State Education Aid, Student Performance, and School District Efficiency in New York State

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Executive Summary

One of the best known theorems in public finance is that a matching grant has a more stimulative effect on public outputs than does an equal-cost lump-sum grant. This theorem is an application of the basic microeconomic principle that a given amount of subsidy will lead to larger behavioral changes if it lowers the relevant price than if it does not. In this report we show, however, that this theorem is not correct under a wide range of circumstances, and we derive more general results that can be used to identify the type of state program that has the largest impact on local government performance. An application of these results to educational aid in New York State indicates that matching grants are indeed more stimulative than equal-cost lump-sum grants under many circumstances. We also find, however, that school district responses to grants limit the effectiveness of matching grants and lead to some circumstances under which lump-sum grants might be more effective.

The standard theorem is incomplete because it leaves out several key aspects of the problem, namely, the so-called flypaper effect, the technology of public production, and the impact of aid programs on the efficiency with which public services are delivered. The flypaper effect refers to the well-documented finding that state aid given directly to a jurisdiction has a larger impact on the jurisdiction's decisions than does an equivalent amount of money given to the voters in the jurisdiction. This phenomenon is relevant here because operating aid has a flypaper effect, but matching grants do not. The standard theorem also simplifies public production and ignores the efficiency with which school districts produce student performance. In this report we present a model that incorporates these three factors and shows how they influence the impact of various types of state aid on student performance, as measured by the New York State Department of Educations' principal test-score index. This model can be summarized in two equations: (1) a so-called cost equation that relates spending per pupil to student performance and to various factors influencing school district costs or school district efficiency and (2) a demand equation that relates student performance to income, state aid, local voters' share of additional school spending (called the tax share), school district costs, and efficiency (obtained from the first equation), and various other demand variables. Each of these equations includes a flypaper effect. These flypaper effects measure the impact of lump-sum aid on either school district efficiency (the first equation) of voter demand for student performance (the second equation).

Our results are based on the estimation of these two equations using data for New York school districts from 2000 to 2007. Most of the data used in the analysis were provided by the New York State Education Department (SED) in the form of published and unpublished sources. The dependent variable for the cost equation is operating spending (less transportation) per pupil. Student performance, which is an explanatory variable in the first equation and the dependent variable in the second equation, is an index of student test scores developed by SED. In most cases, the regressions perform as expected. We find that voters respond to the fiscal incentives created by New York State's education finance system; for example, the demand for student performance is higher when the tax share is lower or when the education costs are higher. Unfortunately, however, we are not able to estimate the flypaper effects with precision.

We then use our results to simulate the impact of a new open-ended matching grant on the demand for student performance along with the impact of a new, equal-cost lump-sum grant. We find that matching grants are more stimulative than equal-cost lump-sum grants in all types of district, in the sense that they have a larger impact on student performance on key state tests. Although open-ended matching grants are often not popular with legislatures because their cost implications are not known at budget time, this result suggests that they deserve a second look by legislatures interested in boosting student performance.

The impact of matching grants on student performance is much smaller, however, than the standard theorem suggests, because these grants (like lump-sum grants) undermine the efficiency with which school districts produce student performance, as measured by the SED index. Moreover, the stimulative advantage of matching grants depends on the flypaper effects in both the expenditure and demand equations, which we are not able to estimate with precision. Relatively small changes in these flypaper effects can lead to a stimulative advantage for lump-sum grants. Further research is needed to better understand the complex effects of grants on school district efficiency and to help design grant and accountability programs that maximize the impact of grants on a state's student performance targets.

I. Introduction

One of the best known theorems in public finance is that a matching grant has a more stimulative effect on public outputs than does a lump-sum grant. In this report we show that this theorem is not correct under a wide range of circumstances, and we derive more general results that can be used to identify the type of state program that has the largest impact on local government performance.

This aid theorem is, of course, a version of the basic microeconomic result that a price subsidy is more stimulative than an equal-cost income grant. The application of this logic to intergovernmental aid was developed in a line of research by Bradford and Oates (1971a, 1971b) and Oates (1972). In Bradford and Oates (1971a), they demonstrate that, "under a reasonably broad class of processes of collective decision making" (p. 434), there is a formal equivalence, in terms of impact on a jurisdiction's choices, between payments made directly to voters and an increase in appropriately weighted lump-sum aid to the jurisdiction. In Bradford and Oates (1971b), they use a similar framework to show that "under simple majority rule with fixed tax shares and a single public good, a matching grant will always lead to a larger public expenditure than will a lump-sum grant of the same amount" (p. 441).

The broad acceptance of the conclusion that matching grants are more stimulative can be seen in the following quotations from public finance textbooks.

> [A]n open-ended matching grants is expected to increase government expenditure on the aided service by a greater amount than an equal-size lump-sum grant, where "equal size" is defined to mean a lump-sum grant large enough to allow the government the same expenditure as selected with the matching grant. (Fisher, 2006, pp. 226)

> Evidence on actual government behavior supports our prediction that matching grants are more simulative for local government spending than block grants. (Stiglitz, 2000, p. 747)

In this paper we expand the reach of these theorems to include (a) a flypaper effect, (b) a more complete treatment of the technology of public production, and (c) the possibility that aid programs influence the efficiency with which public services are delivered. We show that these extensions fundamentally alter the traditional result, such that lump-sum grants are more stimulative under some circumstances. Our analysis incorporates and extends an argument made by Barnett (1993), namely, that a new matching grant might not have a larger impact on spending than a new, equal-cost lump-sum grant because the matching grant lowers the stimulative power of existing lump-sum grants.

After developing our conceptual model, which draws heavily on Eom, Duncombe, and Yinger (2007), we compare the stimulative impact of equal-cost matching and lump-sum grants using data for school districts in New York State. Our statistical analysis provides estimates of the key behavioral parameters that determine the impact of various grants on school district outcomes. Based on these estimates, we show how the simulative impact of different types of grants varies across types of district. We also show how the results change in response to changes in key behavioral parameters. The final section discusses some of the implications of our results for the design of intergovernmental grant programs.

II. The Demand for School Quality

State aid, both lump-sum and matching, affects local demand for school quality, as measured by student performance. Our approach to modeling this impact begins with a specification of the voter and school-district budget constraints. To begin, let V stand for the market value of a voter's home, t indicate the effective property tax rate, Y equal a voter's income, and Z equal spending on everything except school property taxes. Then a voter's budget constraint is

$$Y = Z + tV \tag{1}$$

A school district's cost function is $C\{S\}$, where C is total cost per pupil and S is an index of student performance measures, such as test scores and graduation rates. The derivative $\partial C/\partial S$ equals marginal cost or MC. Cost is defined as spending using best practices, which is not observed. What is observed instead is actual spending per pupil, E, which reflects actual practices, not best practices. In recognition of this fact, we introduce school-district efficiency, e, which is defined to equal 1.0 in a district that makes full use of best practices and to fall below one in districts with less effective practices, i.e. districts that are inefficient. With this definition, E is defined to be $C\{S\}$ divided by e.

As with any technology, public or private, inefficiency arises from spending that does not use best practices to provide the specified output, in this case S. If S is defined to include only math and English test scores, for example, then spending on science and social studies is inefficient to the extent that it does not boost math and English scores. Of course, more obvious types of wasteful spending, such as using outmoded teaching or management techniques or paying overly generous teacher or administrator salaries, are also sources of inefficiency. It is not possible, however, to separate spending on unspecified performance measures from these wasteful spending by this more traditional definition.

