

On the Relative Efficiency of New Jersey Public School Districts

Research Note 2016-#2

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8/3/2016

Contrary to current political rhetoric, New Jersey's least efficient producers of student achievement gains are not the state's large former Abbott districts – largely poor urban districts that benefited most in terms of state aid increases resulting from decades of litigation over school funding equity and adequacy. While some Abbott districts such as Asbury Park and Hoboken rate poorly on estimates of relative efficiency, other relatively inefficient local public school districts include some of the state's most affluent suburban districts and small, segregated shore towns.

Comparing the Relative Efficiency of New Jersey Public School Districts Executive Summary

Contrary to current political rhetoric, New Jersey’s least efficient producers of student achievement gains are not the state’s large former *Abbott* districts – largely poor urban districts that benefited most in terms of state aid increases resulting from decades of litigation over school funding equity and adequacy. While some Abbott districts such as Asbury Park and Hoboken rate poorly on estimates of relative efficiency, other relatively inefficient local public school districts include some of the state’s most affluent suburban districts and small, segregated shore towns. And yet these districts will be, in effect, rewarded under Governor Chris Christie’s “Fairness Formula,”¹ even as equally inefficient but property-poor districts will lose state aid.

Findings herein are consistent with previous findings in cost-efficiency literature and analyses specific to New Jersey:

- There exists some margin of additional inefficiency associated with Abbott status relative to non-Abbott districts in the same district factor group, but the margin of additional inefficiency in the poorest DFG is relatively small.
- The state’s most affluent suburban districts – those with the greatest local fiscal capacity and currently lower overall tax effort – tend to have equal degrees of inefficiency as compared to less-affluent Abbott and non-Abbott districts.
- Districts in factor group I (the second highest category of socio-economic status) have the largest ratio of students enrolled in inefficient relative to efficient districts.

Coupling these findings with those of similar studies in New Jersey and elsewhere, it makes little sense from an “efficiency” standpoint alone to re-allocate resources from high-need, low-income, urban districts to affluent suburban districts for the primary purpose of tax relief. This policy proposal is based on the false assumption that the poor urban districts are substantively less efficient than affluent suburban districts to begin with, and ignores that providing such increases in aid to affluent suburban districts tends to stimulate even greater inefficiency.

Put bluntly, the Governor’s proposal not only fails on a) tax equity and b) student funding equity, as previously explained by Weber and Srikanth, but the “Fairness Formula” proposal also fails on the more conservative economic argument of “efficient” allocation of taxpayer dollars.

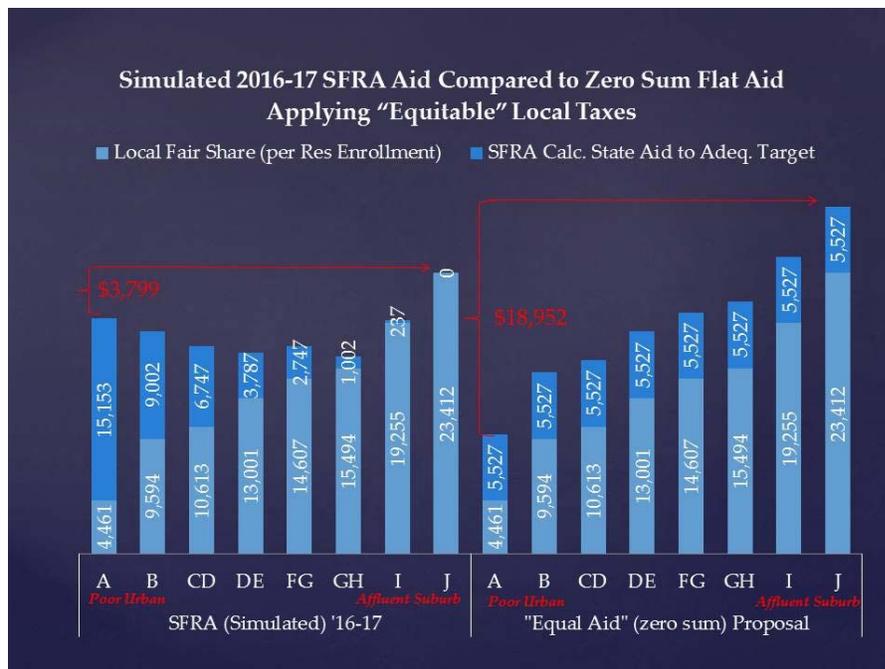
¹ <http://www.nj.gov/governor/taxrelief/pages/formula.shtml>

Introduction

In a recent policy brief Mark Weber and Ajay Srikanth explain that New Jersey Governor Chris Christie has proposed what he refers to as his “Fairness Formula” for school funding. This plan would re-allocate state aid currently targeted to low-wealth, high-need communities as flat per pupil allocations with the primary goal of providing property tax relief to more affluent New Jersey communities.² The governor has asserted that this shift in resources would be both more “equitable” by treating all children the same in terms of their state aid allocation and more “efficient” because the vast sums of state aid allocated to poor, urban districts have yielded little or no benefit. The implication of the formula is that re-allocating that aid to more affluent districts, to be used for both tax relief and perhaps additional expenditure, would more “efficient.”

