefficient is negative on average.

<sup>4</sup>Solon (1992) and Mazmunder (2005) estimate intergenerational mobility in the U.S. Becker and Tomes (1979, 1986) and Lee and Seshadri (2014) explore the mechanisms behind income mobility.

reform. For example, Jackson et al. (2016) explore the impact on educational attainment and earnings. Biasi (2015) is the most relevant paper. She studies the consequence of educational reform on intergenerational income mobility. Our approach allows us to obtain a better understanding of the mechanisms at work. Using structural models and a political economy approach, Fernandez and Rogerson (1999, 2003), and Ferreyra (2009) evaluate different funding formulae in terms of the level of educational spending. Different from these papers, we present a dynamic model in order to understand the relationship between educational policy and intergenerational mobility.

The rest of the paper proceeds as follows. Section 2 discusses stylized facts on intergenerational mobility and public school spending across states. In section 3, we describe the model. Section 4 summarizes the estimation method. Section 5 presents the baseline results. Section 6 discusses the counterfactual simulations. Finally, we conclude the paper in Section 7.

## 2 Facts

This section presents some empirical facts on intergenerational mobility and educational policy in the U.S.

### 2.1 Intergenerational Mobility

We use rank-rank slope as a measure of intergenerational mobility. Rank-Rank slope measures the association between parent income rank and their children’s income rank as adults. A higher rank-rank slope indicates a larger dependence of child income on parent income and a lower intergenerational mobility. Relative to other measures like the intergenerational income elasticity (IGE), rank-rank slope is more robust to factors like the presence of low- or zero-income observations.<sup>5</sup> We calculate rank-rank slope for each state as the weighted average of the county level estimates in Chetty et al. (2014),<sup>6</sup> where the weight for each county is its population from the 2000 census.

Table 1 reports states with the lowest and highest rank-rank slope. Hawaii has the lowest rank-rank slope, with a value of 0.236. It suggests that the difference in income rank between two children, one born to the richest parents and the other born to the poorest parents in Hawaii, is

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<sup>5</sup>Estimates of IGE are also very sensitive to variable definitions. For example, IGE in Solon (1992) is 0.4 whereas it’s 0.6 in Mazumder (2005). Mazumder (2005) argues that this difference is mainly attributable to the difference in the number of years used to calculate father’s average income. On the other hand, Chetty et al. (2014) find that rank-rank slope remains unchanged when parent income is ranked in different ways.

<sup>6</sup>Rank-Rank slope for each county is available on Raj Chetty’s website: <http://www.equality-of-opportunity.org/index.php/data>.

Table 1: States with the Lowest and Highest Rank-Rank Slope

	State	Rank-Rank Slope		State	Rank-Rank Slope
1st	Hawaii	0.236	51st	Mississippi	0.414
2nd	California	0.237	50th	Louisiana	0.395
3rd	Utah	0.244	49th	Delaware	0.394
4th	Idaho	0.245	48th	Ohio	0.392
5th	Wyoming	0.254	47th	Alabama	0.390

only about 23.6. In contrast, if the two children were born to the richest and poorest parents in Mississippi, the state with the highest rank-rank slope, the difference in their income ranks will be 41.4. Clearly, there is substantial variation in intergenerational mobility across states, and place of residence while young affects future outcomes significantly.

## 2.2 Public School Spending

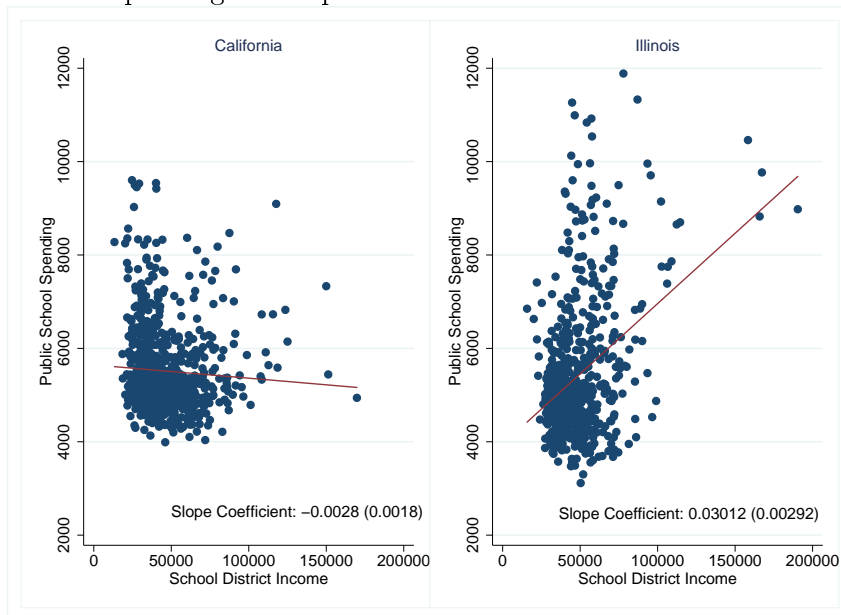
One potential explanation for the cross-state variation in intergenerational mobility is differences in public school spending. If one state spends more on the education of children born to poor parents than another, other things equal, we should expect a higher intergenerational mobility and a lower rank-rank slope. To provide some evidence, we calculate public schooling spending per pupil and median household income for each school district in each state. This allows us to examine whether children in poor school districts benefit more from public school spending or not.

Using the public elementary and secondary education finance data from the U.S. Census Bureau, we calculate public schooling spending per pupil for each school district in each year by dividing total spending by the number of students.<sup>7</sup> Because we are going to relate public school spending to rank-rank slope reported earlier, and rank-rank slope in Chetty et al. (2014) are calculated for individuals born in 1980-1982, we use CPI to adjust the spending in each year and calculate a measure of average public school spending per pupil between 1990 and 1998 for each school district. As a proxy for the income level of a school district, we use median household income obtained from the 2000 school district tabulation of the National Center for Education Statistics.

For each state, we run a regression of average public school spending on median household income across school districts. We use the slope coefficient as a measure of the distribution of public school spending across school districts in a state. The distribution of public school spending varies substantially across states, even among states with similar characteristics. For example, California

<sup>7</sup>Total spending includes current spending for instruction, support services, and other elementary-secondary programs.

Figure 1: Public School Spending Per Pupil and Median Household Income Across School Districts

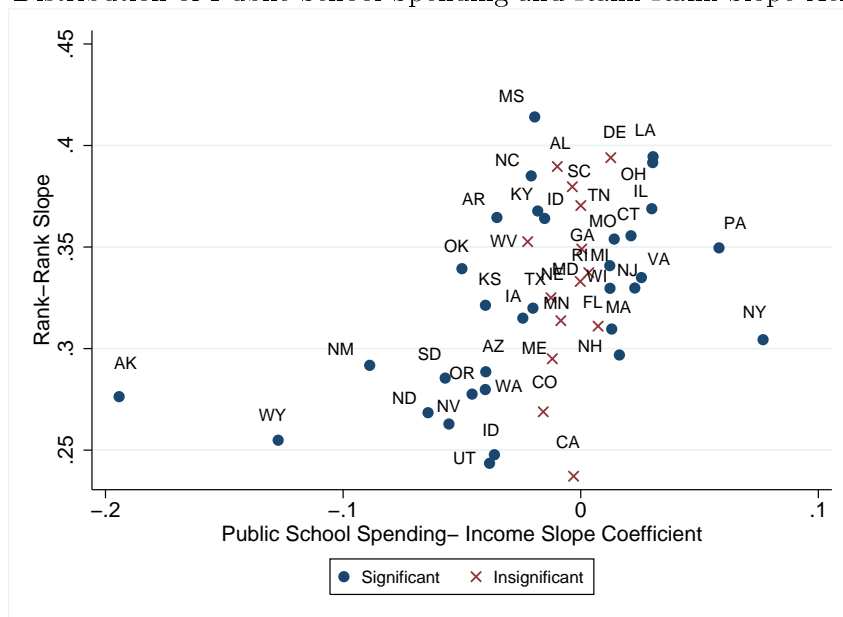


and Illinois have nearly the same number of school districts (989 for California vs 897 for Illinois), and average public school spending per pupil at the state level is also very similar in the two states (\$5,472 in California vs \$5,360 in Illinois). However, as Figure 1 shows, the distribution of public schooling spending is very different between these states. There is the negative but insignificant slope coefficient in California, while the slope coefficient in Illinois is positive and statistically significant at the 1% significance level. This suggests that, relative to California, public school spending in Illinois tends to favor children born to richer parents. Other things equal, this difference could result in a lower intergenerational mobility in Illinois than in California. Consistent with this argument, rank-rank slope is higher in Illinois (0.369) than in California (0.237).

Figure 2 plots the distribution of public school spending measured by the slope coefficient and rank-rank slope across states.<sup>8</sup> States marked with a solid dot are those for whom the estimated the slope coefficient is statistically significant at 5% significance level. Evidently, there is considerable variation in the slope coefficient across states. The slope coefficient is negative in some states, indicating a negative correlation between median household income and public school spending across school districts. Some of the negative coefficients, however, are statistically insignificant. According to our estimation, 19 states have statistically significant negative slope coefficients. More importantly, there is a positive correlation between our measure of the distribution of public school

<sup>8</sup>Not all states are plotted. Montana and Vermont are omitted because they have no unified school districts. D.C. and Hawaii are dropped because data on public school spending is available in only one school district. These same states are dropped in all subsequent analysis.

Figure 2: Distribution of Public School Spending and Rank-Rank Slope Across States



spending and rank-rank slope. Evidence in Figure 2 is consistent with the idea that more educational spending on richer children reduces intergenerational mobility. Clearly, we should take the distribution of public school spending into consideration in order to understand intergenerational mobility in the U.S.