A district's revenue comes from property taxes, lump-sum state aid, and matching aid. A state matching grant with rate *m*, defined as the state share of total spending excluding lump-sum aid, lowers the tax price directly by lowering the amount a district must raise out of its own resources. Now if $\bar{V}$ indicates property value per pupil and *A* indicates state aid per pupil, then the district budget constraint is

$$E \equiv \frac{C\{S\}}{e} = \frac{t\bar{V}}{1-m} + A \tag{2}$$

Equation (2) can be solved for the property tax rate, *t*, that balances the budget. Substituting this expression into equation (1) yields

$$Y + A\left(\frac{V}{\bar{V}}\right)(1-m) = Z + \frac{C\{S\}}{e}\left(\frac{V}{\bar{V}}\right)(1-m) \tag{3}$$

New York State does not provide any general, open-ended matching grants, but the School Tax Relief Program, STAR, provides property tax exemptions that give voters the same incentives as does a matching grant (Duncombe and Yinger 1998a, 2001; Rockoff 2003; Eom et al. 2007). More specifically, the STAR exemption lowers the base for the property tax to $(V - X)$, where *X* equals \$30,000 in most school districts. Hence, the property tax payment in equation (1) is $t(V - X)$. Solving (2) for *t* with no matching rate and substituting the result into (1) with this exemption leads to a version of (3) in which $m = X/V$. In other words, STAR is equivalent to an open-ended matching grant with a matching rate of *X/V*, which obviously varies across school districts. This "matching" rate can be measured and included in our regression analysis.

Tax price, *TP*, is defined to be the amount a voter must pay for an increment in *S*. It can be derived by differentiating a voter's spending, the right side of equation (3), by *S*:

$$TP \equiv \frac{\partial \text{Spending}}{\partial S} = \frac{dC}{dS} e^{-1} \left(\frac{V}{\overline{V}} \right) (1 - m) = (MC) e^{-1} \left(\frac{V}{\overline{V}} \right) (1 - m) \tag{4}$$

This expression confirms the well-known result that a matching grant lowers a voter's tax price. Tax price also increases with the marginal cost of *S* and it decreases with district efficiency. The expression $V / \overline{V}$ is a voter's share of a property tax increase and the expression (1 - *m*) is local voters' share of total spending. We define the product of these two expressions as the voter's tax share. Tax price obviously increases with tax share (and with each component of tax share).

In a standard median-voter model, the demand for *S* is a function of median income, state aid, and median tax price. To specify this model, we (a) interpret equation (1) as the median voter's budget constraint, (b) use a standard multiplicative form for the demand function; (c) add a flypaper effect, *f*; and (d) place other demand determinants in a constant, *K*. The result:[1]

$$S = K \left(Y + f A \left(\frac{V}{\overline{V}} \right) (1 - m) \right)^{\theta} \left((MC) e^{-1} \left(\frac{V}{\overline{V}} \right) (1 - m) \right)^{\mu} \tag{5}$$

where θ is the income elasticity of demand and μ is the (negative) price elasticity of demand.

In equation (4), the tax price has four components: *MC*, e^{-1}, $V / \overline{V}$, and (1 - *m*). These components all have the same elasticity in equation (5), but might have different elasticities in practice; that is, voters' might have a greater awareness of, and responsiveness to one of these components than another. Thus, our strategy is to estimate as many of these elasticities as possible, even though we simplify the presentation by writing a single elasticity in the text.

This specification does not specifically recognize a flypaper effect associated with matching grants. Instead, it simply estimates a price elasticity associated with extent to which the matching grant lowers the tax price. The Slutsky equation from basic microeconomic theory tells us, however, that "the price elasticity of the ordinary demand curve equals the price elasticity of the compensated demand curve less the corresponding income elasticity multiplied by the proportion of total expenditures spent on" the product. (Henderson and Quandt, 1980, p. 27). A flypaper effect can be thought of as a change in the income elasticity, so the price elasticity associated with matching aid (or with any other component of tax price) already captures a flypaper effect, if one exists. No separate specification of a flypaper effect for matching aid is needed—or possible.

Equation (5) also re-affirms a result in Oates (1972), namely, that the value a voter places on $1 of lump-sum aid depends on the voter's tax share, that is, on the extent to which lump-sum aid lowers a voter's taxes (or provides more money for services). More specifically, Equation (5) shows that a voter's valuation of lump-sum aid depends on the product of $V/\bar{V}$ and $(1 - m)$.[2]

Equation (5) cannot be estimated directly without accounting somehow for *MC* and *e*, which requires the estimation of an expenditure equation. We now explain our approach to this step.

III. The Determinants of School Efficiency and Educational Cost

Perhaps the greatest challenge faced by a researcher in estimating equation (5) is that *e* cannot be measured directly but still must be accounted for to obtain unbiased parameter estimates. Our approach, following Duncombe and Yinger (2001), and Eom, et al. (2007), is to identify variables with a conceptual link to efficiency and to include these variables as controls in our expenditure regression.[3] Although the link between a variable and (unmeasurable) efficiency cannot be directly tested, it is possible to determine whether the impact of an efficiency control variable on spending is consistent with the conceptual argument that led to its selection.

We select efficiency control variables in two categories. The first category consists of variables that are likely to influence the extent to which voters monitor school officials and thereby boost school-district efficiency. These variables are reviewed in Duncombe, Miner, and Ruggiero (1997). The second category consists of variables that influence the breadth of the student performance measures that voters expect a school district to provide. Recall that, by definition, efficiency reflects spending on any performance measure other than the ones specified in the cost function, designated *S*. As a result, this category includes factors that give voters an incentive to push for a broader range of performance measures.

Some variables, including median voter income and median tax price, belong in both categories. Higher incomes are associated with higher wages, which raise the opportunity cost of monitoring, but they also are associated with higher demand for a broad range of student performance measures. In both cases, a higher income leads to less efficiency and hence more spending, all else equal. A relatively high tax price indicates that voters must pay a large share of any spending increase out of their own pockets, which both gives them an incentive to monitor public officials and to cut back on their demand for public services. In both cases, a relatively high tax price leads to relatively high efficiency and relatively low spending, all else equal.

By way of clarification, note that income and tax price are included in the second category of *efficiency* factors to be included in the *expenditure* equation because they influence the demand for measures of student performance *beyond* those included in *S*. This point has two implications. First, income and tax price should not be used as instruments for *S* in the estimation of the expenditure equation because they have a direct role in explaining *E* and therefore fail the second test for a valid instrument.[4] Second, because income and tax price are included in the expenditure equation in part because of their link to demand (for measures of student performance other than *S*), it is appropriate to give these variables the same specification in the expenditure equation that they have in the demand equation (equation (5)).[5] As a result, income enters as income augmented by tax-price weighted state aid.

Our next step is to incorporate these two categories of variables into a multiplicative efficiency equation. For expositional purposes (but not in our estimations), we assume that the flypaper effect is the same in the efficiency equation as in the demand equation. Determinants of efficiency other than augmented income and tax-price, which are discussed below, are represented by *M*. This approach leads to the following efficiency equation, where γ is the income elasticity of efficiency, δ is the price elasticity of efficiency, and *k* is a constant:

$$e = k\,M^{\rho}\left(Y + f\,A\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)\right)^{\gamma}\left((MC)\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)\right)^{\delta} \qquad (6)$$

As explained earlier, we expect that γ is negative and δ is positive.