Figure 1 provides an illustration of the equity effects of the “Fair Funding” proposal. On the left are simulated foundation aid allocations per pupil and local revenue raised per pupil, based on full implementation of the parameters of the currently legislated state school finance formula. Districts are organized by “District Factor Groups” which roughly characterize the socio-economic status of families residing in those districts. Districts designated as DFG A tend to be poor, largely urban districts while DFG’s I & J tend to be more affluent suburban districts.³

Figure 1



² <https://njedpolicy.wordpress.com/2016/06/30/how-fair-is-the-fairness-formula-for-new-jersey-school-children-taxpayers/>

³ <http://www.state.nj.us/education/finance/rda/dfg.shtml>

Under current law, state aid is allocated to districts with respect to both a) difference in the local fiscal capacity (income and property values) which determine the ability to raise local revenue, and b) differences in the needs of students served. As such, districts in group A receive more aid, both to compensate for their low wealth and income and to compensate for the increased educational needs of their student populations. Even then, the state aid allotted through the formula falls short of totals that would be raised in affluent suburbs at similar local tax effort. At constant local tax effort (a formula assumption), there remains nearly a \$3,800 per pupil gap in revenues between the most and least affluent districts. The right hand side of the figure shows the redistribution of the same total sum of aid in flat amounts across districts, still holding local tax effort constant. When aid is distributed in this way, the gap between rich and poor increases to nearly \$19,000 per pupil, though certainly some of the aid re-allocated to more affluent districts would be used to decrease property taxes.

Weber and Srikanth have already challenged some of the key assumptions of the governor's proposal, showing, for example, that effective property tax rates (school taxes as a share of aggregate property value) and district tax effort (school taxes paid as a share of aggregate income) actually tend to be lower in the affluent suburban districts that would be the primary beneficiaries of the school funding proposal. A recent feature at NJ.com similarly revealed that towns such as Union City, Irvington, Elizabeth, East Orange and Atlantic City were all among the state's top 15 cities in terms of property taxes paid as a share of household income.⁴

Weber and Srikanth also point out that a vast body of existing research supports the benefits of targeted state aid to districts serving high-need student populations,⁵ while a separate body of empirical literature validates that, in fact, targeted aid for tax relief to affluent communities actually induces inefficiency.⁶ Both sets of findings directly contradict the political rhetoric behind the "Fair Funding" formula. Put simply, aid to schools of children from low-income families provides short and long term benefits, while aid to affluent suburban districts often induces inefficiency. As such, while the Governor's proposal plainly and obviously fails to pass muster from an equity standpoint, it also fails to pass muster from an efficiency standpoint, as least with respect to existing literature.

This policy brief tackles directly the relative efficiency question – that is, which local public school districts in New Jersey at current spending levels tend to be more or less efficient in their production of tested student outcomes? Put bluntly, are the larger sums of state aid

⁴ http://www.nj.com/politics/index.ssf/2016/07/nj_towns_where_property_taxes_hurt_the_most.html#15

⁵ Baker, B. D. (2016). Does Money Matter in Education?. *Albert Shanker Institute*.
http://www.shankerinstitute.org/sites/shanker/files/moneymatters_edition2.pdf

⁶ See for example:

Eom, T. H., & Rubenstein, R. (2006). Do State-Funded Property Tax Exemptions Increase Local Government Inefficiency? An Analysis of New York State's STAR Program. *Public Budgeting & Finance*, 26(1), 66-87.
& Rockoff, J. E. (2010). Local response to fiscal incentives in heterogeneous communities. *Journal of Urban Economics*, 68(2), 138-147.

allocated to these districts being squandered, with little to show for it in terms of those outcomes deemed most important to state (and federal) policymakers? By contrast, are the state's most affluent suburban districts, which would be the primary beneficiaries of the Fair Funding proposal, models of efficient production of student outcomes? As noted above, existing literature supports a different hypothesis – one which we test herein.

An important note: this analysis omits charter schools. We do so for several reasons:

- The spending measure we use below does not account for the differences in spending responsibilities between charter and public district schools. An analysis that does not account for these differences is likely to inappropriately bias the efficiency estimates of charter schools upward.⁷
- It is practically impossible to determine which DFG to assign to any particular charter school when the socio-economic status of a charter may differ significantly from its hosting district.⁸
- While unobserved variables may bias estimates in any regression analysis, they are a particular concern when including charter schools, whose students endogenously “opt in” to their schools.⁹

The inefficiencies introduced by charter schools are a serious policy concern¹⁰; we set those concerns aside, however, to sharpen the focus of our analysis on differences in spending efficiencies between public district schools.

Understanding Efficiency in Education

Efficiency analysis can be viewed from either of two perspectives: production efficiency or cost efficiency. Production efficiency (also known as “technical efficiency of production”) measures the outcomes of organizational units such as schools or districts given their inputs and given the circumstances under which production occurs. That is, *which schools or districts get the most bang for the buck?* Cost efficiency is essentially the flip side of production efficiency. In cost efficiency analyses, the goal is to determine the minimum “cost” at which a given level of

⁷ For a discussion of the difficulties in comparing charter school spending patterns to those of district public schools, see: <http://nepc.colorado.edu/thinktank/review-charter-funding-inequity>

⁸ For one example of a New Jersey charter sector that differs significantly in SES from its host district, see: Makris, M. *Public housing and school choice in a gentrified city: Youth experiences of uneven opportunity*. Springer, 2015.

⁹ For a discussion of the problems of omitted variable bias in charter school evaluations, see:

<http://nepc.colorado.edu/thinktank/review-charter-expansion>

¹⁰ Arsen, D. D., & Ni, Y. (2012). Is administration leaner in charter schools? Resource allocation in charter and traditional public schools. *Education Policy Analysis Archives*, 20, 31.

Bifulco, R., & Reback, R. (2014). Fiscal Impacts of Charter Schools: Lessons from New York. *Education Finance & Policy*, 9(1), 86-107.

outcomes can be produced under given circumstances. That is, *what's the minimum amount of bucks we need to spend to get the bang we desire?*

In either case, three moving parts are involved. First, there are measured outcomes, such as student assessment outcomes or graduation rates. Second, there are existing expenditures by those organizational units. Third, there are varying conditions, such as differences in student population characteristics, the sizes and locations of schools or districts, differences in competitive wages for teachers, health care costs, heating and cooling costs, transportation costs, and so on.