### 2.3 Public School Finance Systems

One important determinant of the distribution of public school spending in a state is the school finance system. According to the American Education Finance Association (1992, 1995), there are four school finance systems: a flat grant program, a full state funding program, a foundation program, and an equalization program. In this paper, we focus on a foundation program and a full state funding program.

We model a foundation program because it is the most popular program in the U.S. For example, 37 states in 1990-1991 and 39 states in 1993-1994 employed this finance system.<sup>9</sup> In a foundation

<sup>9</sup>American Education Finance Association (1992, 1995) includes California in a foundation program. However, we do not in light of its finance system. Two states (Delaware and North Carolina) employed a flat grant program and 6 states (Connecticut, Indiana, New York, Pennsylvania, Rhode Island, and Wisconsin) used an equalization program in 1993-1994.

In a flat grant program, an equal amount of aid is guaranteed. This level is determined by the state government. In an equalization program, the state government sets a targeted fiscal goal. If a school district's actual fiscal level cannot reach this goal, the state government fills the gap. The aim of this system is to make spending across school districts more equalized. However, this program does not equalize public school spending in practice, partly because school districts with above average tax bases usually impose higher tax rates. Fernandez and Rogerson (2003) points out this tendency. In 2000s, New York and Pennsylvania switched from the equalization program to the foundation



program,<sup>10</sup> the state government sets a minimum amount of public school spending guaranteed for all school districts, and local governments are allowed to levy taxes to increase their public school spending. This is different from a full state funding system where all public school spending is financed by statewide taxes, and local governments cannot impose taxes to raise spending on their public schools. A full state funding system was used in California, Hawaii and Washington.<sup>11</sup> We consider this system because it is the ideal system if the goal is to equalize public school spending across school districts within a state.

Figure 3 plots our measure of the distribution of public school spending and rank-rank slope for states using the two finance systems. States marked with either a solid dot or an X employ a foundation program, while other states adopt a full state funding program. Additionally, either a solid dot or a triangle have an estimated slope coefficient that is statistically significant at the 5% level. Two salient features can be seen from the figure. First, there is considerable variation in both the distribution of public school spending and rank-rank slope among states using the foundation program. Secondly, rank-rank slope is much lower in states employing a full state funding system (California and Washington), likely because public school spending is more equally distributed in these states.<sup>12</sup>

### 3 Model

We present a model to capture the relationship between public school spending and intergenerational mobility presented in the previous section. Our model is an extension of Fernandez and Rogerson (2003) who explore the implications of public school finance systems in the U.S.

#### 3.1 Model Environment

We consider a three-period model economy. The first period is 18 years, and the last two periods are 6 years each. We keep track of each child from birth until the age of 30. There is a continuum

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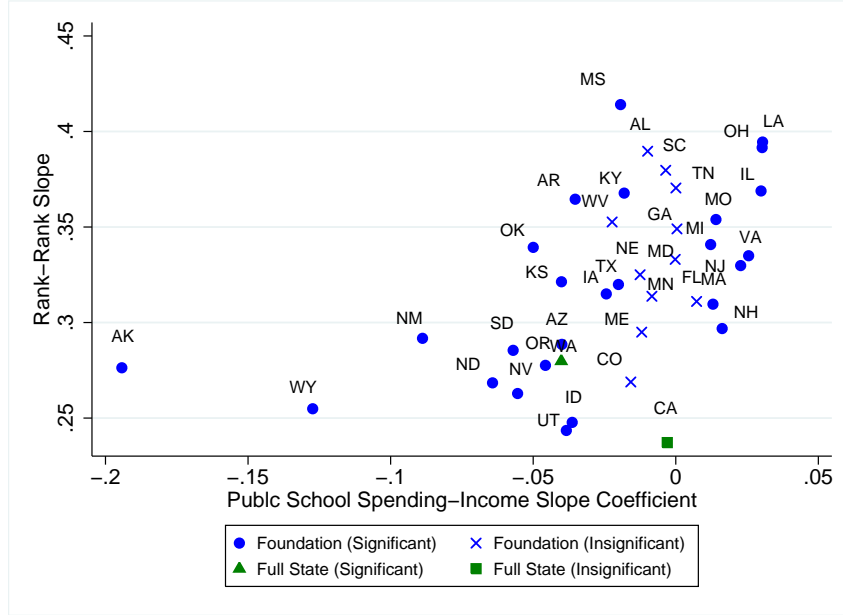
program.

<sup>10</sup>Card and Payne (2002) call this system a minimum foundation program.

<sup>11</sup>In a technical sense, the characterization of full state funding in each state is different. Hawaii purely used full state funding. Washington was classified as full state funding because it was forced to use the basic support program fully by its constitution. In California, the maximal revenue was limited by state government. Therefore, California virtually employs full state funding.

<sup>12</sup>For comparison, rank-rank slope is also higher in states using either an equalization program or a flat grant program. For example, for states using an equalization program, rank-rank slope is 0.356 in Connecticut, 0.364 in Indiana, 0.304 in New York, 0.350 in Pennsylvania, 0.337 in Rhode Island, and 0.330 in Wisconsin. For the two states using a flat grant program, rank-rank slope is 0.394 in Delaware and 0.385 in North Carolina.

Figure 3: Public School Spending and Rank-Rank Slope by Finance System



of individuals whose population is normalized to be one. In each state, there are  $n$  school districts. The income of parents in school district  $j (\in \{1, 2, \dots, n\})$  is denoted by  $y_j$ . For simplicity, we assume there is no income heterogeneity within a school district, and assume that the distribution of parental income  $y_j$  across school districts in a state is exogenous.

In the first period, parents in each school district  $j$  invest in their children, choose their consumption  $c_{j1}$ , and leave the rest of their income  $g_j$  as a transfer to their children who can use these resources in the second period. They do so to maximize their utility given by

$$u(c_{j1}) + \theta V(a_j, h_{j2}, g_j),$$

where  $u(c_{j1})$  is the utility from consumption,  $V(a_j, h_{j2}, g_j)$  is the lifetime utility of their children starting from the second period which is specified in more detail later, and  $\theta$  is a measure of parental altruism.

We assume all children attend public schools in the school district where they were born. We also assume that  $g_j \geq 0$  so that parents cannot leave debt to their children. This is an important friction in the model. It leads to intergenerationally constrained and unconstrained families and hence a role for government intervention to improve allocative efficiency.

Different from Fernandez and Rogerson (2003) who only consider the quantity of a child's education from public resources, we allow the amount of human capital that a child can accumulate

in the first period to depend on (1) public resources, (2) private inputs, and (3) a child's learning ability. Specifically, for children in school district  $j$ , the stock of human capital at the beginning of the second period,  $h_{j2}$ , is given by

$$h_{j2} = a_j[\omega x_{j1}^\phi + (1 - \omega)\bar{x}_j^\phi]^\frac{\gamma}{\phi}, \quad (1)$$

where  $a_j$  is a learning ability,  $x_{j1}$  and  $\bar{x}_j$  represent private and public inputs, respectively,  $\omega$  is the share of private inputs,  $\phi$  is the elasticity of substitution between private and public inputs, and  $\gamma$  is a measure of returns to scale.

Children become independent at the beginning of the second period. They make decisions on human capital accumulation and consumption in the second and third period to maximize utility

$$V(a_j, h_{j2}, g_j) = \max_{\{c_{j2}, c_{j3}, n_{j2}, x_{j2}\}} u(c_{j2}) + \beta u(c_{j3})$$

subject to the budget constraint

$$c_{j2} + \frac{c_{j3}}{1+r} = \bar{w}h_{j2}(1 - n_{j2}) + \frac{\bar{w}h_{j3}}{1+r} + g_j,$$

and the human capital production function

$$h_{j3} = a_j(n_{j2}h_{j2})^m + h_{j2}, \quad (2)$$

where  $\beta$  is the discount factor,  $r$  is the interest rate,  $\bar{w}$  is the rental rate of human capital, and  $n_{j2}$  is the time spent on human capital accumulation in the second period. Equation (2) is a standard human capital accumulation function à la Ben-Porath (1967). It allows individuals to accumulate human capital in the second period if they received too little education in the first period either due to the state of birth or by virtue of having poor parents. This extra margin of adjustment leads to a more flexible relationship between first-period investments and earnings at later ages which we believe is important in understanding the data. With the last two periods, we can relate  $n_{j2}$  to college education and  $\bar{w}h_{j3}$  to earnings at age 30. There are no borrowing constraints in the last two periods.

For simplicity, we assume there is a common wage rate  $\bar{w}$  for all school districts in all states. This will be the case if there is no moving cost so that any spatial difference in the wage rate will be eliminated by migration. Given the large fraction of workers who do not live in their state of

birth, we consider this simplification as a useful benchmark.

The solution of the model in the last two periods is straightforward. In particular, individuals invest to maximize lifetime income as in Ben-Porath (1967), then allocate consumption across the two periods to maximize discounted utility. While in the first period, the solution depends on the school finance system that determines public inputs  $\bar{x}_j$ . For simplicity, we assume  $\bar{x}_j$  is funded by proportional taxation of income.<sup>13</sup> We discuss the solution of the model under each of the two systems in turn.

### 3.2 The Full State Funding Program

With full state funding, public school spending is financed only by a statewide income tax. Every school district has the same amount of public resources. Let  $\bar{x}$  be the spending common to all school districts, we have

$$\bar{x} = \tau \frac{1}{n} \sum_{j=1}^n y_j, \quad (3)$$

where  $\tau$  is the tax rate applicable to all school districts. Let  $\mu \equiv \frac{1}{n} \sum_{j=1}^n y_j$  denote the average income in a state.