Our next step is to specify a cost function, which can be combined with the efficiency equation using equation (2). Following standard practice (Downes and Pogue, 1994; Duncombe and Yinger, 1997, 1998b, 2000, 2001; Reschovsky and Imazeki, 1998, 2001, 2003), we assume that educational cost depends, in a multiplicative way, on teacher salaries, *W*, student enrollment, *N*, and pupil characteristics, *P*:

$$C\{S\} = \kappa S^{\sigma} W^{\alpha} N^{\beta} P^{\lambda} \tag{7}$$

where κ is a constant and σ measures returns to quality scale; $\sigma < 1.0$ indicates increasing returns and $\sigma > 1$ indicates decreasing returns.[6] With this cost function, marginal cost is not constant:

$$MC \equiv \frac{\partial C\{S\}}{\partial S} = \sigma \kappa S^{\sigma-1} W^{\alpha} N^{\beta} P^{\lambda} \tag{8}$$

As indicated earlier, $E = C\{S\}/e$, so we can use equations (6)-(8) to write:

$$E = \mathrm{K}\left(S^{\sigma-\delta(\sigma-1)}\right)\left(W^{\alpha} N^{\beta} P^{\lambda}\right)^{1-\delta}\left(M^{-\rho}\left(Y + fA\left(\frac{V}{\overline{V}}\right)(1-m)\right)^{-\gamma}\left(\left(\frac{V}{\overline{V}}\right)(1-m)\right)^{-\delta}\right) \tag{9}$$

where

$$\mathrm{K} = \frac{\kappa^{1-\delta}}{k\sigma^{\delta}} \tag{10}$$

This equation identifies the parameters in equations (6) and (7). The efficiency price elasticity, δ, equals minus one multiplied by the coefficient of the tax-share variable. Once δ is known, the values of the cost parameters, α, β, and λ, can be determined from the coefficients of the cost variables. Since δ is expected to be positive, omitting this correction is likely to result in an *understatement* of the impact of wages, enrollment, and student characteristics on educational costs. The efficiency income elasticity, γ, is the negative of the coefficient of ln(Y), and the flypaper effect, f, is the coefficient of the aid variable divided by -γ. The economies-of-scale parameter, σ, can be found using the coefficient of ln(S) and the estimate of δ.

IV. Estimating the Demand Equation

Out ultimate objective is to estimate the demand function, so that we can determine the impact of state aid on the demand for student performance. It might seem as if one could first estimate equation (9) and then use the estimated parameters, along with equations (6) and (8), to calculate indexes of MC and e for every district. The problem with this approach is that both MC and e (through MC) are functions of S, so that these two variables are endogenous by definition.[7] Moreover, it may be impossible to find instruments for addressing this endogeneity because variables correlated with the impact of scale economies in MC and e, which operate through S, are, by definition, correlated with the dependent variable, namely, S.

As a result, we use a different approach, namely to exploit the multiplicative form of these equations to solve for S, that is, to eliminate S from the right side of the demand equation. This approach complicates the interpretation of the estimated parameters in the demand equation, but it eliminates the troublesome endogeneity described in the previous paragraph. The first step in this approach is to define an index for the elements of MC and e that do not involve S:

$$C^{*} = \sigma \kappa W^{\alpha} N^{\beta} P^{\lambda} \tag{11}$$

$$e^{*} = M^{-\rho}\left(Y + fA\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)\right)^{-\gamma}\left(C^{*}\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)\right)^{-\delta} \tag{12}$$

Now substituting equations (6), (8) and (11) into (5) yields our final form for the demand function, namely,

$$S = K^{*}\left(C^{*}\right)^{\mu^{*}}\left(e^{*}\right)^{-\mu^{*}}\left(Y + f\,A\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)\right)^{\theta^{*}}\left(C^{*}\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)\right)^{\mu^{*}} \qquad (13)$$

where

$$K^{*} = \left(\frac{K}{k^{\mu}}\right)^{\frac{1}{1-\mu(\sigma-1)(1-\delta)}} \qquad (14)$$

$$\theta^{*} = \frac{\theta}{1-\mu(\sigma-1)(1-\delta)} \qquad (15)$$

and

$$\mu^{*} = \frac{\mu}{1-\mu(\sigma-1)(1-\delta)} \qquad (16)$$

Note that with constant returns to quality scale ($\sigma = 1$), $\theta = \theta^{*}$ and $\mu = \mu^{*}$.

To estimate equation (13), we re-write the income term as follows:

$$\left(Y + f\,A\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)\right) = Y\left(1+\left(\frac{fA\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)}{Y}\right)\right) \qquad (17)$$

Then take the logs of both sides of (13) and use the approximation that $\ln\{1+a\} \cong a$ when a is close to zero.[8] These steps yield:

$$\ln\{S\} = \ln\{K^{*}\} + \mu^{*}\ln\{C^{*}\} - \mu^{*}\ln\{e^{*}\} + \theta^{*}\ln\{Y\} + f\theta^{*}\left(\frac{A\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)}{Y}\right) + \mu^{*}\ln\left\{\left(\frac{V}{\overline{\overline{V}}}\right)(1-m)\right\} \qquad (18)$$

This equation can be estimated with standard regression techniques with a separate value of μ for each component of tax price. The flypaper effect, which need not equal the flypaper effect in (9) and (13), equals the coefficient of the aid term divided by the coefficient of the income term. The other structural parameters can be identified based on the estimates from this equation and from the expenditure equation (9).

One important lesson from equation (13) (or equation (18)) is that the coefficients of the income and price terms in a demand equation do not equal the income and price elasticities unless there are constant returns to quality scale and an efficiency measure is included in the equation. To be specific, if e^* is omitted, the estimated "income" elasticity is $(\theta^* - \gamma\mu^*)$ and the estimated "price" elasticity is $\mu^*(1 - \delta)$, which are smaller (in absolute value) than θ and μ, respectively (or than θ^* and μ^*). To the best of our knowledge, the only previous studies that include efficiency in a demand function are Duncombe and Yinger (1997, 1998b, 2000, 2001) and Eom et al. (2007). Equation (13) implies that all other studies understate the absolute values of the income and price elasticities of demand for local public services.

V. Estimates of Cost and Demand Equations

In this section we present estimates for the cost and demand equations using information on New York school districts from 2001 to 2007. Most of the data used in the analysis were provided by the New York State Education Department (SED) in the form of published and unpublished sources. Table 1 presents descriptive statistics for the variables used in the analysis.

Data and Measures

Per Pupil Spending: The dependent variable in the cost function is per pupil spending. More specifically, our spending measure is total expenditure per pupil minus transportation expenditure and debt service. Expenditure information is published by SED in the *Fiscal Profile*. By this measure, average spending per pupil in New York school districts was close to $15,000 in 2007.