It is important to understand that all efficiency analyses, whether cost efficiency or production efficiency, are relative. Efficiency analysis is about evaluating how some organizational units achieve better or worse outcomes than others (given comparable spending), or how and why the “cost” of achieving specific outcomes, using certain approaches and under certain circumstances, is more or less in some cases than others. Comparisons can be made to the efficiency of average districts or schools, or to those that appear to maximize output at given expense or minimize the cost of a given output. Efficiency analysis in education is useful because there are significant variations in key aspects of schools: what they spend, who they serve and under what conditions, and what they accomplish.

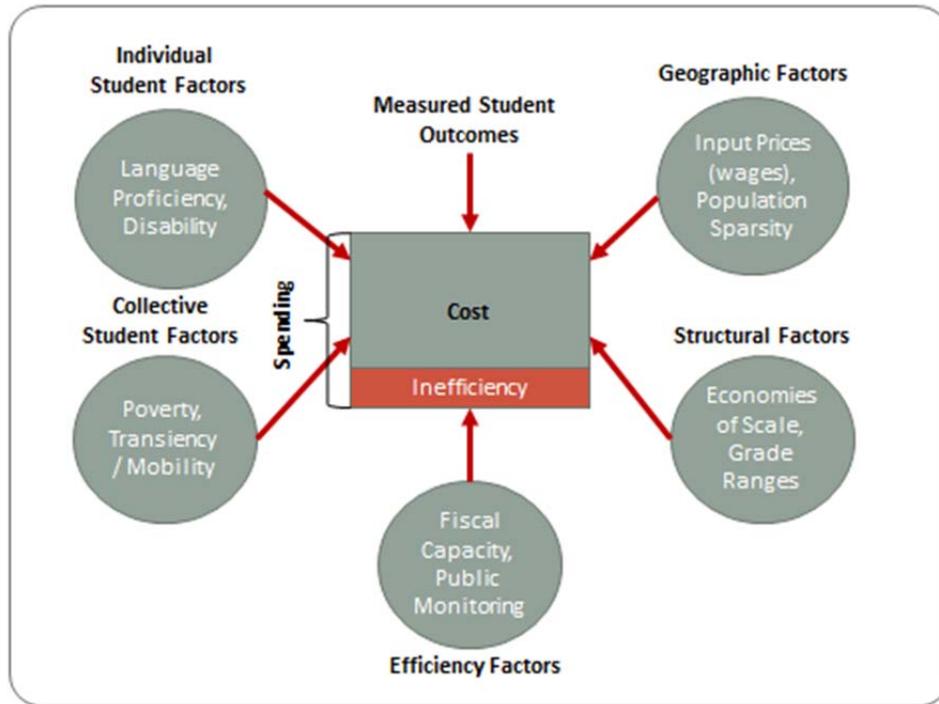
Efficiency analyses involve estimating statistical models to large numbers of schools or districts, typically over multiple years. While debate persists on the best statistical approaches for estimating cost efficiency or technical efficiency of production, the common goal across the available approaches is to determine which organizational units are more and less efficient producers of educational outcomes. More precisely: the goal of efficiency analysis is to determine which units achieve specific educational outcomes at a lower cost.

The Education Cost Model

Our analyses herein apply cost-efficiency analysis; that is, the dependent measure in our analysis is how much each local public school district in New Jersey spends to achieve their current student outcomes. A thorough cost model, as depicted in Figure 2, considers spending as a function of a) measured outcomes, b) student population characteristics, c) characteristics of the educational setting (economies of scale, population sparsity, etc.), d) regional variation in the prices of inputs (such as teacher wages), e) factors affecting spending that are unassociated with outcomes (“inefficiency” per se), and f) interactions among all of the above.

Figure 2

Components of the Education Cost Function



Here, our interest lies in simply identifying the extent of the variation in inefficiency across New Jersey districts without necessarily considering those factors that predict that margin of inefficiency (the bubble at the bottom of the figure). Follow up analyses might explore such questions. But caution is warranted in interpreting the “inefficiency” margin.

Inefficient “spending” in a cost function is that portion of spending variation across schools or districts that is not associated with variation in measured student outcomes, after controlling for other factors. The appearance of inefficiency might simply reflect the fact that there have been investments made that, while improving the quality of educational offerings, may not have a measurable impact on the limited outcomes under investigation, such as test scores in English language arts or math. “Inefficient” spending might, for example, have been used to expand the school’s orchestra or jazz program, which may be desirable to local constituents. These programs and services may affect other important student outcomes including persistence, completion, and college access; they may even indirectly affect the measured outcomes. Yet they would likely be deemed “inefficient” in a cost analysis that only factored in test results.

Factors that contribute to this type of measured “inefficiency” are also increasingly well-understood, and include two general categories – *fiscal capacity* factors and *public monitoring*

factors (Borge, Falch & Tovmo, 2008)¹¹. Fiscal capacity addresses the idea that local public school districts with greater ability to raise and spend more funds are more likely to do so. These districts may spend more in ways that do not directly affect measured student outcomes. That is not to suggest that this additional spending is necessarily frivolous, especially where outcome measurement is limited to basic reading and math achievement. A cost efficiency analysis, however, may find that a district with the capacity to spend more on personnel, programs, and capital that do not directly affect tested outcomes is “inefficient” when assessed solely by reading or math scores. Public monitoring factors often include such measures as the share of school funding coming from state or federal sources, where higher shares of intergovernmental aid are often related to reduced local public involvement (and monitoring). Empirical analyses similar to those herein have also found that state constraints regarding the use of specific revenue sources (categorical aid programs) may also induce inefficiency.¹²

Applying Cost Efficiency Modeling to New Jersey

In this analysis we adopt a simple cost model, applying two alternatives to New Jersey school and district data from 2012 to 2014. As our district expenditure measure we use the New Jersey Department of Education’s Comparative Spending Guide Indicator 1 – Budgetary per Pupil Cost from the Department’s Taxpayers’ Guide to Education Spending.¹³ NJDOE describes BPP Cost: “Generally, the BPP measures the annual costs incurred for students educated within district schools, using local taxes and state aid. These costs are considered to be more comparable among districts, and may be useful for budget considerations.”