First, the problem can be solved as though each school district could choose its own  $\tau$ . Then, statewide  $\tau$  is ultimately determined through majority voting. Specifically, in the first step, in addition to  $\tau$ , parents in school district  $j$  choose consumption  $c_{j1}$ , private spending on child's human capital  $x_{j1}$  and parental transfers  $g_j$  by solving the follow problem

$$\max_{c_{j1}, x_{j1}, g_j, \tau} u(c_{j1}) + \theta V(a_j, h_{j2}, g_j)$$

subject to (1), a budget constraint

$$c_{j1} + x_{j1} + g_j = (1 - \tau)y_j,$$

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<sup>13</sup>This assumption is the same as Fernandez and Rogerson (2003). In reality, however, public school spending relies heavily on property tax. In order to consider property tax, we have to include housing consumption separately as Fernandez and Rogerson (1999), Epple and Ferreyra (2008) and Ferreyra (2009) do. However, incorporating housing consumption and property tax complicate the model substantially. We abstract from them for simplicity.

and a non-negativity condition

$$g_j \geq 0. \tag{4}$$

The first-order conditions for  $\tau$ ,  $x_{j1}$ , and  $g_j$  are

$$\tau : \theta V'_{h_{j2}}(a_j, h_{j2}, g_j) ((1 - \omega) \gamma a_j \bar{x}^{\phi-1} [\omega x_{j1}^\phi + (1 - \omega) \bar{x}^\phi]^{\frac{\gamma-\phi}{\phi}}) \mu = u'(c_{j1}) y_j,$$

$$x_{j1} : \theta V'_{h_{j2}}(a_j, h_{j2}, g_j) (\omega \gamma a_j x_{j1}^{\phi-1} [\omega x_{j1}^\phi + (1 - \omega) \bar{x}^\phi]^{\frac{\gamma-\phi}{\phi}}) = u'(c_{j1}),$$

$$g_j : \theta V'_{g_j}(a_j, h_{j2}, g_j) \leq u'(c_{j1}),$$

where  $V'_{h_{j2}}(a_j, h_{j2}, g_j)$  and  $V'_{g_j}(a_j, h_{j2}, g_j)$  are the derivatives of  $V(a_j, h_{j2}, g_j)$  with respect to  $h_{j2}$  and  $g_j$ , respectively, and  $u'(c_{j1})$  denotes the derivative of  $u(c_{j1})$  with respect to  $c_{j1}$ . The first two conditions imply that the optimal tax rate and private investment would equate the marginal benefits for children in the last two periods with the marginal costs incurred by parents in the first period. The last condition holds with equality if  $g_j > 0$ . In this case, the value of a dollar to the parent is the same no matter whether it's consumed or left to the children. Otherwise, if the value of a dollar to the parent is larger when it's consumed even if  $g_j = 0$ , the inequality in the third condition would be strict. Let the solution to this equation for school district  $j$  be denoted by  $\tau_j$ . Given  $\tau_j$  for each school district, statewide tax rate  $\tau$  is pinned down by majority voting.

In our calibration, parental preferences are single-peaked in  $\tau$ . Therefore, the existence of a majority voting equilibrium is guaranteed. However, as we allow a learning ability  $a_j$  to be a random variable, the single crossing property does not necessarily hold as in Fernandez and Rogerson (2003). Therefore, a school district with the median income is not always a median voter. Alternatively, the equilibrium income tax rate  $\tau$  must satisfy

$$\int I_{\{\tau_j \geq \tau\}} dF(y_j) \geq \frac{1}{2},$$

and

$$\int I_{\{\tau_j \leq \tau\}} dF(y_j) \geq \frac{1}{2},$$

where  $I$  is an indicator function and  $F(y_j)$  is the cumulative distribution function of income  $y_j$ .

Given the statewide choice of  $\tau$ , individuals solve the problem in the first step to obtain  $c_{j1}$ ,  $x_{j1}$  and  $g_j$ .

### 3.3 The Foundation Program

In a foundation program, there is a minimum level of public spending guaranteed for every school district that is funded by a statewide income tax. Additionally, if a school district wants to spend more, it can do so by imposing a local tax. Public spending  $\bar{x}_j$  is

$$\bar{x}_j = \tau \frac{1}{n} \sum_{j=1}^n y_j + \tau_j^* y_j, \quad (5)$$

where  $\tau$  is the statewide tax rate and  $\tau_j^*$  is the local tax rate for school district  $j$ .

Following Fernandez and Rogerson (2003), we assume that  $\tau$  and  $\tau_j^*$  are chosen sequentially in two stages. First, given  $\tau$ , each school district chooses  $c_{j1}$ ,  $x_{j1}$ ,  $g_j$  and  $\tau_j^*$  to solve the following problem

$$\max_{c_{j1}, x_{j1}, g_j, \tau_j^*} u(c_{j1}) + \theta V(a_j, h_{j2}, g_j)$$

subject to (1), (4), a budget constraint

$$c_{j1} + x_{j1} + g_j = (1 - \tau - \tau_j^*) y_j,$$

and a non-negative condition for local tax rate

$$\tau_j^* \geq 0.$$

The last constraint is necessary because, when  $\tau$  is high enough, it may be optimal for some school districts to redirect some of the resources from the state government toward other uses. The non-negative condition rules out this possibility.

The optimal condition for  $\tau_j^*$  is given by

$$\theta(V'_{h_{j2}}(a_j, h_{j2}, g_j))((1 - \omega)\gamma a_j \bar{x}_j^{\phi-1} [\omega x_{j1}^{\phi} + (1 - \omega)\bar{x}_j^{\phi}]^{\frac{\gamma-\phi}{\phi}}) \leq u'(c_{j1}),$$

which holds with equality for  $\tau_j^* > 0$ . The decision problem for  $x_{j1}$  and  $g_j$  given  $\tau$  is the same as in full state funding.

Let  $c_{j1}(\tau)$ ,  $h_{j2}(\tau)$  and  $g_j(\tau)$  be the solutions to the above problem given  $\tau$ . The optimal statewide tax rate  $\tau$  chosen by school district  $j$  is the solution to

$$\max_{\tau} u(c_{j1}(\tau)) + \theta V(a_j, h_{j2}(\tau), g_j(\tau)).$$

Finally,  $\tau$  is determined by majority voting.

## 4 Estimation

### 4.1 Fixed Parameters

We assume a standard CRRA utility function over consumption

$$u(c) = \frac{c^{1-\alpha}}{1-\alpha}.$$

We set  $\alpha = 2$ ,  $\beta = 0.96^6$  and  $r = (1 + 0.04)^6 - 1$ , where 6 is the number of years in each of the last two periods of our model.

To calibrate the wage rate  $\bar{w}$ , we assume that parental income in school district  $j$  is given by

$$y_j = w_j \underbrace{\exp(\psi \times school_j)}_{\equiv h_{j0}}.$$

In this equation, parental income  $y_j$  is decomposed into two components: wage rate  $w_j$  and human capital  $h_{j0}$ . Since data on  $y_j$  is available, we can pin down  $w_j$  if we know  $h_{j0}$ . As we do not model parental human capital accumulation, we assume  $h_{j0}$  is a function of parental schooling  $school_j$  with a coefficient  $\psi$ , where  $school_j$  is the average schooling for school district  $j$  available from the Census 2000 school district demographic data files.<sup>14</sup>

<sup>14</sup>The Census 2000 school district demographic data files have data on educational attainment for the population of 25 years old and above. Using this data, we can compute the average schooling in each school district.

Table 2: Fixed Parameters

Description	Parameter	Value
CRRA coefficient	$\alpha$	2.0
Discount factor	$\beta$	0.96 <sup>6</sup>
Return to schooling	$\psi$	0.1
Average wage rate in the U.S.	$\bar{w}$	0.302
Interest Rate	$r$	$(1 + 0.04)^6 - 1$

We set the return to schooling  $\psi = 0.1$  as estimated in Mincer (1974). We calibrate  $w_j$  to match  $y_j$ .<sup>15</sup> Once we have the estimates of  $w_j$  for each school district in each state, we average them to obtain  $\bar{w} = 0.302$ .

Table 2 summarizes the fixed parameters of our model.

## 4.2 Parameters to be Estimated

Following Lee, Roys, and Seshadri (2015), we assume parental human capital  $h_{j0}$  and a child's learning ability  $a_j$  follow a joint log normal distribution in each state

$$\begin{bmatrix} \log h_{j0} \\ \log a_j \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_{h_0} \\ \mu_a \end{bmatrix}, \begin{bmatrix} \sigma_{h_0}^2 & \rho_{h_0a}\sigma_{h_0}\sigma_a \\ \rho_{h_0a}\sigma_{h_0}\sigma_a & \sigma_a^2 \end{bmatrix}\right).$$

Given  $school_j$  and  $\psi$ , parental human capital  $h_{j0} = exp(\psi \times school_j)$  is available for each school district  $j$ . As a result, the mean ( $\mu_{h_0}$ ) and standard deviation ( $\sigma_{h_0}$ ) of initial human capital in a state can be calculated. This allows us to focus on the conditional distribution of  $a_j$

$$\log a_j | \log h_{j0} \sim \mathcal{N}\left(\mu_a + \rho_{h_0a} \frac{\sigma_a}{\sigma_{h_0}} (\log h_{j0} - \mu_{h_0}), \sigma_a^2 (1 - \rho_{h_0a}^2)\right). \quad (6)$$

In addition to state-specific parameters  $\{\mu_a, \sigma_a, \rho_{h_0a}\}$  that allow the model to match the variation in public school spending and income across states, we also need to estimate five parameters  $\{\theta, \phi, \omega, \gamma, \eta_1\}$  common to all states, where  $\theta$  is the degree of parental altruism, and the rest are parameters governing human capital accumulation in the first two periods. We estimate these parameters in two steps. In the first step, we estimate  $\{\theta, \phi, \omega, \gamma, \eta_1\}$  and  $\{\mu_a, \sigma_a, \rho_{h_0a}\}$  for Colorado by matching the data moments in Colorado. We choose Colorado because (1) Colorado uses a

<sup>15</sup>The estimates of these parameters are available upon request.



foundation program, the most popular program in the U.S; (2) the average public school spending per pupil in Colorado is close to the U.S. average,<sup>16</sup> and (3) Colorado has a relatively large number of school districts. In the second step, we estimate  $\{\mu_a, \sigma_a, \rho_{h_0a}\}$  for the rest of the states that use a foundation program.