Student Performance Measure. The student performance measure used in the cost function and the demand function is a composite based on math and reading tests for several grades. Specifically, we employ the index used by SED in its accountability system, which ranges from 0 to 200. The first part of this index is based on 4th and 8th grade math and English language arts exams. The share of students reaching level 2 (multiplied by 100) is added to the share of students reaching levels 3 or 4 (multiplied by 200). In the case of high school, this index is based on the cohort exam results in math and English with the same weights; level 2 is defined as a score of 55 to 64 and level 3 or 4 is defined as a score above 64. The overall index is the simple average of these weighted scores across all grades. Student performance information is available from SED in either the *Chapter 655 Report* or *School Report Cards*.[9]

Teacher salaries: The cost of providing education services varies across districts, in part because of differences in prices that districts have to pay for resources, such as teachers. To measure salaries for comparable teachers, we use information on individual teachers with 1 to 5 years of experience collected in the Personal Master File (PMF) of the Basic Education Data System (BEDS). Data on inexperienced teachers is used, because it is more apt to reflect variation in the underlying cost of hiring comparable teachers and not differences in teacher contract provisions. To control for variation in education and experience across districts, the natural logarithm of teacher salaries is regressed on the log of total experience and an indicator variable for whether the teacher has a graduate degree. We use the regression to estimate average salaries for teachers in each district with the statewide average experience (between 1 and 5 years) and the statewide average percent of teachers with a graduate degree. The predicted salary in 2007 in the average district was over $43,000.

Enrollment variable: A key variable in a cost model is the number of students served by the district. The student count measure used in this report is average daily membership (dcaadm), which is a measure of average enrollment over the course of the year. Average enrollment provides a better estimate of the underlying enrollment of the district during the year and is less sensitive to unusual results than is a single enrollment count. The relationship between enrollment and per pupil spending has often been found to have a nonlinear functional form. As a result, we include dummy variables for different enrollment classes; each variable equals 1 if the district falls into a particular enrollment class and 0 otherwise.

***Student measures*:** One of the key factors affecting the cost of reaching a given performance level is the share of students in a district requiring additional assistance. Poverty has consistently been found to be an indicator of the student disadvantages that require additional assistance. The most commonly used measure of poverty in education research is the share of students receiving free or reduced price lunch in a school. For this analysis we use the measure in SED's aid formulas, which is the share of K6 students receiving free or reduced price lunch. Another indicator of students requiring additional services is the percent of students with limited English proficiency. We use the share of

LEP students reported in the *Chapter 655 Report*, which is derived from BEDS Institutional Master File (IMF) data. Students with special needs often require additional services and support, which can substantially increase school spending. Using data from the State Aid Files produced by SED, we define a variable for students with major disabilities, namely, students outside the classroom more than 60 percent of the time, students requiring teacher services, and students labeled as high-cost students.[10]

Efficiency-related measures. As discussed earlier, the cost model includes efficiency control variables that are likely to influence the extent to which voters monitor school officials or variables that influence the breadth of the student performance measures that voters expect a school district to provide. The first set of such variables are related to a school district's fiscal capacity. (These variables are also included in the demand model.) The most basic measure is per pupil adjusted gross income (AGI). AGI by school district is provided to SED from the New York State Department of Taxation and Finance. Another important measure is the aid ratio for operating plus categorical aid.[11] As discussed previously, the aid ratio equals per pupil aid divided by per pupil income and multiplied by the tax share (discussed below). The data on state aid is extracted from the State Aid Files provided by SED.

The other set of efficiency variables are directly related to incentives to monitor district operations. One of these variables is tax share. As discussed above, tax share has two components. The first is the ratio of median residential property values divided by average (per pupil) property values in a district. Average property value is reported by the New York Office of the State Comptroller for each school district. Median residential property values was calculated using detailed parcel-level data from the New

York Office of Real Property Tax Services (ORPS).[12] The second component is one minus the matching rate. As discussed above, the STAR program is equivalent to a matching aid program with a matching rate of *X/V*, where *X* is the basic homestead exemption and *V* is median residential property value. The tax share variable included in both the cost and demand models is the product of these two components.

Other monitoring variables included in the cost model include the percent of housing units that are owner occupied and the percent of the population that is 65 years or older. The latter two variables come from the *2000 Census of Population and Housing*.

Other demand variables. Besides measures of income, aid, and tax share, the demand model also includes two measures derived from the cost model. The first is estimated exogenous component of marginal cost as represented by equation (11) and the second is the estimated exogenous component of efficiency in equation (12). In calculating these measures, we used the coefficients of the cost function to derive the underlying structural parameters.

Estimates of the Cost and Demand Equations

Cost Equation: The cost model, equation (9), was estimated using seven years of data for approximately 652 school districts (n=5218). Because expenditure, teacher salaries, and performance targets are set as part of the district planning and budgeting processes, salaries and performance measure need to be treated as endogenous variables in the cost model. We select instruments related to performance and salaries but not independently related to the error term of cost function regression.[13] STAR tax prices may be endogenous because they can affect both local taxes and spending and also housing prices through household sorting across school districts. Since the STAR tax price is used to calculate both the aid ratio and the tax share variables, these variables are treated as endogenous variables in the cost model.[14]

The cost model is estimated with an instrumental variable regression method. We performed various tests to screen out inappropriate instruments. A weak instrument test was used to identify instruments that are strongly correlated with salaries and the performance measure (Bound, Jaeger, and Baker, 1995) and an overidentification test (Woolridge, 2003) was used to test whether the instruments are exogenous.[15]

We have also taken two steps to remove potential biases in the standard errors due to serial correlation or heteroscedasticity. First, we include year fixed effects to remove district-invariant factors (such as general economic growth), which may be correlated over time. Second, we use the method developed by Newey and West, which produces heteroskedasticity- and autocorreation-consistent (HAC) estimates of the standard errors (Baum, Schaffer, and Stillman, 2007).[16]

The results for the cost model are reported in Table 2. Most of the cost-related coefficients are statistically significant at the conventional 5 percent level and all the coefficients have the expected sign. For example, we find that higher student performance, higher teacher salaries, and a greater share of subsidized lunch students, LEP students, and special needs students are positively related to higher spending. The regression coefficients on the enrollment category variables can be interpreted as the percent change in costs for a district in this enrollment category compared to a district with less than 500 students. As expected the costs per pupil fall substantially as the district size increases up to an enrollment of level between 3,000 to 5,000 students.

Finally, all of the efficiency variables have the expected sign and all but per pupil income and percent of population 65 years and older are significant at the 5 percent level.

The results of the cost function are consistent with those found by the authors in several previous cost functions studies for New York school districts (Duncombe and Yinger, 2005, 2000; Duncombe, Yinger, and Lukemeyer, 2003). The average pupil weight for subsidized lunch students is 0.98 indicating that in the average district an additional student in poverty is estimated to require almost twice the spending to reach the same performance level as a nonpoor student. The pupil weights for LEP students and for students with major disabilities are 0.55 and 1.36 respectively. However, the coefficient on the LEP variable is not statistically significant at conventional levels.

One measure of relative cost differences is a cost index. A cost index measures the percent difference in spending in a particular district, due to factors outside of district control, to reach a given student performance level compared to a district with average characteristics. Cost indices can be calculated using the regression coefficients on the cost variables. We find cost indices of 225 for New York City, 216 for Yonkers, and 148 for the Big Three upstate cities. These indices imply that these school districts will require between 48 and 125 percent more spending than the average district for their students to reach the same performance level (holding efficiency constant). Costs are also found to be above average in the downstate small cities and in a number of downstate suburban districts and upstate rural districts. The lowest costs are found in the upstate suburban districts.