As our student outcome measure, we use an index of the combined Median Student Growth Percentiles (school level) for all schools (for which SGPs are available) for 2012, 2013 and 2014.¹⁴ NJDOE description states: “SGP is a measure of how much a student improves his or her state test performance from one year to the next compared to students across the state with a similar score history.”

Our model, then, is framed in terms of:

- How much is being spent (BPP Cost) to achieve specific rates of student achievement growth (SGP) across New Jersey schools nested within districts?

As illustrated in Figure 2 above, modeling this input-outcome relationship requires consideration of various measures which affect the cost of achieving those outcomes. We apply two different specifications, combining school and district level measures of variations in student needs. We

¹¹ Borge, L. E., Falch, T., & Tovmo, P. (2008). Public sector efficiency: the roles of political and budgetary institutions, fiscal capacity, and democratic participation. *Public Choice*, 136(3-4), 475-495.

¹² Duncombe, W., & Yinger, J. (2011). Making do: State constraints and local responses in California’s education finance system. *International Tax and Public Finance*, 18(3), 337-368.

¹³ <http://www.state.nj.us/education/guide/>

¹⁴ <http://www.state.nj.us/education/AchieveNJ/teacher/percentile.shtml>

test school-level measures of a) the percentage of children with limited English language proficiency, b) three year average percent of children with disabilities, and c) percent of children qualified for free lunch (<130% income threshold for poverty). We test district level measures of a) U.S. Census poverty rate for residents within district geographic boundaries, and b) the district-wide share of children with disabilities whose disabilities are non-severe (mild specific learning disability, speech language impairment, or other health impairment).

We also include Taylor’s (2016) Education Comparable Wage Index¹⁵ to adjust for variations in labor costs across the state, and we include measures of districtwide enrollment and grade ranges served to account for structural variations in costs and for economies of scale. Notably, to any extent we find that very small and/or non-unified (k12) districts face higher per pupil costs, these costs may be perceived as inefficiency if they could be eliminated through consolidation.

We use an estimation technique referred to as Stochastic Frontier Modeling to generate our cost efficiency estimates. While it sounds complex, it actually differs little from traditional multiple linear regression analysis. We include a more comprehensive discussion of this technique in Appendix A. For now: a typical regression model fits a trendline through the middle of a distribution of points, so that some fall above and others below the line. If we are modeling spending and outcomes, those above the line would be districts that spent more than average to achieve the given outcome and those below the line would be the ones that spent less than average to achieve given outcomes. A frontier model, rather than fitting a line through the middle of the points, fits the line to the outer edge, along the “frontier” of the “most efficient” districts, and then bases efficiency estimates on distances from that frontier (with consideration for the fact that some of that distance may be random, or stochastic, error).

Findings

Table 1 provides the estimates of our two cost models, which produce logical results with respect to a) the outcome measure (growth percentiles) and b) the various cost factors. To summarize, model estimates reveal:

- Greater test score growth (school median SGP) comes at a statistically significant higher cost.
- As ELL concentrations increase, the costs of achieving common test score growth increase.
- As low income shares or poverty rates increase, the costs of achieving common test score growth increase.
- As school and/or district disability shares increase, the costs of achieving common test score growth increases;

¹⁵ http://bush.tamu.edu/research/faculty/Taylor_CWI/

- However, these increases are moderated by the share of children with disabilities whose disabilities are not severe.
- Districts operating in labor markets with higher labor prices have higher costs of achieving common test score growth.

Nearly every factor included in our model correlates with the outcome with a very high degree of statistical significance ($p < 0.01$).

Table 1. Model Estimates

| | Frontier Model 1 | | Frontier Model 2 | |
|--|------------------|--------------|------------------|--------------|
| | coef | se | coef | se |
| School SGP (ln) (school) | 0.030*** | 0.012 | 0.036*** | 0.012 |
| Student Population | | | | |
| % ELL (school) | 0.223*** | 0.034 | 0.081** | 0.038 |
| 3yr Mean % Special Ed (school) | 0.530*** | 0.043 | | |
| % Free Lunch (school) | 0.121*** | 0.012 | | |
| Special Education Classification Rate (district) | | | 0.008*** | 0.001 |
| % Special Ed that are Low Severity [1] (district) | -0.195*** | 0.033 | -0.156*** | 0.035 |
| Small Area Income & Poverty Estimates - % Poverty (district) | | | 0.420*** | 0.036 |
| District Scale | | | | |
| Total Enrollment (ln) | -0.433*** | 0.024 | -0.327*** | 0.025 |
| Total Enrollment (ln) Squared | 0.026*** | 0.001 | 0.019*** | 0.001 |
| Education Comparable Wage Index [Taylor] | 0.104*** | 0.020 | 0.238*** | 0.027 |
| Year of Data (2012 = Base Year) | | | | |
| Year = 2013 | 0.033*** | 0.005 | 0.033*** | 0.005 |
| Year = 2014 | 0.048*** | 0.005 | 0.031*** | 0.005 |
| District Grade/Size/Structure Group (A. K-6 = Base Group) | | | | |
| B. K-8 / 0-400 | 0.001 | 0.015 | 0.014 | 0.015 |
| C. K-8 / 401-750 | 0.036*** | 0.013 | 0.031** | 0.014 |
| D. K-8 / 751 + | 0.091*** | 0.013 | 0.075*** | 0.013 |
| E. K-12 / 0-1800 | 0.073*** | 0.015 | 0.050*** | 0.015 |
| F. K-12 / 1801 - 3500 | 0.104*** | 0.015 | 0.074*** | 0.015 |
| G. K-12 / 3501 + | 0.130*** | 0.016 | 0.126*** | 0.016 |
| H. 7-12 / 9-12 | 0.134*** | 0.024 | 0.147*** | 0.024 |
| Constant | 10.842*** | 0.115 | 10.143*** | 0.214 |
| /lnsig2v | -4.282*** | 0.051 | -4.251*** | 0.464 |
| /lnsig2u | -4.289*** | 0.141 | -5.980 | 7.175 |
| Number of observations (Schools x 3yrs) | 4,919 | | 4,211 | |