### 4.3 Moments

We estimate the parameters using the Method of Simulated Moments. Let  $\Theta_s$  be the set of parameters to be estimated using data moments  $M_s$  from state  $s$ , we obtain the estimated  $\Theta_s$  as

$$\hat{\Theta}_s = \arg \min_{\Theta_s} [M_s(\Theta_s) - M_s]' W_s [M_s(\Theta_s) - M_s],$$

where  $M_s(\Theta_s)$  is the simulated model moments, and  $W_s$  is a weighting matrix. In practice, we use the variance-covariance matrix of  $M_s$  as the weighting matrix  $W_s$ .

We use three sets of moments for Colorado. The first set includes average public school spending per pupil for four groups of school districts categorized by average schooling level. Group 1 includes school districts with average schooling  $school_j$  below 12. Group 2 ( $school_j$  between 12 and 13), group 3 ( $school_j$  between 13 and 14) and group 4 ( $school_j$  above 14) are defined similarly. The corresponding model moments are  $\mathbb{E}[\bar{x}_j | \text{Group}K]$  for  $K \in \{1, 2, 3, 4\}$ . The second set of moments includes average child income at age 30. Chetty et al. (2014) provide estimates of median child income at age 30 at the county level.<sup>17</sup> With these county level estimates, we compute average child income for the four groups of school districts defined above as follows. First, let the average human capital of children in county  $i$  in the third period be  $h_{i3} = \sum_{j \in i} \omega_j h_{j3}$  where  $h_{j3}$  is the human capital of children in school district  $j$  in the third period, and  $\omega_j$  is the population of school district  $j$  that acts as the weight. With  $h_{i3}$ , the corresponding model moments are  $\mathbb{E}[\bar{w}h_{i3} | \text{Group}K]$  for  $K \in \{1, 2, 3, 4\}$ . The final moment we use is average years of college education for people born in Colorado. We can compute the moment based on individuals' education attainment. This information is available in the 2000 Census.<sup>18</sup> The corresponding model moment is  $6 \times \mathbb{E}[n_{j2}]$  because the second period counts 6 years in our model. Table 3 summarizes the moments for Colorado.

<sup>16</sup>Average public school spending in Colorado and U.S. average are \$5,996 and \$5,960, respectively.

<sup>17</sup>Chetty et al. (2014) have data on child's family income, which may be different from her earnings. We use this because it is the best data for child income conditional on birthplace that we are aware of.

<sup>18</sup>In this computation, we treat individuals who go to college for less than 1 year as 0. In addition, the sample is restricted to working age population (between age 25 and 62). We do not consider race nor gender.

Table 3: Data Moments for Colorado

Moments	Value
Average public school spending per pupil in group 1	\$6,047
Average public school spending per pupil in group 2	\$6,210
Average public school spending per pupil in group 3	\$6,146
Average public school spending per pupil in group 4	\$5,894
Average child income in group 1	\$26,990
Average child income in group 2	\$27,908
Average child income in group 3	\$28,795
Average child income in group 4	\$29,606
Average years of college education for people born in Colorado	1.8567

School districts in other states are categorized into four groups based on parental schooling. As in Colorado, we can calculate average public school spending per pupil  $\mathbb{E}[\bar{x}_j|\text{Group}K]$  and average child income  $\mathbb{E}[\bar{w}h_{i3}|\text{Group}K]$  for each group in each state. For each state, we use four moments,  $\mathbb{E}[\bar{x}_j|\text{Group}K]$  and  $\mathbb{E}[\bar{w}h_{i3}|\text{Group}K]$  for the two largest groups, to identify the three state-specific parameters  $\{\mu_a, \sigma_a, \rho_{h_0a}\}$ . The detailed choice for each state is available in the Appendix. This choice is important for identification which is discussed later.

#### 4.4 Targeted States

Not all states are used for estimation. First, as discussed in Section 2, Montana, Vermont, Washington D.C. and Hawaii are dropped due to data issues. Second, since we focus on states which employed a foundation program for the period we consider, the following states are omitted: Delaware, California, Connecticut, Indiana, New York, North Carolina, Pennsylvania, Rhode Island, Washington, and Wisconsin. Recall that Delaware and North Carolina employ a flat grant program, California and Washington use a full state funding program, and the rest use an equalization program. Third, we drop states in which the slope coefficient is negative and statistically significant. In our simple model, the value of  $\rho_{h_0a}$  needs to be negative to generate the negative slope coefficient. This is unrealistic because negative  $\rho_{h_0a}$  leads to negative rank-rank slope which is inconsistent with data. Finally, we drop Minnesota, Missouri and Nebraska because average child income in these states are high relative to level of public school spending. In such a case, a negative value of  $\rho_{h_0a}$  would be obtained.<sup>19</sup> These leave us with 17 states for estimation.

<sup>19</sup>High average child income in each group leads to a higher estimated  $\mu_a$  and higher average public school spending in our model. If the moments for average public school spending are not high, our model requires a larger  $\sigma_a$ , so that the average level of public school spending in each group becomes lower. Consequently, the gap in child income between low schooling and high schooling groups becomes wider than the data. Thus,  $\rho_{h_0a}$  becomes negative to match the moments for average child income. Our estimation result does show that the value of  $\rho_{h_0a}$  is negative in all three states.

## 4.5 Identification

Generally speaking, the parameters are jointly identified from all moments. However, some moments are particularly helpful in identifying certain parameters. For example, the moment on college education is most useful in identifying  $\eta_1$ . The moments on public school spending are particularly useful in identifying parameters governing human capital accumulation in the first period,  $\{\phi, \omega, \gamma\}$ . In particular, the variation in public school spending across school districts allows us to identify  $\phi$  and  $\gamma$ .

$\{\mu_a, \sigma_a, \rho_{h_0a}\}$  are identified from moments on both child income and public school spending. Recall that child income and public school spending for two groups of school districts are used for each state. Equation (6) implies that if child income in both groups increases equally, it must come from an increase in  $\mu_a$ . On the other hand, a differential increase could be attributed to either  $\sigma_a$  or  $\rho_{h_0a}$ . To identify  $\sigma_a$  and  $\rho_{h_0a}$  separately, we could use the moments on public school spending. In particular, in our model, public school spending in rich school districts is more sensitive to  $\sigma_a$ . A larger  $\sigma_a$  leads to a wider range of  $a_j$ . Since the impact of small  $a_j$  on public school spending is weak because a minimum level of spending is guaranteed in a foundation program, a larger  $\sigma_a$  leads to more spending in rich school districts. Meanwhile, public school spending in poor school districts decreases. As a result, the effect of school district income on public school spending increases with  $\sigma_a$ . This cannot happen with  $\rho_{h_0a}$ . Hence, moments on child income and public school spending allows separately identification of  $\mu_a$ ,  $\sigma_a$ , and  $\rho_{h_0a}$ .

Lastly,  $\theta$  is mainly identified from the correlation between child income and parental schooling because the degree of altruism affects parental investments in children as well as the intergenerational correlation in human capital and earnings.

## 5 Results

We report the estimation results in this section and compare model moments with corresponding data moments whenever possible.

### 5.1 Estimated Parameters

Table 4 reports the estimated parameters common to all states. Estimates of  $\{\mu_a, \sigma_a, \rho_{h_0a}\}$  for each state are available in the Appendix. As explained earlier, when estimating the parameters for states other than Colorado, we take the estimates in table 4 as given. We take this into consideration

Parameter	$\theta$	$\phi$	$\omega$	$\gamma$	$\eta_1$
Estimate	0.629	0.589	0.324	0.334	0.252
	(0.305)	(0.250)	(0.028)	(0.070)	(0.024)

Note: Standard errors are in the parentheses.

Figure 4: The Variation in  $\sigma_a$  and  $\rho_{h_0a}$  across States



when calculating the standard errors of state-specific estimates.<sup>20</sup> Figure 4 highlights substantial variation in  $\sigma_a$  and  $\rho_{h_0a}$ . As discussed in the previous section, this reflects the variation in public school spending and child income. The variation in  $\rho_{h_0a}$  deserves some discussion. This variation indicates that in some states, parental schooling (ability) has a much stronger effect on the child's ability to learn than in other states. What could this be capturing? The natural suspect is differences in early childhood education, quality of preschools, and access to enriched learning environments, as well as other attributes such as neighborhoods and learning environments that are correlated with parental schooling.

## 5.2 Targeted Moments

Table 5 reports model moments for Colorado and compares them with corresponding data moments. The model does a good job in matching the data moments for average child income and average years of college education for individuals born in Colorado. However, our model cannot replicate

<sup>20</sup>See, for example, Newey and McFadden (1994) for the detailed calculation of standard errors in a two-step estimation.