Demand Equation: The results for the education demand model, equation (18), are reported in Table 3. .The dependent variable in the demand model is the log of the student performance index. Because STAR exemptions might affect property values, we treat the STAR component of the tax share variable as endogenous. [17]

The augmented income variables are positively related to student performance and are statistically significant at the 5 percent level. The structural parameters for these variables are reported in Table 4. The estimated income elasticity is low (0.104), which is consistent with most previous research (Duncombe and Yinger 2000, 2001; Fisher and Papke 2000). The estimated flypaper effect for state aid (1.82) suggests that lump-sum state aid may have a more stimulative impact on student performance than does an equivalent increase in household income. This result also is consistent with previous research (Hines and Thaler 1995). However, we cannot reject the hypothesis at conventional levels that there is no flypaper effect, i.e., that the flypaper coefficient is equal to one.

The coefficients on the tax share and efficiency variables have the expected sign and are statistically significant. The estimated price elasticities are -0.115 for tax share, -0.326 for marginal costs, and -0.501 for inefficiency. These results support the view that voters respond to the financial incentives created by the education finance system, including the incentives associated with educational costs and school-district inefficiency.

In the case of the preference variables we find that higher shares of college graduates and of occupied housing units are associated with increased demand for education. See Table 3.

VI. The Impact of State Aid on the Demand for School Performance: Simulations

Equations (12) and (13) can be used to determine the impact of lump-sum aid, A, or matching aid, m, on the demand for S. Our objective is to compare the stimulative impact of *equal-cost* lump-sum and matching aid programs. We can ensure that two programs we compare have the same costs using the community budget constraint, equation (2). Suppose there is an existing lump-sum aid program that provides $\$A_1$ per pupil, where $A_1 \geq 0$, and there is no existing matching grant. Then the question is whether a new matching grant program with rate m would be more stimulative than a new lump-sum aid program with the same cost. One could, of course, assume that there is an existing matching grant, too. In fact, however, open-ended matching grant programs are fairly rare.[18] As a result, we compare the stimulative impact of matching and lump-sum aid when each of them is added (separately) to an existing lump-sum aid program.

According to equation (2), the cost of a matching grant program is $m(E - A_1)$ dollars per pupil; that is, it is the state's share of the spending covered by the matching grant. To make the cost of the two programs equal, therefore, we simply set the amount of the new aid program, $\$A_2$, equal to $m(E - A_1)$. This is a fairly complicated calculation, however, because E depends on S, which depends on m. Our approach is to select a value for m, use equations (12) and (13) to find the corresponding S_m, solve for $E_m = C\{S_m\}/e$ using equations (6)-(8), and then set $A_2 = m(E_m – A_1)$.[19]

We carry out calculations of this type using data from school districts in New York State and the structural parameters implied by our expenditure and demand regressions. Although New York State does not currently use a broad-based open-ended matching grant, our tax share variable includes the "matching" rate in the STAR program, which is equivalent to a matching grant. Our calculations are based on the assumption that the price elasticity for a matching grant would be the same as the price elasticity associated with a district's tax share, which is the product of the property tax share, $V/\overline{V}$, and one minus the "matching" rate in STAR. This assumption appears quite reasonable since the price elasticity we estimate, -0.115, is similar to the elasticities estimated for matching grant programs in other states (Fisher and Papke 2000). Nevertheless, voters' responses to the matching rate in a state aid program might differ from our estimate, so we explore results not only with the price elasticity we estimate, but also with both smaller and larger price elasticities

The results of our calculations are presented in Table 5. The entries equal the difference in student performance (using our index) with a matching grant and with an equal-cost lump sum grant as a percentage of the change in performance induced by the matching grant alone. A large positive entry in this table, such as 90 percent, does not indicate that matching grants are effective, only that their impact on student performance is large relative to the impact of lump-sum aid. Cases in which a lump-sum grant is more stimulative appear with a negative sign and are indicated in boldface. These results combine our estimated structural parameters with data for New York school districts in 2007.

The first panel of this table explores calculations based on all the structural parameters in Table 4 and varying matching rates. With a matching rate of 20 percent, which we treat as our baseline rate, the standard theorem is upheld in all types of district. After accounting for its direct effect on the demand for student performance and its indirect effect on school district efficiency and the value to voters of existing lump-sum aid, we find that this matching aid program would raise student performance in the average district by 0.276 percent. Our estimates also imply that a new equal-cost lump-sum grant program would not raise student performance, but would in fact lower performance a tiny amount (0.047 percent). The figure in the table equals the difference between these two effects divided by the matching grant effect: [0.276-(-0.047)]/0.276 = 1.1693 = 116.93 percent. The first and third rows of this panel show that changing the matching rate has little impact on the advantage of matching aid, although it obviously has a huge impact on the cost of the aid program.

This tiny negative impact of lump-sum aid on student performance reflects the large flypaper effect in the efficiency equation; an increase in lump-sum aid leads to a significant decrease in school district efficiency (presumably as school district use a large share of the aid to promote performance measures other than those in our test-score measure). This increase in efficiency represents an increase in the price of student performance and hence induces voters to cut back their demand. We also find a flypaper effect in the demand equation, which increases the stimulative effect of lump-sum aid, but the flypaper effect in the efficiency equation, which lowers the stimulative effect, is almost seven times as large as the flypaper effect in the demand equation.

Although the aid variables are statistically significant at the 5 percent level in both the expenditure and demand equations, the flypaper effects, which depend on the income and aid variables, are not significantly different from 1.0 at even the 10 percent level.[20] See Table 4. A value of 1.0 would indicate that aid (adjusted for tax share) and income have the same impact on school district efficiency (the expenditure equation) or on the demand for student performance (the demand equation). As a result, we are not confident that these flypaper effects exist, and we also, as discussed below, conduct simulations using other values for these flypaper effects.

Also note that these flypaper effects, even if accurately estimated, reflect the impact of existing lump-sum aid programs, both restricted and categorical, on efficiency and demand. One reason for the large flypaper effect in the efficiency equation, for example, could be requirements in existing categorical aid programs that make it difficult for school districts to use the funds to boost student performance on the tests in the SED performance index. A new, unrestricted lump-sum aid program would not include these requirements and therefore might not have such a large impact on school district inefficiency. Moreover, if this new lump-sum aid program were coupled with an effective accountability program it might not boost school-district inefficiency at all.

The second panel of Table 5 examines the impact of an increase in the price elasticity of demand for student performance. This is an important case to consider because a matching grant appear to provide a more visible price signal than either the property distribution, $V/\overline{V}$, or the implicit matching rate in STAR. As a result, a school district's response to a matching grant might be greater than the response to its tax share, which is what we estimate. The results in Table 5 suggest that a larger price elasticity lowers the stimulative advantage of matching aid. This result is counter-intuitive because the standard theorem emphasizes that the stimulative advantage of matching aid comes from the fact that it alters the price of student performance increases. In fact, however, a higher price elasticity does increase the stimulative power of matching aid in our model, but our measure of relative stimulative power requires careful interpretation when one type of aid lowers student performance. In the example given earlier, the stimulative advantage of a matching grant was [0.276-(-0.047)]/0.276 = 116.93 percent. If the price elasticity triples, the comparable numbers are [3.00-(-0.056)]/3.00 = 101.86 percent. The percentage difference is smaller in the second case, but this cannot be interpreted as a decline in the advantage of matching aid—which is already over 100 percent.