note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[1] where lower severity includes specific learning disability, speech language and other health impairment

Given the rational estimates of our cost models, the next step is to evaluate those deviations from the cost frontier, or the technical cost efficiency of New Jersey school districts. TE (Technical Efficiency) cost ratios have a base value of 1.0; districts achieving this ratio fall on the cost frontier, or, with respect to the distribution, are perfectly efficient. Margins above 1.0 indicate the relative degrees of “inefficiency.” Remember that “inefficiency” herein simply represents additional dollars spent which do not statistically translate to additional student growth in reading and math as picked up by SGPs. Those dollars might have been spent on an

exceptional cultural experience or a state champion lacrosse team. Whether this constitutes “waste” in the eyes of state and federal policymakers is a question that is not addressed by our models.

Table 2 summarizes the average TE ratios (weighted by student enrollment) by district factor grouping and Abbott status (those districts which had received more substantial increases in state aid as a result of decades of litigation). Others have found, applying similar modeling techniques, that aid increases to Abbott districts led to some increased inefficiency in those districts relative to otherwise similar districts.¹⁶ Again, higher TE ratios indicate greater inefficiency. In our model 1 (school-level free lunch and special education percentages) both Abbott and Non-Abbott poor urban districts (DFG A) have similar degrees of inefficiency, and those degrees of inefficiency are nearly the same in the state’s most affluent districts (around 1.11). Abbott districts in DFG B and DFG CD are relatively inefficient compared to their non-Abbott counterparts, in either model. But again, they are not too far out of line with inefficiency in the state’s most affluent districts. Hoboken itself does stand out here as relatively inefficient, but we will see later where Hoboken fits among individual districts. The most cost efficient districts, at least by the models estimated here and on average, are those non-Abbotts in DFGs DC and DE. Notably, however, there exists substantial variation within each DFG and among the Abbott districts.

Table 2. How Do Inefficiencies Vary by District Factor Group¹⁷ and Abbott Status?

| Abbott Status | DFG | Model 1 | | Model 2 |
|------------------|-----|---------|--|---------|
| Non-Abbott | A | 1.115 | | 1.041 |
| Abbott | A | 1.119 | | 1.044 |
| Non-Abbott | B | 1.083 | | 1.038 |
| Abbott | B | 1.119 | | 1.046 |
| Non-Abbott | CD | 1.071 | | 1.037 |
| Abbott | CD | 1.116 | | 1.043 |
| Non-Abbott | DE | 1.076 | | 1.037 |
| Non-Abbott | FG | 1.090 | | 1.039 |
| Abbott (Hoboken) | FG | 1.267 | | 1.077 |
| Non-Abbott | GH | 1.100 | | 1.042 |
| Non-Abbott | I | 1.107 | | 1.043 |
| Non-Abbott | J | 1.111 | | 1.044 |

¹⁶ Eom, T. H., & Lee, S. H. (2014). A longitudinal analysis of impacts of court-mandated education finance reform on school district efficiency. *Journal of Public Budgeting, Accounting & Financial Management*, 26(1), 1.

Baker, B. D., & Green III, P. C. (2009). Equal Educational Opportunity and the Distribution of State Aid to Schools: Can or Should School Racial Composition Be a Factor?. *Journal of Education Finance*, 289-323.

¹⁷ See: <http://www.state.nj.us/education/finance/rda/dfg.shtml>

Table 3 summarizes the Top 15 “Most Efficient” districts according to each model. The two models yield a relatively consistent list and one that includes some of the state’s poorest districts (DFG A) and a mix of districts from B through FG. Many of these are relatively small districts both in terms of the geographic space served and in terms of their total student enrollments.

Table 3. Top 15 by Model

| | District Name | DFG 2000 | Efficiency Ratio |
|---------|---|----------|------------------|
| Model 1 | | | |
| | Fairview Public Schools | A | 1.026 |
| | GUTTENBERG SCHOOL DISTRICT | B | 1.031 |
| | East Newark | A | 1.032 |
| | JAMESBURG PUBLIC SCHOOLS | DE | 1.033 |
| | Elmwood Park Board of Education | CD | 1.034 |
| | South River Public Schools | CD | 1.037 |
| | Woodlynne Boro Public School | B | 1.038 |
| | MAYWOOD BOARD OF EDUCATION | FG | 1.040 |
| | Garwood Boro | DE | 1.041 |
| | Little Ferry Public Schools | CD | 1.042 |
| | Elsinboro Township School District | DE | 1.042 |
| | Kingsway Regional School District | FG | 1.043 |
| | Hammonton School District | B | 1.044 |
| | Clifton Public Schools | CD | 1.044 |
| | Freehold Borough Public Schools | B | 1.045 |
| Model 2 | | | |
| | Fairview Public Schools | A | 1.019 |
| | GUTTENBERG SCHOOL DISTRICT | B | 1.022 |
| | East Newark | A | 1.022 |
| | Elmwood Park Board of Education | CD | 1.023 |
| | Woodlynne Boro Public School | B | 1.024 |
| | JAMESBURG PUBLIC SCHOOLS | DE | 1.024 |
| | MAYWOOD BOARD OF EDUCATION | FG | 1.025 |
| | South River Public Schools | CD | 1.025 |
| | Garwood Boro | DE | 1.026 |
| | Little Ferry Public Schools | CD | 1.026 |
| | Prospect Park | B | 1.026 |
| | SOUTH HARRISON TOWNSHIP SCHOOL DISTRICT | FG | 1.027 |
| | Freehold Borough Public Schools | B | 1.027 |
| | Hammonton School District | B | 1.027 |
| | Kingsway Regional School District | FG | 1.027 |