Table 5: Targeted Moments for Colorado

Moments	Data	Model
Average public school spending per pupil in group 1	\$6,047	\$5,702
Average public school spending per pupil in group 2	\$6,210	\$5,862
Average public school spending per pupil in group 3	\$6,146	\$5,945
Average public school spending per pupil in group 4	\$5,894	\$6,013
Average child income in group 1	\$26,990	\$27,494
Average child income in group 2	\$27,908	\$27,912
Average child income in group 3	\$28,795	\$28,586
Average child income in group 4	\$29,606	\$29,019
Average years of college education for people born in Colorado	1.8567	1.8758

the negative correlation between public school spending and parental education across groups 2 to 4 observed in data. In our model, public school spending is nearly constant across the four groups. As mentioned in the previous section, a negative  $\rho_{h_0a}$  is required to match this negative correlation in data. However, a negative  $\rho_{h_0a}$  leads to a negative correlation between child income and parental schooling across the four groups. Obviously this is inconsistent with data.

Figure 5 plots average public school spending per pupil implied by the model and compares them with data. Figure 6 is a similar plot for average child income. As mentioned earlier, for each state, we use two moments for average public school spending and two moments for average child income. So not all states are plotted in all panels. Most of the states are close to the 45 degree line in both figures, indicating that our model does a fairly good job in matching these moments. In particular, the model fits child income is reasonably well.

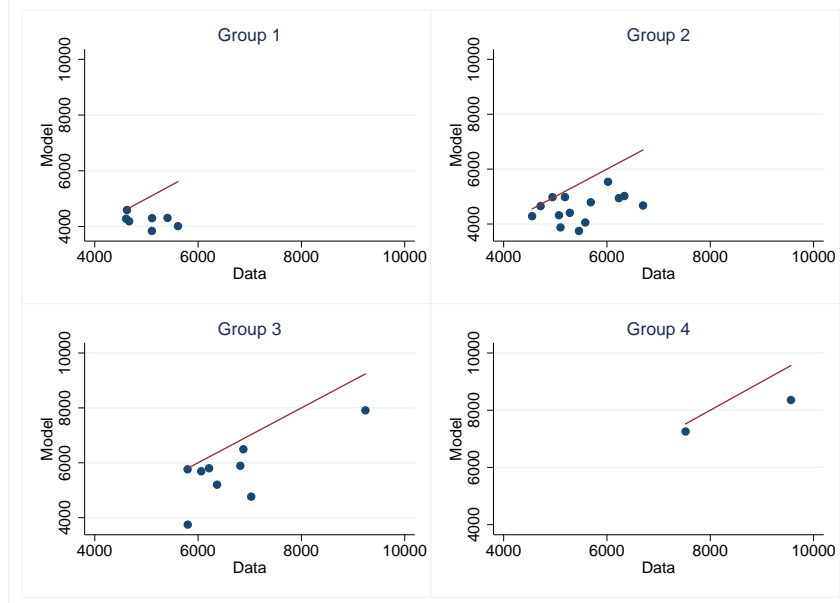
### 5.3 Non-Targeted Moments

In this subsection, we examine how well the model performs matching the two moments discussed earlier in section 2: the distribution of public school spending and rank-rank slope. Because these moments are not targeted directly in the estimation, matching these moments increases our confidence in the mechanisms at work.

#### 5.3.1 Distribution of Public School Spending

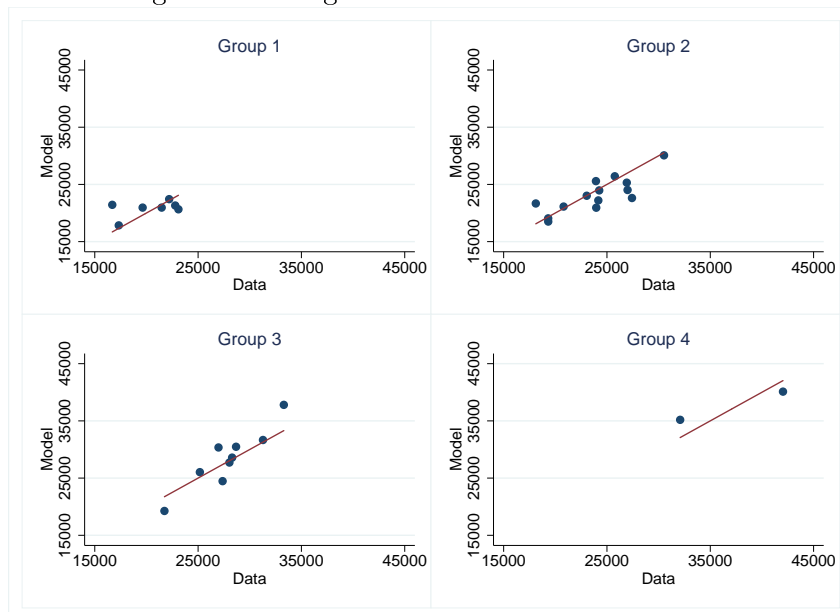
An important feature of our model is that it can generate different distributions of public school spending across states even when all states use the same public school finance system. As an example, Figure 7 plots public school spending against income across school districts for Colorado and

Figure 5: Average Public School Spending Per Pupil: Model vs Data



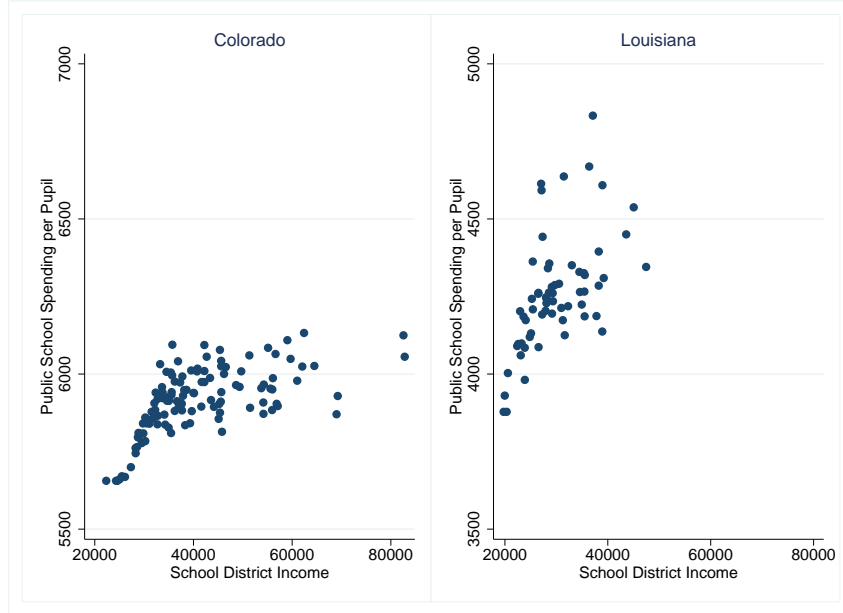
Note: Each dot is a state, and the line in each panel is the 45 degree line.

Figure 6: Average Child Income: Model vs Data



Note: Each dot is a state, and the line in each panel is the 45 degree line.

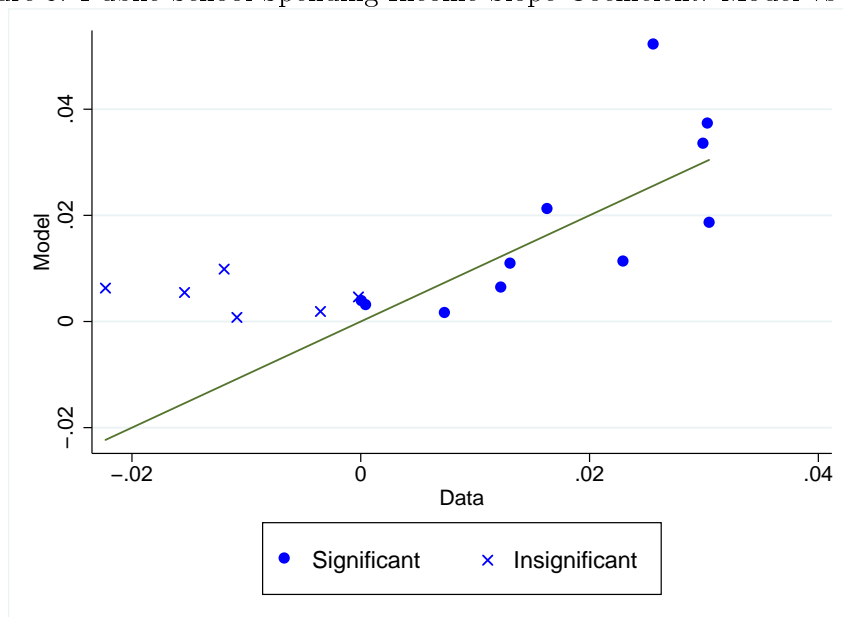
Figure 7: Distribution of Public School Spending Across School Districts: Colorado and Louisiana



Louisiana. In Colorado, public school spending is fairly equally distributed across school districts. In Louisiana, however, there is a strong positive correlation between public school spending and income, so that rich school districts spend more on public schools than their poorer counterparts. This feature of our model is novel relative to Fernandez and Rogerson (2003). They simulate the case where a state employs a foundation program. Their results suggest that public school spending is constant across school districts at the lower end of the income distribution. This is because, for poor school districts, the guaranteed funding is sufficiently large. Consequently, there is no need to impose additional local taxes. In their model, only rich school districts have an incentive to raise spending through local taxes, and public school spending increases monotonically with income for school districts at the upper end of the income distribution. However, their model is not able to explain a variation in the distribution of public school spending conditional on the same school finance system. Relative to their model, which does not incorporate a nonnegative transfer to their children and a random component, our model contains a non-negative constraint on transfer and a random component  $a_j$ . As we demonstrate in the counterfactual simulations, these components allow us to generate more realistic variation across states.