It is also worth pointing out that matching grants have a less stimulative impact in our analysis than in a standard model, because the direct impact of a lower tax share in the demand equation is largely offset by the indirect effect of these grants on demand through school district efficiency. By lowering voters' tax share, matching grants discourage monitoring and encourage spending on school outputs other than our measure of student performance, thereby decreasing district efficiency and lowering the demand for student performance. This indirect effect is about four-fifths the magnitude of the direct effect, so this offset is quite large.[21]

The third and fourth panels present results for alternative values of the two flypaper effects. The third panel shows that a flypaper effect in the demand equation that is as large as the flypaper effect in the efficiency equation would eliminate the stimulative advantage of matching aid in the average district and in every class of district. This result is not surprising, since a higher value for this flypaper effect directly boosts the stimulative power of a new lump-sum grant while at the same time increasing a matching grant's negative impact on the stimulative power of existing lump-sum aid. Indeed, some of the entries in this row are greater (in absolute value) than -100 percent, which indicates that the matching grant has a negative impact on performance when this flypaper effect is so large. The fourth panel shows that setting the flypaper effect in the efficiency equation equal to the flypaper effect in the demand equation would reverse the stimulative advantage of matching grants in every class of district except New York City and the downstate small cities. The reversals are particularly dramatic in the upstate Big Three and Yonkers. Overall, this large cut in the flypaper effect in the efficiency equation not only ensures that lump-sum aid always has a positive impact on student performance, but also boosts this impact above the impact of an equal-cost matching grant in most districts..

The final panel presents two simulations in which both flypaper effects are changed. The first row eliminates both flypaper effects. The result is a large decrease in the stimulative advantage of matching grants, and a reversal of this advantage in Yonkers. The last row doubles the flypaper effect in the demand equation and eliminates it in the efficiency equation. These changes are enough to reverse the stimulative advantage of matching grants in every district category except New York City

Note that in the last row, as in the first row of the previous panel, the stimulative advantage of lump-sum aid is particularly large in the Big Three and in Yonkers because they have considerably more total aid per pupil than the districts in the other categories and, in the case of Yonkers, an unusually high tax share. As explained earlier, a matching grant lowers the impact of existing aid on the demand for school quality because it lowers a voter's savings with each dollar of aid. Without matching aid, a dollar of lump-sum aid saves a voter an amount equal to the voter's tax share, which is the amount the voter would have had to pay if the money were raised through property taxes. After the implementation of a new matching grant with matching rate m, a dollar of lump sum aid to a voter is reduced because the voter only saves the expected local contribution, (1 - *m*), multiplied by the tax share. This effect is minimized when the tax share is low, as in New York City, because a low tax share implies that existing aid does not have a very stimulative effect to begin with. This effect is maximized with a relatively high value for either the amount of existing aid per pupil (as in the Big Three) or the tax share (as in Yonkers).[22] In contrast, an additional lump-sum grant does not alter the simulative effect of existing lump-sum aid.

A full explanation of this effect is complicated because a matching grant also lowers the impact of existing aid on school district efficiency.[23] This leads to an increase in efficiency and hence to an increase in the demand for school quality, which offsets the direct effect in the previous paragraph. With the baseline values of our parameters, which are the ones we estimate, this indirect effect is actually larger than the direct effect in the previous paragraph. When the flypaper effect in the demand equation is greater than or equal to the flypaper effect in the efficiency equation, however, the direct effect is larger, a matching grant works against itself by lowering the stimulative impact of existing aid programs, and this effect can be large enough to reverse the standard theorem, particularly in the Big Three and Yonkers.

VII. Conclusions

The theorem that matching grants are more stimulative than equal-cost lump-sum grants is popular in public finance text books, but it fails to consider several key features of educational spending and demand. In addition to the direct effects of state aid on the demand for student performance, an analysis of grants must consider the impact of grants on school district efficiency, along with the impact of matching grants on the stimulative effect of existing lump-sum aid. We estimate expenditure and demand functions for school districts in New York State and use the results to incorporate these additional factors into a comparison of grant types.

Simulations based on our parameter estimates support the standard theorem: matching grants are indeed more stimulative than equal-cost lump-sum grants. Open-ended matching grants are not popular with legislatures. This result appears to reflect the budgetary uncertainty associated with these grants. More specifically, the cost of an open ended matching grant depend upon district responses—namely, the type of responses estimated in this report—that are not known when the grant is implemented. As a result, legislatures stick to lump-sum grants or place a binding limit on matching grants, which converts them to lump-sum grants. Nevertheless, this result suggests that open-ended matching grants may have an important role to play in boosting student performance.

Our simulation results also provide two important qualifications to this conclusion. First, we were not able to estimate with precision the flypaper effect in either the efficiency or demand equation, and indeed, did not obtain statistically significant estimates for either of these important parameters. Obtaining more precise estimates of these two flypaper effects, along with determining whether flypaper effects differ for unrestricted and categorical grants, are key challenges for future research.

Second, we cannot estimate a price elasticity of demand for a matching grant, but instead rely on a price elasticity for a district's tax share. Although the tax share has the same effect on voters' and public officials incentives as a matching grant, it operates through different institutions and may lead to different behavioral responses. Future research may be able to determine whether the price elasticity differs for the two components of tax share, $V/\overline{V}$ and the implicit matching rate in STAR. It is not possible, however, to estimate the price elasticity for a general open-ended matching grant program, at least not in New York, because no such program exists.

Although this study focuses on a comparison of matching and lump-sum grants, it also indicates that both types of aid programs face severe challenges to their effectiveness. The most important challenge is that both types of programs appear to undermine the efficiency with which school districts deliver the key student performance objective in New York State's accountability program. Lump-sum grants raise voter's effective incomes and thereby encourage voters to spend money on all types of school outputs, not just on programs to boost one student performance measure. Matching grants undermine this effectiveness by lowering voters' tax price and thereby also encouraging them to spend on all types of school outputs. In the case of matching grants, however, this effect is offset to some degree by the fact that matching grants lower the negative impact on efficiency of existing lump-sum grants. The precise magnitude of these effects is difficult to determine, however, because they depend on the flypaper effect in the efficiency equation, which we cannot estimate with precision. Another challenge for future research is to better understand these complex effects of grants on efficiency and to help design grant and accountability programs that maximize the impact of grants on a state's student performance targets.

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Table 1. Descriptive Statistics for Variables in Education Cost and Demand Models (New York School Districts in 2007)

Variables	Average	Standard Deviation
COST MODEL:		
Per pupil current expenditures	$15,192.9	$4,169.9
Student performance index	167.4	14.5
Average teacher salary	$43,498.0	$7,708.0
Student characteristics:		
Percent of students receiving subsidized lunch	31.170	20.101
Percent of students with Limited English Proficiency	1.896	3.548
Percent of students with major disabilities	7.584	3.412
Enrollment classes:[1]		
500 to 1,000 students	0.175	0.380
1,000-2,000 students	0.310	0.463
2,000-3,000 students	0.129	0.335
3,000-5,000 students	0.149	0.356
5,000-10,000 students	0.100	0.300
Over 10,000 students	0.029	0.167
Efficiency variables:		
Per pupil income	$177,266	$179,492
Per pupil state aid[2]	$4,382	$2,187
State aid ratio[2]	0.080	0.079
Tax share[3]	2.255	1.211
Percent owner occupied housing (2000)	85.857	15.015
Share of population 65 years or older	0.142	0.036
Instruments:		
Comparable wage index (labor market area)	1.191	0.149
Median house value	$133,896.2	$86,948.4
Percent nonwhite enrollment	13.936	10.173
County population	462,825	591,935
DEMAND MODEL:		
Tax price variables:		
Log of cost measure[4]	-7.671	0.299
Log of efficiency measure[4]	4.427	0.132
Preference variables:		
Fraction of population 5 to 17 years of age (2000)	0.190	0.026
Percent occupied housing units (2000)	85.857	15.015
Adjusted share of college graduates[4]	-0.032	0.073
Sample Size	659	

[1]The base enrollment is 0 to 500 students. The coefficients can be interpreted as the percent change in costs from being in this enrollment class compared to the base enrollment class.