Table 4 summarizes the bottom 15 districts, or those with the greatest “inefficiency” as measured by our models. Once again, the lists are relatively consistent, but some districts are excluded in our Model 2 due to insufficient data. Indeed, Asbury Park, a commonly cited model of inefficiency in New Jersey political rhetoric is on this list, but notably is second to Avalon – a district which does not receive the same media attention for inefficiency. Nor do Alpine or Mountain Lakes, which fall next in line behind Asbury Park and ahead of Hoboken. In fact, in Model 2, Mountain Lakes takes the top spot with the highest inefficiency ratio, with Hoboken in second. Franklin Lakes, Saddle River and Spring Lake, LBI CSD among others, make both lists.

Table 4. Bottom 15 by Model

| | District Name | DFG 2000 | Efficiency Ratio |
|---------|--|----------|------------------|
| Model 1 | | | |
| | Keansburg School District | A | 1.215 |
| | Princeton Public Schools | I | 1.222 |
| | Pemberton Township Schools | B | 1.227 |
| | FRANKLIN LAKES PUBLIC SCHOOLS | I | 1.235 |
| | Spring Lake Borough | I | 1.237 |
| | NORTH WILDWOOD SCHOOL DISTRICT | A | 1.247 |
| | Harding Township | J | 1.251 |
| | Margate City School District | DE | 1.255 |
| | SADDLE RIVER SCHOOL DISTRICT | J | 1.274 |
| | Hoboken Public Schools | FG | 1.283 |
| | Long Beach Island Consolidated School District | FG | 1.287 |
| | Mountain Lakes Board of Education | J | 1.291 |
| | Alpine Elementary School District | I | 1.298 |
| | Asbury Park School District | A | 1.407 |
| | AVALON ELEMENTARY SCHOOL | FG | 1.620 |
| Model 2 | | | |
| | North Hanover Township School District | CD | 1.062 |
| | Spring Lake Borough | I | 1.063 |
| | NORTH WILDWOOD SCHOOL DISTRICT | A | 1.064 |
| | OCEAN CITY SCHOOL DISTRICT | DE | 1.065 |
| | FRANKLIN LAKES PUBLIC SCHOOLS | I | 1.065 |
| | Princeton Public Schools | I | 1.066 |
| | Keansburg School District | A | 1.066 |
| | Pemberton Township Schools | B | 1.067 |
| | SADDLE RIVER SCHOOL DISTRICT | J | 1.068 |
| | Harding Township | J | 1.069 |
| | Margate City School District | DE | 1.073 |
| | Lebanon Borough School District | I | 1.075 |
| | Long Beach Island Consolidated School District | FG | 1.079 |
| | Hoboken Public Schools | FG | 1.079 |
| | Mountain Lakes Board of Education | J | 1.080 |

Not found on the list of least efficient districts are large, urban Abbott districts such as Newark, Jersey City, or Camden. Interestingly, despite years of media accolades, neither Elizabeth nor Union City were found on the most efficient districts list. Table 5 lists those districts from near

the middle of the pack which have efficiency ratios similar to Newark Public Schools. Again, the list includes an eclectic mix across district factor groups from A to J. Both lists include a handful of Abbott districts such as Phillipsburg, Trenton and Elizabeth.

Table 5. Districts with Inefficiency Similar to Newark

| | District Name | DFG 2000 | Efficiency Ratio |
|----------------|---|----------|------------------|
| Model 1 | | | |
| | Elizabeth Public Schools | A | 1.108 |
| | Phillipsburg School District | B | 1.108 |
| | Upper Township | FG | 1.108 |
| | Trenton Public Schools | A | 1.108 |
| | UPPER SADDLE RIVER SCHOOL DISTRICT | J | 1.109 |
| | Summit Public Schools | I | 1.109 |
| | HOWELL TOWNSHIP PUBLIC SCHOOLS | FG | 1.109 |
| | THE NEWARK PUBLIC SCHOOLS | A | 1.109 |
| | Washington Township School District | GH | 1.109 |
| | PINE HILL BOROUGH BOARD OF EDUCATION | B | 1.109 |
| | CINNAMINSON TOWNSHIP PUBLIC SCHOOLS | FG | 1.109 |
| | Hackettstown Public Schools | DE | 1.110 |
| | BERKELEY HEIGHTS PUBLIC SCHOOLS | I | 1.110 |
| | Oceanport School District | GH | 1.110 |
| | West Long Branch Board of Education | FG | 1.110 |
| | ROSELLE PUBLIC SCHOOLS | B | 1.110 |
| Model 2 | | | |
| | Roselle Park Board of Education | DE | 1.043 |
| | Lawnside School District | B | 1.043 |
| | ORANGE BOARD OF EDUCATION | A | 1.043 |
| | Sussex-Wantage Regional School District | DE | 1.043 |
| | West Long Branch Board of Education | FG | 1.043 |
| | Jefferson Township | GH | 1.043 |
| | Trenton Public Schools | A | 1.043 |
| | Long Hill Township School District | I | 1.043 |
| | ROOSEVELT PUBLIC SCHOOL DISTRICT | GH | 1.043 |
| | Linden City Board of Education | B | 1.043 |
| | Roxbury Township Public Schools | GH | 1.043 |
| | Downe Township School District | A | 1.043 |
| | Watchung Borough Public School District | I | 1.043 |
| | THE NEWARK PUBLIC SCHOOLS | A | 1.043 |
| | NEPTUNE TOWNSHIP SCHOOL DISTRICT | CD | 1.043 |
| | Woodcliff Lake School District | J | 1.043 |
| | Hazlet Township Public Schools | DE | 1.043 |
| | Fair Lawn Public Schools | GH | 1.043 |
| | Montclair Public Schools | I | 1.043 |
| | WAYNE TOWNSHIP PUBLIC SCHOOLS | GH | 1.043 |

