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Technical Questions & Current Specifications:
Using Predicted District Effectiveness Rates as a Performance Benchmark

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Contents

Purposes

The purpose of this paper is to open the methods, construction and assumptions of a new performance benchmark to examination, critique, and improvement by technical experts.

The paper begins with known technical questions about this new benchmark. In includes suggestions made by technical advisors. It then details the construction of the benchmark's measures, and reports the relevant statistics.

KSDE's new performance measure, the effectiveness rate, measures school districts' effectiveness in enrolling their students in postsecondary education for two continuous years after graduation, or in getting students certified in an industry-recognized skill.

Its companion benchmark, the predicted effectiveness rate and the focus of this paper, uses linear regression to describe districts' mean effectiveness rates after adjusting for risk factors largely beyond the districts' control. By comparing districts' actual effectiveness rates to their predicted rates, while accounting for student and environmental risk factors like cumulative poverty, the model assumes that the residuals contain some comparable measure of district performance.

With some important qualifications, KSDE's calculation of an effectiveness benchmark is a simplified application of a value-added model. In the late 1980s through the first decade of the 2000s, most notably with papers by Willms, Raudenbush, Bryk, Sanders, and McCaffrey,[1] scholars developed various accountability models that controlled for an assortment of student and environmental background characteristics.

The current benchmark model differs from these earlier value-added models in notable ways:

1. It does not use state assessments as its dependent variable;
2. It does not attempt to isolate teacher effects;
3. It does not threaten district or school personnel with punitive measures, but seeks to motivate them with demonstrably achievable measures;
4. Many of the variables it uses as controls are based on proportionate measures of student exposures to particular statuses, for example, how long students were eligible for free lunch, or how long they were classified as having a disability; and
5. It uses multiple cohorts (five of them), in its dependent variable.[2]

It also shares some problems with the previous generation of value-added models. Most notably, it has no direct or observed measures of district practices. It just assumes they

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[1] For a brief summary of these models and the scholarly debate about them, see Raudenbush, S.W. (2004), What are value-added models estimating and what does this imply for statistical practice? *Journal of Educational and Behavioral Statistics,* spring, vol. 29, 1, 121-129. The same journal volume also has articles from other scholars debating the features of value added models.

[2] Raudenbush, op. cit., recommends multiple cohorts.

are included in the residuals. It also assumes that these practices are not correlated with other school and student-level independent variables.

Technical Questions

So far, KSDE staff identified the technical questions below. We are including the responses and additions made by the first group to review the model,[3] the assessment program's Technical Advisory Committee (TAC).

1. Is the current application of a simple, ordinary least squares regression model appropriate at the district level?

   The TAC had no objections to the linear regression model applied at the district level.

2. KSDE has plans to develop effectiveness benchmarks at the school level. Applied at the school level, is the appropriate model a hierarchical model, specifically, a generalized linear mixed model that would treat the district level variables as random effects and the independent variables as fixed effects?

   The TAC recognized that the school-level model should be hierarchical, with a provision for capturing and setting aside district-level effects. It did not have an opinion about whether the model should include a district-by-school interaction term, or whether the district level effects should be treated as random effects, or the independent predictors as fixed effects. The TAC did suggest getting advice from the Regional Education Laboratory technical advisors already working with KSDE on this project.

3. At the district level, there was very little missing data, but there may be more cases of missing data at the school level. What is the best way to handle these cases of missing data?

   The TAC recognized that missing data at the school level is more likely to be a problem than at the district level. While inserting mean values might be an acceptable solution, the TAC noted that there are more sophisticated tools for imputation of missing data and that KSDE should consider them.

   KSDE's answer:

   SPSS offers a specialized tool for applying algorithms to fill missing data. It costs $847 per user with a yearly renewal fee. Is the potential improvement in accuracy worth this investment?

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[3] The Kansas Technical Advisory Committee (TAC) works with KSDE's Career, Standards, and Assessment Services to guide the State's K-12 assessment program. They reviewed the model at their October 18th, 2017 meeting.