[2]Total formula state aid minus Building Aid and Transportation Aid. The aid ratio is measured as per pupil state aid divided by per pupil income and multiplied by the tax share.

[3]Measured as the ratio of median residential property values divided by property values per pupil multiplied by the STAR tax price. The STAR tax price is equal to one minus the ratio of the basic STAR exemption divided by median residential property value.

[4]Measure is constructed using regression cofficients. See text for a discussion of how these variables are constructed.

Table 2. Results of the Education Cost Model[1]
(New York School Districts from 2000-2007)

Variables	Coefficient	Significance level
Constant	-31.0639	0.00
Student performance index	4.2377	0.02
Average teacher salary[2]	1.7819	0.00
Student characteristics:		
Percent of students receiving subsidized lunch	0.0084	0.01
Percent of students with Limited English Proficienc	0.0055	0.28
Percent of students with major disabilities	0.0130	0.00
Enrollment classes:[4]		
500 to 1,000 students	-0.2669	0.00
1,000-2,000 students	-0.4016	0.00
2,000-3,000 students	-0.4716	0.00
3,000-5,000 students	-0.5104	0.00
5,000-10,000 students	-0.5180	0.00
Over 10,000 students	-0.4034	0.00
Efficiency variables:		
Per pupil income[2]	0.0786	0.20
State aid ratio[5]	0.9613	0.00
Tax share[6]	-0.1944	0.00
Percent owner occupied housing (2000)	-0.0095	0.01
Share of population 65 years or older	-0.1862	0.55
Indicator variable for year:		
2001	-0.0564	0.16
2002	0.0356	0.26
2003	-0.1317	0.05
2004	-0.1724	0.04
2005	-0.2542	0.06
2006	-0.0245	0.59
2007	-0.1614	0.12
Instrument tests:		
Partial F-test (Student performance index)	6.91	0.00
Partial F-test (Average teacher salaries)	229.60	0.00
Partial F-test (State aid ratio)	530.15	0.00
Partial F-test (Tax share)	1597.20	0.00
Overidentification test (Hansen J statistic)	3.51	0.17
Sample Size	5218	

[1]Estimated with linear IV estimator with student performance, teacher salaries, the tax share, and state aid ratio treated as endogeous. See text for discussion of instruments. To reduce possible weak instrument bias we used a Fuller k-class LIML estimator (α=1). The dependent variable is the log of per pupil current expenditure.

[2]Expressed as a natural logarithm.

[3]Expressed as a percent.

[4]The base enrollment is 0 to 500 students. The coefficients can be interpreted as the percent change in costs from being in this enrollment class compared to the base enrollment class.

[5]Measured as per pupil state aid divided by per pupil income and multiplied by the tax share.

[6]Measured as the ratio of median residential property values divided by property values per pupil multiplied by the STAR tax price. The STAR tax price is equal to one minus the ratio of the basic STAR exemption divided by median residential property value. The tax share is expressed as a natural logarithm.

Table 3. Results of the Education Demand Model[1]
(New York School Districts from 2000-2007)

Variables	Coefficient	Significance level
Constant	2.0707	0.00
Augmented income variables		
Per pupil income[2]	0.0541	0.00
State aid ratio	0.0986	0.04
Tax price variables:		
Tax share[2]	-0.0601	0.00
Cost measure[2]	-0.1698	0.00
Efficiency measure[2]	0.2613	0.00
Preference variables:		
Percent of population 5 to 17 years of age (2000)	-0.0112	0.87
Percent occupied housing units (2000)	0.0011	0.00
Adjusted share of college graduates[3]	0.2465	0.00
Copy-cat variables (for comparison districts):		
Comparable wage index (labor market area)	-0.1760	0.00
Median house value[4]	0.0000	0.00
Percent nonwhite enrollment[4]	0.0019	0.00
County population[2]	-0.0039	0.08
Indicator variable for year:		
2001	0.0211	0.00
2002	0.0078	0.24
2003	0.0346	0.00
2004	0.0498	0.00
2005	0.0747	0.00
2006	0.0666	0.00
2007	0.0820	0.00
Instrument tests:		
Partial F-test (State aid ratio)	1105.40	0.00
Partial F-test (Tax share)	1404.15	0.00
Sample Size	5264	

[1]Estimated with linear 2SLS estimator with the tax share and state aid ratio treated as endogeous. See text for discussion of the instrument. The dependent variable is the log of the student performance index.

[2]Expressed as a natural logarithm.

[3]The residual from a regression of percent college graduates (2000) regressed on per pupil income.

[4]Calculated as the average of the other districts in the same labor market area.

Table 4. Structural Paramenters from Education Cost and Demand Models[1]

Variables	Coefficient	Significance level
Cost Model:		
σ (Student performance index)	5.019	0.01
α (Average teacher salary)	2.212	0.00
β_1 (Subsidized lunch)	0.010	0.01
β_2 (Limited English proficiency)	0.007	0.28
β_1 (Major disabilities)	0.016	0.00
f_1 (State aid ratio)[2]	12.230	0.33
Demand Model:[3]		
θ_1 (Per pupil income)	0.104	0.00
f_1 (State aid ratio)[2]	1.823	0.27
μ1 (Tax share)	-0.115	0.00
μ2 (Cost measure)	-0.326	0.00
μ3 (Efficiency measure)	-0.501	0.00

[1]Structural parameters are identified using equations 5) to 17) in the text. Hypothesis tests are based on a Wald test where null hypothesis is zero.

[2]Null hypothesis for hypothesis tests for aid ratios parameters is one.

[3]The hypothesis testing results for the demand model parameters (except for aid ratio) should be viewed with caution, since they only test the coefficients in the demand model. All of the parameters in the demand model but flypaper effect are calculated using parameters from the cost model, which are assumed to be fixed. We were not able to carry out cross equation hypothsis tests for instrumental variable regression models.