Finally, Table 6 shows the distribution of students across schools by quintiles of efficiency ratios – the highest quintile being the most inefficient and the lowest quintile being the least inefficient (or most efficient). Cells are shaded from red, for large numbers of children, to green for smaller numbers of children. In the far right column, we calculate the ratio, for each district factor group, of the numbers of children in relatively inefficient district schools to the numbers of children in relatively efficient schools (highest two groups over lowest two groups).

Note that the total number of children represented here is much less than the statewide total of children, because it represents only a) those enrolled in schools with reported growth percentiles from 2012 to 2014 and b) schools and districts for which all other measures were available for all years.

In DFG A, the largest number of children is in districts of average efficiency. That said, there are still nearly twice as many children in less efficient districts as there are in more efficient districts. However, this ratio is much worse for DFG I, where 2.34 times as many children attend less efficient districts as attend more efficient districts. By contrast, and consistent with the findings above, much larger shares of children attend relatively efficient districts in DFG CD and DE.

Table 6. Distribution of Enrolled Children (school level) by Inefficiency Group (2014)

| DFG | Relative Degree of Inefficiency (Model 1) | | | | | Ratio of Inefficient to Efficient |
|-----|---|--------|----------|--------|-----------|-----------------------------------|
| | 1-Lowest | 2-Low | 3-Middle | 4-High | 5-Highest | |
| A | 7,594 | 28,915 | 49,897 | 34,371 | 38,182 | 1.99 |
| B | 31,700 | 12,139 | 12,042 | 23,636 | 16,343 | 0.91 |
| CD | 41,329 | 16,129 | 10,935 | 8,047 | 3,649 | 0.20 |
| DE | 49,937 | 24,215 | 14,946 | 9,465 | 7,684 | 0.23 |
| FG | 23,078 | 30,688 | 10,843 | 17,291 | 17,185 | 0.64 |
| GH | 12,541 | 29,816 | 17,098 | 30,051 | 21,035 | 1.21 |
| I | 10,162 | 19,206 | 51,935 | 33,835 | 34,885 | 2.34 |
| J | - | 7,517 | 12,972 | 5,054 | 5,869 | 1.45 |

Conclusions & Policy Implications

Findings herein are consistent with previous findings in cost-efficiency literature and New Jersey specific analyses.

- There exists some margin of additional inefficiency associated with Abbott status relative to non-Abbott districts in the same district factor group, but the margin of additional inefficiency in the poorest DFG is relatively small.

- The state’s most affluent suburban districts – in other words, those with the greatest local fiscal capacity and currently lower overall tax effort – tend to have equal degrees of inefficiency as do poor Abbott and non-Abbott districts.
- Districts in factor group I, the second highest in socio-economic status, have the largest ratio of students enrolled in inefficient relative to efficient districts. Districts in factor group CD, the third lowest in SES, have the smallest ratio.

Coupling these findings with those of similar studies in New Jersey and elsewhere, it makes little sense from an “efficiency” standpoint alone to re-allocate resources from high-need, low-income, urban districts to affluent suburban districts for the primary purpose of tax relief. This policy proposal is based on the false assumption that the poor urban districts are substantively less efficient than affluent suburban districts to begin with, and ignores that providing such increases in aid to affluent suburban districts tends to stimulate even greater inefficiency.

Put bluntly, the Governor’s proposal not only fails on a) tax equity and b) student funding equity, as previously explained by Weber and Srikanth; the “Fairness Formula” also fails on the more conservative economic argument of “efficient” allocation of taxpayer dollars.

Appendix A: Technical Notes

A handful of technical debates persist over whether and how we might best determine which are the most and which are the least effective schools or school districts in any given system:

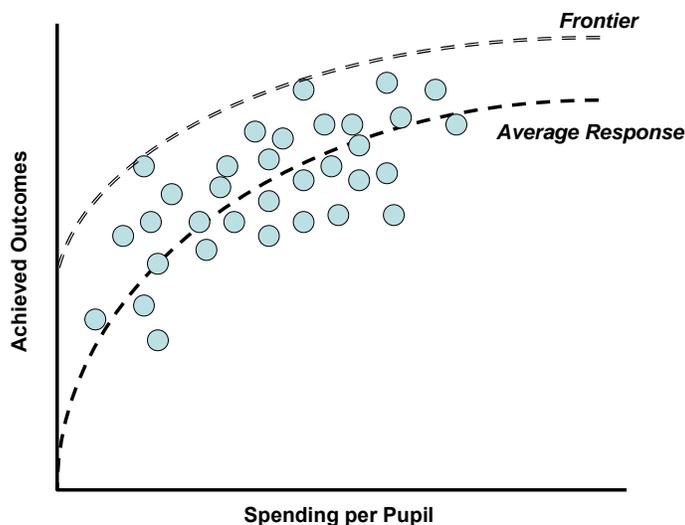
- a) Whether to evaluate relative efficiency of schools or districts with respect to the *frontier* (frontier cost and production functions) or the *average* (average response function);
- b) Whether to set *a priori* assumptions about the nature, or shape (functional form) of the input-outcome relationship, or whether to fit the efficiency model or frontier more flexibly;
- c) Whether to assume that the entire distance from each school or district's actual position to the frontier or average response is inefficiency, or whether some portion of that distance is random error.