Given data for all school districts in a state, we compute the slope coefficient as a measure of the distribution of public school spending in the state. Figure 8 plots this measure for each state using both the actual data and simulated data from the model. For states with a positive correlation between public school spending and income across school districts, our model does a good job in

Figure 8: Public School Spending-Income Slope Coefficient: Model vs Data



Note: For each state, we run a regression of public school spending against school district income using data from each school district. The estimated coefficient in front of income is our measure of the distribution of public school spending reported in the figure. Also plotted is the 45 degree line.

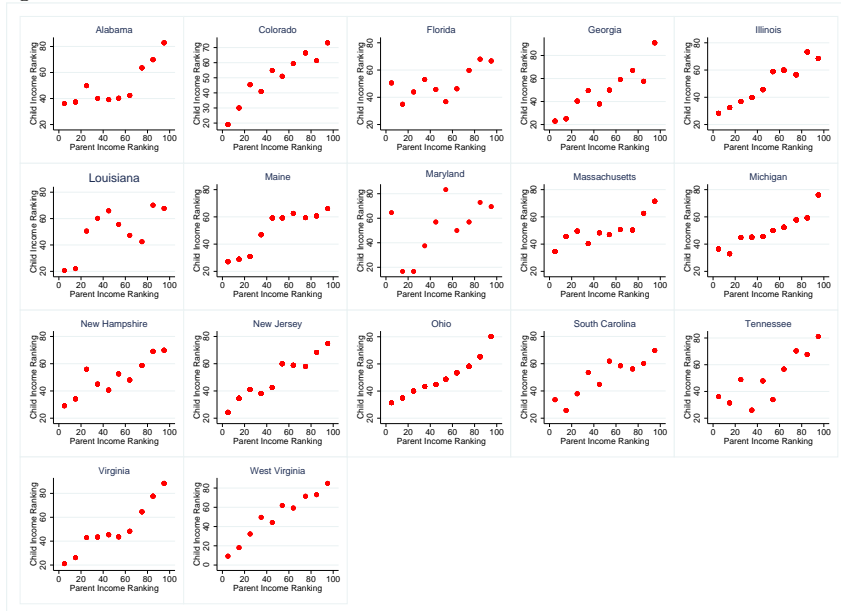
fitting this correlation. For states where public school spending is negatively correlated with income but the correlation is statistically insignificant in data (marked by X), the slope coefficient from the model is largely close to 0.

### 5.3.2 Rank-Rank Slope

A remarkable feature of U.S. data as documented by Chetty et al. (2014) is the near linear relationship between child income rank and parent income rank. As a validation exercise, we plot this rank-rank relation for each state in Figure 9. Following Chetty et al. (2014), we compute  $E[R_i|P_i = p]$  in each state where  $R_i$  and  $P_i$  represent child income rank and parent income rank, respectively. In our computation, we set  $p \in \{10, 20, \dots, 100\}$ . Note that we compute income rank within a state. Ideally, we should have computed it at the national level as Chetty et al. (2014) do. However, our model uses average school district income as parent income while Chetty et al. (2014) use the individual data. When we make adult income rank at the national level, the income distribution is not uniform in some states. For example, income in most school districts in Alabama is below then median income in the U.S. whereas income in most school districts in New Jersey is



Figure 9: Child Income Rank and Parent Income Rank Across States



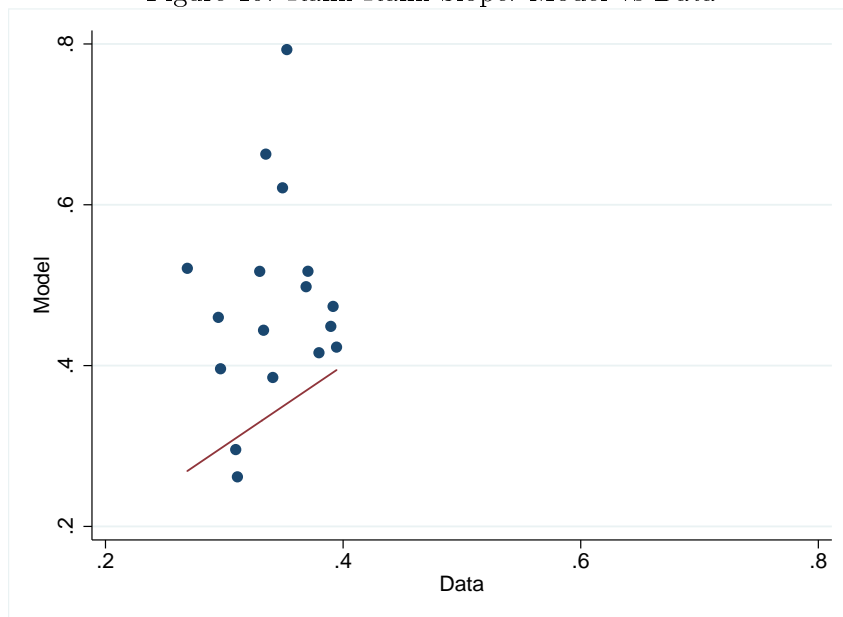
above the median income.<sup>21</sup> Therefore, this approach is not feasible. In addition, computing income rank within a state is not problematic because Chetty et al. (2014) point out that the results are similar in these two approaches. Hence, we compute rank-rank slope at the state level. Figure 9 shows that the relation between child income rank and parent income rank is close to linear in most states.

For each state plotted in Figure 9, we run a simple regression of child income rank on parent income rank to obtain the state’s rank-rank slope generated by our model. Figure 10 plots the model generated rank-rank slope against rank-rank slope in the actual data for all states considered in the paper. As in Section 2.1, we compute rank-rank slope for each state as the weighted average of the county level estimates in Chetty et al. (2014), where the weight for each county is its population from the 2000 census. Although the model is able to match rank-rank slope for several states, it has a tendency to overestimate rank-rank slope. One explanation is that rank-rank slope in the model is calculated using simulated data at the school district level, while the actual rank-rank slope in Chetty et al. (2014) is calculated using individual level data.

Figure 11 plots rank-rank slope against our measure of the distribution of public school spending, the relation of interest for this paper. The left panel plots the relation with the actual data, and the right panel plots the same relation from the model. Because the model overestimates rank-rank

<sup>21</sup>By contrast, Chetty et al. (2014) show that the adult income distribution at the national level and the local level are similar in large community zones.

Figure 10: Rank-Rank Slope: Model vs Data



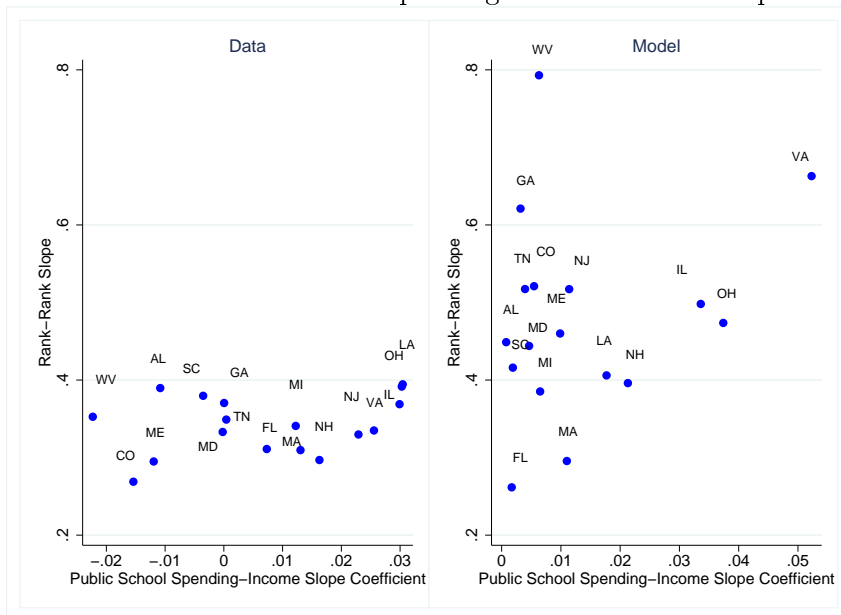
Note: The line in the graph is the 45 degree line.

slope for most states, it cannot match data in levels. However, our model does capture a salient fact: there is a positive correlation between the distribution of public school spending and rank-rank slope. We view this as an indication that the model is successful in capturing the key relation between educational policy and intergenerational mobility.

## 6 Counterfactual Simulations

To improve our understanding of the forces at work in our model that help explain the variation in intergenerational mobility, we use the estimated model to conduct three counterfactual simulations. The first counterfactual simulation examines what would happen if there were no correlation between a child’s learning ability and parental human capital ( $\rho_{h_0a} = 0$ ). In the previous section, we find considerable variation in  $\rho_{h_0a}$  as well as  $\sigma_a$ . In this simulation, we study how important  $\rho_{h_0a}$  is in generating the linear relationship between parent income rank and child income rank. The second counterfactual simulation relaxes the non-negativity constraint on parental transfers. Since this relaxation would allow poor school districts to spend more on public school spending, this exercise allows us to quantify the contribution of borrowing constraints to intergenerational mobility. Finally, we explore what would happen if each state were to employ a full state funding program. As we see in the Section 2, states with a full state funding program tend to have higher intergenerational

Figure 11: Distribution of Public School Spending and Rank-Rank Slope: Model vs Data



Note: The left panel is data, and the right panel is model.

mobility. Therefore, we would like to discuss the importance of changing educational policy.