Table 5. Difference in the Performance Impact of a Matching Grant and an Equal Cost Lump-Sum Grant

	Downstate Small Cities	Downstate Suburbs	New York City	The Big Three	Upstate Rural	Upstate Small Cities	Upstate Suburbs	Yonkers	State Average	Memo: Cost ($000,000)
Vary *m*										
m=.10	148.96%	140.60%	123.70%	95.56%	114.73%	119.06%	120.15%	105.50%	118.77%	$2,034
m=.20	143.70%	136.17%	122.99%	95.05%	113.21%	116.67%	117.55%	101.24%	116.93%	$4,279
m=.333	137.21%	130.66%	121.98%	94.33%	111.19%	113.62%	114.25%	96.51%	114.52%	$7,700
Vary μ										
μ = -0.1152	143.70%	136.17%	122.99%	95.05%	113.21%	116.67%	117.55%	101.24%	116.93%	$4,279
μ = -0.3456	104.64%	103.89%	102.20%	99.48%	101.44%	101.78%	101.86%	99.98%	101.86%	$5,331
Vary *f*										
f = 1.8230	143.70%	136.17%	122.99%	95.05%	113.21%	116.67%	117.55%	101.24%	116.93%	$4,279
f = 12.2301	**-114.17%**	**-122.04%**	**-33.37%**	**-258.46%**	**-171.12%**	**-155.25%**	**-152.41%**	**-152.12%**	**-157.89%**	$4,107
Vary *g*										
g = 1.8230	6.44%	**-0.15%**	84.93%	**-96.77%**	**-9.77%**	**-24.70%**	**-26.69%**	**-81.66%**	**-1.28%**	$4,272
g = 12.2301	143.70%	136.17%	122.99%	95.05%	113.21%	116.67%	117.55%	101.24%	116.93%	$4,279
Vary Multiple Parameters										
f = 1.00; *g* = 1.00	54.39%	52.84%	91.93%	26.43%	57.27%	47.84%	46.08%	**-22.06%**	58.28%	$4,298
f=3.6459; *g*=1.00	**-87.65%**	**-95.53%**	50.20%	**-226.10%**	**-137.19%**	**-127.67%**	**-125.82%**	**-137.65%**	**-124.72%**	$4,223

Notes: A positive sign indicates that a matching grant is more stimulative; a negative sign (and bold type) indicates that a lump-sum grant is more stimulative. Each entry is the difference in student performance, *S*, with a new matching grant and with an equal-cost lump-sum grant divided by the difference in *S* with the most stimulative new grant and with existing grants only. Thus, each entry is a relative change in performance—not absolute change. Baseline values are underlined.

Endnotes

[1] Hines and Thaler (1995) review the literature on the flypaper effect.

[2] The impact of matching grants on the stimulative effect of lump-sum aid was pointed out by Barnett (1993). An equivalent result, discussed in a later section, is that property tax exemptions affect the value of lump-sum aid. See Eom, Duncombe and Yinger (2007), Duncombe and Yinger (1998a, 2001) and Rockoff (2003).

[3] Other approaches to efficiency are reviewed in Duncombe and Yinger (2007).

[4] Many early studies of public service demand, including some of our own, make this mistake.

[5] We exclude the efficiency component of tax price from the expenditure equation, however; including it would be circular reasoning.

[6] We are talking here about returns to quality scale as defined in Duncombe and Yinger (1993), not returns to population scale, which are captured by an enrollment variable.

[7] To the best of our knowledge, the only previous research that recognizes that *MC* is a function of *S*, which implies that *S* belongs on the right side of the demand function, as well as on the left side, is Eom, Duncombe, and Yinger (2007).

[8] These steps and this approximation also can be used to estimate equation (9).

[9] For school districts not serving all grades, we imputed performance measures for the missing grades in several ways. For central high school districts we used 4th and 8th exam results for their feeder K8 districts; for these K8 districts we used regents exam scores for their central high school district. For other K8 and K6 districts we do not know for sure

which middle school or high school their students attended. For K8 districts we imputed high school test scores by assuming that the district's performance on the 8th grade exam in the same subject relative to the state average applies for high school test results. For K6 districts we assume that the district's performance on the 4th grade exam in the same subject relative to the state average applies for 8th grade and high school test results.

[10] This special education measure was only available through 2005. We used 2005 data for 2006 and 2007, which assumes that the relative relationship across districts in 2005 applied for 2006 and 2007. Data were also missing for 2003; we used 2002 data for 2003, as well.

[11] In other words, our aid variable is total formula aid.

[12] The data from ORPS is from their Real Property System (RPS). It measures the assessed value of individual parcels. Market value was calculated by divided assessed value by the equalization ratio for a particular property class and assessing unit. To calculate the median residential market we kept parcels with the following property tax codes: 200, 210, 220, 230, 240, 270, 271, 280 and 281. For some years there were significant missing observations. To impute these variables we estimated a model of median house value regressed on per pupil income in a district, per capita income in the county, the share of county personal income in wages and salaries, and per capita taxable retail sales in the county. The adjusted R-square for this regression was 0.805. The predicted value for this regression was used to impute missing observations for median residential property values.

[13] The set of instruments for teacher salaries include the comparable wage index (CWI) for labor market areas developed for NCES by Taylor and Fowler (2006) and the logarithm of county population For student performance, we use the percent non-white students and median housing value for other school districts in the labor market area as instruments.

[14] The instrument we use for the STAR tax price is the basic STAR divided by the median residential value in 1998, which is the year before basic STAR was implemented. To calculate the aid ratio we estimate a regression in which the ratio of the STAR exemption to the median value is regressed on all the exogenous variables in the cost model. One minus the predicted value for this regression is multiplied by ratio of state aid to income and by the local tax share.

[15] As indicated by the partial F-statistics in Table 2, the instruments for teacher salary, aid ratio, and tax share variables are very strong but those for student performance are below the threshold of 10 often used to identify weak instruments (Stock and Watson, 2003). Because of the possibility of bias caused by weak instruments we use a method, which "performs reasonably well …even when instruments are weak." (Murray, 2005, p. 28) Specifically, we use the k-class limited information maximum likelihood method developed by Fuller (1977). We tested the results when the parameter is set equal to 1 or 4. The results for a parameter of 1 are reported in Table 2. The Fuller method is available in STATA using the ivreg2 procedure (Baum, Schaffer, and Stillman, 2007). We also checked for the appropriateness of the instruments using an overidentification test (Hansen j Statistic). We find that it is not possible to reject the null hypothesis that

the instruments are exogenous (Table 2). This test is only appropriate when at least one of the instruments is exogenous.

[16] The Newey-West estimation involves specifying the maximum lag to be considered in the autocorrelation structure Newey and West (1987). A common rule for specifying the lag length is $T^{(1/3)}$, which in this case is approximately equal to 2 (Baum, Schaffer, and Stillman, 2007).

[17] The tax price and aid variables in the demand model also need to be treated as endogenous variables. The same instrument used for the tax price variable in the cost model is used in the demand model. The instrument for the state aid ratio is calculated in a similar way. The ratio of the STAR exemption to median residential value is regressed on all of the exogenous variables in the demand model. One minus the predicted value for this variable is multiplied by the ratio of state aid to income and by the local tax share.

[18] We suspect the rarity of open-ended matching grants reflects the fact that the cost of such a program is not known—at least not without a model of the demand for local public services. State elected officials are uncomfortable with this cost uncertainty.

[19] One additional complexity is that the flypaper effects in the cost model are much larger than the flypaper effects in the demand model. The equations in the text assume these effects are the same, but our simulations allow them to be different.

[20] In case of the flypaper effect in the efficiency equation, we cannot even reject (at the 5 percent level) the hypothesis that the flypaper effect equals zero, a value implying that aid has no impact on efficiency.

[21] Because this offset is so large, lowering the price elasticity on the tax share (and hence the matching grant) in the demand equation lowers the direct effect below the indirect effect. In this case, a new matching grant would result in lower student performance.

[22] Because Yonkers is predominantly residential whereas New York City is a commercial center, Yonkers has the highest tax share of any category in Table 5 whereas New York City has the lowest.

[23] The effect was not considered by Barnett (1993).