The most common definition of the term “cost” in this context is that the “cost” of producing a given set of outcomes is the “minimum cost” of producing those outcomes in any given context. This might be either a theoretical minimum cost, attained by no school districts in reality; it might be the actual minimum cost or expenditure associated with a given level of outcomes in a district with specific characteristics. It is implausible for us, or anyone, to identify the theoretical minimum that might be attainable if resources were organized and practices carried out in their most efficient manner. But in any cost or production function, one can find those school districts that run along the edge of the distribution – either producing the highest outcomes for given conditions and spending (production frontier), or achieving the lowest spending at specific outcomes and conditions (cost frontier). If “cost” is the theoretical or measured minimum expenditure associated with a given level of outcomes, then “inefficiency” is any deviation from the expected costs of achieving those outcomes, where that deviation can exist only in one direction (one cannot spend less than the minimal cost to achieve a given level of outcomes). One potential concern with models based on these districts or schools along the outer edges of the distribution is that these districts or schools may lie where they do because of substantial unmeasured differences in their characteristics, or even due to measurement error.

Alternatively, one can evaluate “relative efficiency” against the average spending associated with any given level of outcomes under specific conditions. This is the average response function approach, as characterized in Figure 3. That is, one can fit the cost or production model through middle of the field of data points rather than along the edge and evaluate whether districts spend more than average for achieving a given level of outcomes, under current conditions, or less than average. This approach is particularly reasonable if we enter into the analysis with the assumption that on average, New Jersey school districts are producing outcomes at reasonable levels of efficiency.

Figure 3

Average Response versus Frontier Estimation



The second issue raised above may also significantly affect which districts are identified as deviating the most, either from the middle or the edges of the pack, in terms of spending or outcomes. One can adopt conventional assumptions of diminishing marginal returns, and apply what is known as a Cobb-Douglas specification, where the natural logarithm of schooling inputs is associated with the natural logarithm of outcomes. Or, one can assumption the relationships to be more complex, with characteristics of schools and students interacting to affect to the costs of achieving outcomes. As noted previously, Figlio (2001) applies a *translog* functional form, which includes numerous non-linearities and interactions to characterize education production. Gronberg, Taylor, Jansen and Booker (2004)¹⁸ use a *translog* approach to estimate a cost function using Texas data. Alternatively, one can use non-parametric methods such as *Data Envelopment Analysis* to identify the cost or production frontier based on the extreme – most efficient – cases in the distribution.

A secondary advantage of Data Envelopment Analysis is that DEA models can include multiple outcome measures. However, this advantage is somewhat diminished when the various outcomes are highly correlated, in which case the outcomes might best be collapsed into a single measure suitable for use in a stochastic frontier or conventional OLS regression equation. From the outset of the current project we have focused only on state assessment outcomes in math and

¹⁸ Gronberg, T., Jansen, D., Taylor, L., Booker, K. (2004) *School Outcomes and Schools Costs: The Cost Function Approach*. (College Station, TX: Busch School of Government and Public Service, Texas A&M University). Retrieved March 1, 2006 from http://bush.tamu.edu/research/faculty_projects/txschoolfinance/papers/SchoolOutcomesAndSchoolCosts.pdf

language arts. Across schools or across districts these measures are highly correlated and, as such, they were collapsed into a single outcome measure.

Critics of educational efficiency analysis point to substantial shortcomings in the precision or accuracy in correctly identifying more and less efficient school districts regardless of method, pointing to significant problems associated with measurement error in student outcomes (Bifulco & Duncombe, 2001; Bifulco, Bretschneider, 2001).¹⁹ Ruggiero (2007), however, counters that models may be more reliable and less susceptible to such statistical noise when multiple years of data, or panel data, are used. Specifically, Ruggiero compares traditional regression models adjusted to the cost frontier (Corrected Ordinary Least Squares, COLS), *Stochastic Frontier Analysis*, and Data Envelopment Analysis using simulated data. Ruggiero notes that SFA and DEA are perhaps the most common approaches to school district cost-efficiency analysis. The advantage of SFA is that it assumes a portion of the distance from each district to the frontier to be random error. As such SFA might better handle “noisy” data.²⁰ That said, Ruggiero (2007)²¹ showed that SFA models often produce largely the same results as COLS models. In his comparison across the three approaches, Ruggiero finds that

These results suggest that the stochastic frontier model holds no real advantage over DEA. In particular, the purported advantage of the stochastic frontier, i.e. the ability to allow measurement error, can be overcome by averaging the data to smooth production. DEA maintains the advantage of being nonparametric and allowing multiple outputs. While this paper shows that **DEA and the stochastic frontier produces similar results**, more work is needed. (p. 266)

¹⁹ Robert Bifulco & William Duncombe (2000) Evaluating School Performance: Are we ready for prime time? In William Fowler (Ed) *Developments in School Finance, 1999 – 2000*. Washington, DC: National Center for Education Statistics, Office of Educational Research and Improvement. Robert Bifulco and Stewart Bretschneider (2001) Estimating School Efficiency: A comparison of methods using simulate data. *Economics of Education Review* 20.

²⁰ Others, including Bifulco and Duncombe, however, point out that this advantage only exists if the distribution of the noise in the data is correctly specified in the SFA model, a choice that must be made by the researcher, and made somewhat blindly.

²¹ Ruggiero, J. (2007) A comparison of DEA and Stochastic Frontier Model using panel data. *International Transactions in Operational Research* 14 (2007) 259-266