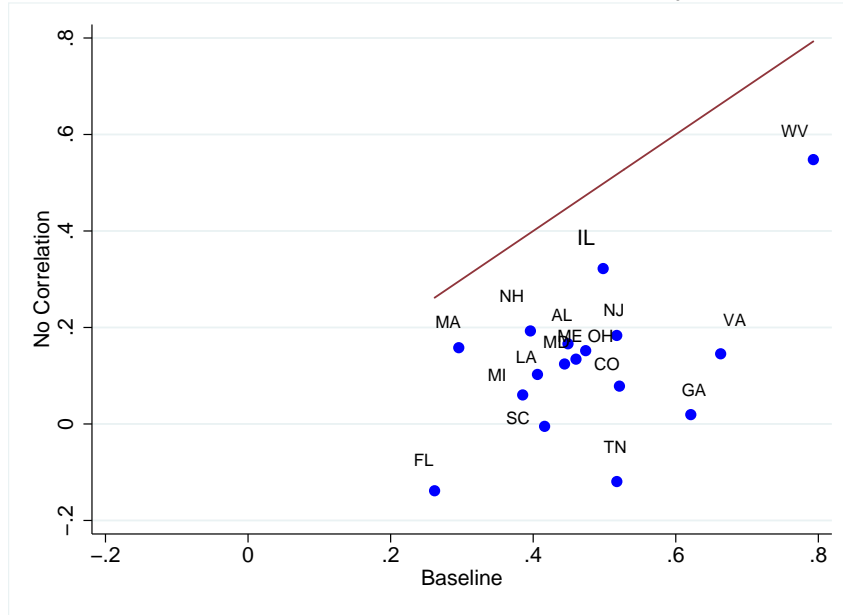
### 6.1 $\rho_{h_0a} = 0$

To understand the role played by  $\rho_{h_0a}$ , we set  $\rho_{h_0a} = 0$  for each state, solve the model to obtain child income in each school district, and then compute rank-rank slope. Figure 12 compares rank-rank slopes when  $\rho_{h_0a} = 0$  with the baseline case. When  $\rho_{h_0a} = 0$ , rank-rank slope becomes much smaller in all states and rank-rank slope is less than or close to 0.2 in most states. Therefore, without  $\rho_{h_0a}$ , there would be virtually no correlation between parent income and child income. Clearly, this is not consistent with data in which rank-rank slope in all states is above 0.2. Hence, the positive correlation between a child’s learning ability and parental human capital is an important contributor to the positive and large rank-rank slopes observed in data. This correlation, in a sense, stands in for any exogenous trait correlated across generations and related to parental education.

### 6.2 Natural Borrowing Constraints on Parental Transfers

Our baseline model assumes that parents cannot leave debt to their children. While this is a reasonable assumption and one that is commonly employed in models of intergenerational wealth transmission, it is interesting to examine what would happen if this constraint were relaxed. Instead of a non-negative constraint on parental transfers, we consider a natural borrowing con-

Figure 12: Rank-Rank Slope: Baseline vs  $\rho_{h_0a} = 0$



Note: The line in the graph is the 45 degree line.

straint which allows parents to borrow up to child total income from the last two periods such that  $g_j \geq -\left[\bar{w}h_{j2}(1 - n_{j2}) + \frac{\bar{w}h_{j3}}{1+r}\right]$ .

We solve the model with this new constraint and use simulated data to compute the effect of parent income on public school spending across school districts. Table 6 reports the slope coefficient and rank-rank slope under both constraints in five states: Illinois, Maine, Ohio, New Hampshire, and New Jersey. The slope coefficient is smaller under the natural borrowing constraint than the baseline case. In other words, when parents are allowed to borrow against their children’s income, the distribution of public school spending becomes more equalized. This finding is intuitive because poor parents who were borrowing constrained in the baseline case can now increase spending on their children by borrowing against their children’s income. The magnitude of this effect depends positively on children’s potential income relative to public school spending: the higher the child’s potential income, the more poor parents can borrow, and the more equalized public school spending would be. This is why the change in the slope coefficient is more dramatic in Illinois. As the distribution of public school spending become more equalized, rank-rank slope is also affected. In all five states, a decrease in the slope coefficient is associated with a decrease in rank-rank slope. In particular, rank-rank slope in Illinois decreases substantially because of the large decrease in the slope coefficient.

This result in Table 6 is consistent with Biasi (2015). She estimates the causal effect of inequality

Table 6: The Distribution of Public School Spending and Rank-Rank Slope in Selected States: Baseline vs Natural Borrowing Constraint: Case 1

State	Slope Coefficient		Rank-Rank Slope	
	Baseline	Natural Borrowing	Baseline	Natural Borrowing
Illinois	0.035	0.005	0.516	0.253
Maine	0.010	0.003	0.460	0.382
Ohio	0.037	0.020	0.474	0.420
New Hampshire	0.021	0.015	0.396	0.353
New Jersey	0.011	0.005	0.517	0.476

in public school expenditure across school districts on intergenerational mobility within a commuting zone. Her study finds that a reduction in inequality in public school expenditure by education reform improves intergenerational mobility in the long run.<sup>22</sup> Our result is consistent with her conclusion.

More interestingly, however, we find that reductions in rank-rank slope may not be positively related to improvement in the distribution of public school spending. We illustrate this in Table 7. We select Maine, Louisiana, and Virginia. When we replace the zero borrowing constraint in the baseline with the natural borrowing constraint, the distribution of public school spending would be more equal in all states. The size of this change in the slope coefficient is larger than Maine. The reduction in rank-rank slope, however, is the largest in Maine. This result can be attributed to the ratio of  $\rho_{h_0a}$  to  $\sigma_a$ . The larger this ratio, the higher the correlation between parental income and a child’s learning ability. In other words, when  $\rho_{h_0a}$  is large relative to  $\sigma_a$ , children born to poor parents have, on average, a lower learning ability. This reduces the marginal return to parental investments and the effect of borrowing constraints on intergenerational mobility. Therefore, high  $\rho_{h_0a}$  suppresses the impact of changes in public school spending on intergenerational mobility.

This surprising result might seem more reasonable once  $\rho_{h_0a}$  is interpreted as capturing all other factors that account for the variation in intergenerational mobility across states. As Chetty et al. (2014) point out, segregation, social capital and family structure are all potential forces. These forces are likely captured by  $\rho_{h_0a}$  in our model thereby creating a strong correlation between child income and parent income. Hence, whether more equalized distribution of public school spending would be effective hinges on the presence and strength of these other forces. As for the rest of the

<sup>22</sup>In reality, the revision of the state financing formula for public school spending is an example of how to achieve more equal spending. Although our model does not take this into account, each state in a foundation program uses a different formula for public school spending. This formula depends heavily on property values. California was the first state to change the formula. In the 1970s, the California State Supreme Court ordered the state government to use a revised formula where school support did not depend on district wealth (*Serrano vs Priest*). Following California’s decision, some states have carried out finance reforms to equalize public school spending (Biasi (2015) reports the list of school finance reforms).

Table 7: The Distribution of Public School Spending and Rank-Rank Slope in Selected States: Baseline vs Natural Borrowing Constraint: Case 2

State	Slope Coefficient		Rank-Rank Slope	
	Baseline	Natural Borrowing	Baseline	Natural Borrowing
Maine	0.010	0.003	0.460	0.382
Louisiana	0.018	0.009	0.406	0.366
Virginia	0.052	0.039	0.662	0.626

states, the natural borrowing constraint hardly changes the distribution of public school spending, which obviously leads to little impact on rank-rank slope.

### 6.3 Full State Funding

As we see in Figure 3, rank-rank slope is relatively small in California and Washington. The interesting aspect of this piece of evidence is that both states employ full state funding. Recall that in a full state funding program, public school spending comes only from statewide taxes. Therefore, the distribution of public school spending is uniform across school districts. As a matter of fact, this slope coefficient is negative in Washington and close to 0 in California. Since this educational policy equalizes public school spending across school districts, it is interesting to see what would happen if full state funding were employed in every state.

We solve the model under a full state funding program and obtain child income to compute rank-rank slope. Table 8 reports rank-rank slope in Illinois, Maine, Ohio, New Hampshire and New Jersey. In all of the five states, rank-rank slope falls significantly. Particularly, in Illinois, the slope coefficient is initially one of the largest in the United States. This leads to a large effect of full state funding on rank-rank slope. However, with regards to the other states, rank-rank slope changes modestly even when full state funding is employed. Average level of a change in rank-rank slope is -0.011. Again, this ineffectiveness is largely due to high values of  $\rho_{h_0a}$  relative to  $\sigma_a$ . When  $\rho_{h_0a}$  is high, the impact of implementing new educational policy is small.<sup>23</sup>

### 6.4 Discussion

Table 8 also summarizes rank-rank slope in three cases: baseline, natural borrowing constraint and full state funding. Recall that educational policy employed in the second case is a foundation program. Interestingly, the effect of switching from a foundation program to a full state funding

<sup>23</sup>The other reason for modest change in rank-rank slope is that the slope coefficient is close to 0 in the baseline. Undoubtedly, intergenerational mobility does not improve even though a full state funding program is employed.

Table 8: Rank-Rank Slope in Selected States: Foundation (Baseline) vs Full State Funding vs Natural Borrowing Constraint

State	Foundation	Natural Borrowing Constraint	Full State Funding
Illinois	0.516	0.253	0.337
Maine	0.460	0.382	0.405
Ohio	0.474	0.420	0.429
New Hampshire	0.396	0.353	0.356
New Jersey	0.517	0.475	0.487

program is smaller than the effect of switching from a foundation program to natural borrowing constraint in all states.

This surprising result (relatively modest effect of switching to a full state funding program on rank-rank slope) reflects the upside and downside of a full state funding program. The upside is that the distribution of public school spending is uniform. The downside is that public school spending relies only on statewide taxes determined by median voting. Therefore, poor districts gain from full state funding, but the gains are modest. More importantly, unlike a foundation program, imposing local taxes is not allowed. Thus, middle-income school districts would not benefit from full state funding. Figure 13 illustrates the two forces at work in Ohio.

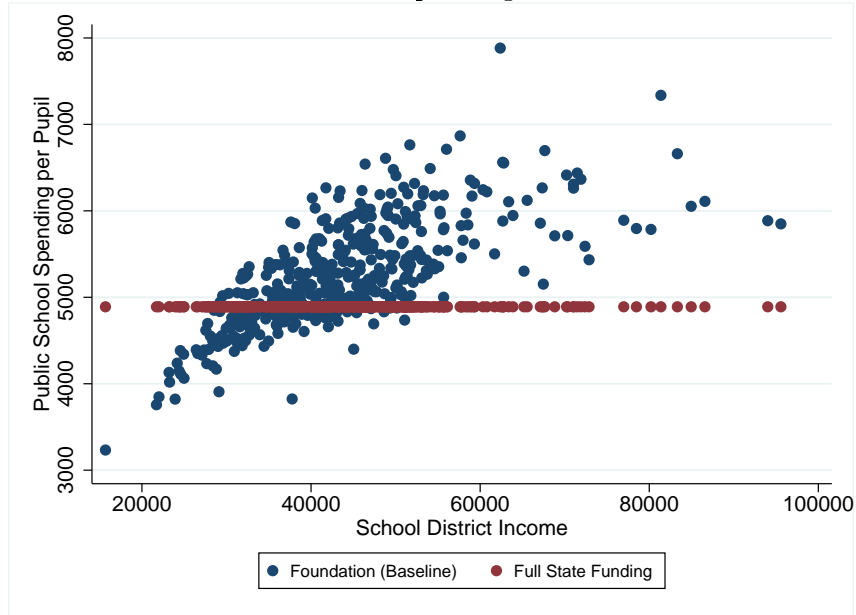
In this exercise, since the downside hinders intergenerational mobility, rank-rank slope does not fall substantially when we switch to full state funding. Furthermore, implementing an alternative policy to achieve a more equalized distribution of public school spending in a foundation program might be better at improving intergenerational mobility since a foundation program does not place a restriction on public school spending. From this perspective, switching to a full state funding program is not all that favorable.

## 7 Conclusion

Our paper explores the connection between public school spending and intergenerational mobility in the United States. We argue that the distribution of public school spending across school districts can help account for the variation in rank-rank slope across states. If public school spending is unequally distributed towards rich districts, intergenerational mobility will be low.

We model public school spending through majority voting under two public school finance systems: a full state funding program and a foundation program. Our model extends Fernandez and Rogerson (2003) by taking into account children’s human capital formulation both in school

Figure 13: Distribution of Public School Spending in Two Educational Policies in Ohio



and at work. The highlight of our model is that children’s human capital depends not only on public resources from the state and local government, but also private resources from parents and their own learning ability. We also allow a nonnegative parental transfer when children become independent. The estimation results show that our model fits data fairly well. In particular, our model can replicate the positive correlation between the distribution of public school spending and rank-rank slope. However, our estimation was conducted in a limited set of states. This highlights a failure of our model: our simple model is not able to rationalize the behavior in states where the slope coefficient is negative. In this case, a negative value of  $\rho_{h_0a}$  would be obtained and rank-rank slope would be negative.

With the estimated model, we conduct three counterfactual simulations to understand the determinants of intergenerational mobility. The first simulation shows that the correlation between parental human capital and a child’s learning ability plays an important role in explaining intergenerational mobility. The second simulation shows that allowing parents to borrow against their children’s future income and using it to invest in their children leads to a more equal distribution of public school spending. The effect on rank-rank slope, however, depends negatively on the correlation between parental human capital and a child’s learning ability. With a smaller correlation, allowing parents to borrow against their children’s future income improves intergenerational mobility significantly. Otherwise, the effect is modest. In the third simulation, we find that switching to a full state funding program also improves intergenerational mobility. Comparing the results of



rank-rank slope across simulations in the selected states, however, the impact of switching to a full state funding program is not substantial. This is because imposing statewide taxes only implies that poor school districts are unable to spend much more. Moreover, not allowing local taxes hurts school districts at the middle of the income distribution.

For simplicity, our model abstracts from many interesting features in the real world. For example, we assume there is no heterogeneity in parent income within a school district and children attend public schools in their birth district. If parent income varies within a school district and the parent can choose which school district to reside as in Fernandez and Rogerson (1998), the model may do a better job in capturing rank-rank slopes observed in the data. While endogenizing parental choice of which school district to live in is certainly desirable, we caution here that the few structural models that have been estimated suggest that while differences in amenities across states play an important role, moving costs need to be substantial in order to rationalize the lack of moves in the face of large income differences across states. As more sophisticated data on child income become available (e.g., child income conditional on birthplace), our model can evolve to incorporate migration decisions as well as other features in the real world. We leave these issues for future analysis.

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## Appendix 1: State-Specific Moments Not Reported in the Main Text

State	Moment	Value
Alabama	Average public school spending per pupil in group 1	\$4,607
	Average public school spending per pupil in group 2	\$4,551
	Average child income in group 1	\$19,633
	Average child income in group 2	\$20,805
Florida	Average public school spending per pupil in group 2	\$5,458
	Average public school spending per pupil in group 3	\$5,800
	Average child income in group 2	\$19,313
	Average child income in group 3	\$21,744
Georgia	Average public school spending per pupil in group 1	\$5,106
	Average public school spending per pupil in group 2	\$5,101
	Average child income in group 1	\$17,324
	Average child income in group 2	\$19,318
Illinois	Average public school spending per pupil in group 2	\$4,946
	Average public school spending per pupil in group 3	\$5,797
	Average child income in group 2	\$30,551
	Average child income in group 3	\$31,282
Louisiana	Average public school spending per pupil in group 1	\$4,666
	Average public school spending per pupil in group 2	\$5,282
	Average child income in group 1	\$21,475
	Average child income in group 2	\$24,166
Maine	Average public school spending per pupil in group 2	\$6,337
	Average public school spending per pupil in group 3	\$6,367
	Average child income in group 2	\$23,934
	Average child income in group 3	\$25,172

State	Moment	Value
Maryland	Average public school spending per pupil in group 2	\$6,698
	Average public school spending per pupil in group 3	\$7,029
	Average child income in group 2	\$26,995
	Average child income in group 3	\$27,374
Massachusetts	Average public school spending per pupil in group 3	\$6,877
	Average public school spending per pupil in group 4	\$7,522
	Average child income in group 3	\$28,677
	Average child income in group 4	\$32,085
Michigan	Average public school spending per pupil in group 2	\$6,021
	Average public school spending per pupil in group 3	\$6,061
	Average child income in group 2	\$25,759
	Average child income in group 3	\$28,033
New Hampshire	Average public school spending per pupil in group 2	\$6,231
	Average public school spending per pupil in group 3	\$6,819
	Average child income in group 2	\$27,422
	Average child income in group 3	\$28,296
New Jersey	Average public school spending per pupil in group 3	\$9,562
	Average public school spending per pupil in group 4	\$10,231
	Average child income in group 3	\$33,298
	Average child income in group 4	\$42,039
Ohio	Average public school spending per pupil in group 2	\$5,187
	Average public school spending per pupil in group 3	\$6,213
	Average child income in group 2	\$26,919
	Average child income in group 3	\$26,976

State	Moment	Value
South Carolina	Average public school spending per pupil in group 1	\$5,109
	Average public school spending per pupil in group 2	\$5,071
	Average child income in group 1	\$16,695
	Average child income in group 2	\$18,115
Tennessee	Average public school spending per pupil in group 1	\$4,623
	Average public school spending per pupil in group 2	\$4,716
	Average child income in group 1	\$22,202
	Average child income in group 2	\$23,043
Virginia	Average public school spending per pupil in group 1	\$5,408
	Average public school spending per pupil in group 2	\$5,687
	Average child income in group 1	\$22,789
	Average child income in group 2	\$24,253
West Virginia	Average public school spending per pupil in group 1	\$5,611
	Average public school spending per pupil in group 2	\$5,483
	Average child income in group 1	\$23,908
	Average child income in group 2	\$23,962

## Appendix 2: State-Specific Estimates Not Reported in the Main Text

Parameter	AL	CO	FL	GA	IL	LA	ME	MD	MA	MI
$\mu_a$	0.550 (0.004)	0.756 (0.014)	0.541 (0.004)	0.439 (0.006)	0.734 (0.004)	0.550 (0.004)	0.695 (0.002)	0.695 (0.012)	0.824 (0.012)	0.721 (0.002)
$\sigma_a$	0.039 (0.002)	0.103 (0.036)	0.077 (0.026)	0.096 (0.002)	0.454 (0.010)	0.156 (0.008)	0.106 (0.004)	0.107 (0.020)	0.200 (0.002)	0.116 (0.002)
$\rho_{h_0a}$	0.188 (0.036)	0.133 (0.024)	0.060 (0.029)	0.261 (0.028)	0.045 (0.008)	0.250 (0.030)	0.082 (0.016)	0.107 (0.045)	0.407 (0.020)	0.209 (0.018)

*Note:* standard errors in parentheses.

Parameter	NH	NJ	OH	SC	TN	VA	WV
$\mu_a$	0.724 (0.004)	0.951 (0.008)	0.697 (0.004)	0.570 (0.002)	0.584 (0.004)	0.603 (0.028)	0.544 (0.002)
$\sigma_a$	0.271 (0.004)	0.173 (0.010)	0.277 (0.094)	0.048 (0.006)	0.091 (0.014)	0.322 (0.032)	0.031 (0.004)
$\rho_{h_0a}$	0.261 (0.042)	0.198 (0.032)	0.256 (0.099)	0.141 (0.040)	0.147 (0.056)	0.320 (0.034)	0.174 (0.075)

*Note:* standard errors in parentheses.