4. Based on research measuring the developmental effects of poverty, the model uses longitudinal measures, proportions of student time in particular statuses, rather than cross-sectional snapshots of student statuses, as independent variables. Do we need to demonstrate that the longitudinal measures are more accurate or appropriate? Do you see or anticipate any problems with our current longitudinal construction of these independent variables?

   The TAC felt that the longitudinal use of student measures was generally more reliable than variables constructed from cross-sectional aggregations.

5. What problems should we anticipate from our use of this model at the district or school levels?

   The TAC raised these additional questions:

   1. *How can you be sure that your effectiveness measure is sensitive enough to describe true differences in performance between high schools? Would another outcome measure, for example, the Assessment Performance Index, identify the same set of schools or a different set of schools? How would you explain the differences, if you found them?*

      KSDE answer:

      Because the dependent variable measures postsecondary effectiveness rates, not academic performance, we expect that two models with the same independent variables, but with differing dependent variables, will produce different performance results, but with a lot of correlation, too.

      The distinctive thing about this model, no matter what the dependent variable is, is that it controls for factors beyond the schools' control, like cumulative poverty. Previous school performance measures, like Adequate Yearly Progress under the No Child Left Behind Act, did not account for these influences. They confounded the influences of poverty with measures of academic performance. Ideally, over time, we expect that the Board's initiatives, like the Individual Plans of Instruction, better vocational counseling and postsecondary referrals, better early childhood environments, and new school models, will result in higher effectiveness rates and measures that differentiate performance between high schools with actual measures of what schools are doing, not just inferred differences.

   2. *By leaving the non-significant variables in the model, is statistical noise obscuring some of the signal from the significant variables?*

      KSDE answer:

Originally, a workgroup consisting of representatives from the districts and KSDE staff identified the independent predictors. They expected that the initial nine variables they identified contributed to lower school academic performance. By using these variables in the first models predicting effectiveness rates, we are testing our assumptions about causal factors. Which ones matter most? Which least? It is important for the field and KSDE to see which factors were the most influential over effectiveness rates, and which ones were inconsequential. In a way, the advance is in the collaboration with the field in identifying and testing their theories. They need to see the results so at least initially, we need to include the variables that were insignificant.

Over time, we expect that the significant factors like cumulative poverty will stay in the model, but in the future, insignificant predictors may be dropped, and new variables, like measures of Individual Plans of Study, may be added, or tested for their influence over effectiveness rates.

3. *If a high school's students are already 'beating the odds,' that is, already performing at the highest level possible, how will you know there isn't any room for them to improve any more? Will the residuals still show some measure of performance?*

   KSDE answer:

   This is a question for all value-added models. They identify, quantify, and set aside the influence of some factors, like cumulative poverty, and assume that others, by subtraction, are in the residuals. Until we have measures that matter most in determining postsecondary attendance, the use of residuals will be subject to the suspicion that we might just be measuring natural variation, or mostly natural variation, in the residuals.

4. *Does the postsecondary National Student Clearinghouse data accurately describe postsecondary enrollments?*

   KSDE answer:

   Overall, the NSC data covers about 93 percent of students who actually continue in some postsecondary institution. There are some regional vulnerabilities where a high school might be located near one of the colleges or technical schools that doesn't yet report its enrollments to the NSC but we are working to get all of these schools to begin reporting their enrollments to NSC.

   The bigger problem isn't with the NSC data—we expect it to improve—but with the 30 percent or more of students leaving our high schools who are *entirely unaccounted for. Ideally, we need post-high school income data. Anecdotally, almost everyone knows someone who was an academically poor high school student, but later economically successful. Most also know someone who was a good student, but met with economic problems after high school. Having income data would be a very big help.*

5. *Are there incentives for manipulation of the data? The TAC noted that by including some factors over which schools and districts have some control, for example, suspension and expulsion rates, and chronic absenteeism, we may be creating incentives to manipulate the data. In a sense, by accounting for these factors as independent predictors, KSDE is forgiving them.*

   KSDE answer:

   Ultimately, postsecondary enrollment rates will not be moved upward by manipulating the reporting of suspension and expulsion rates or absences. At most, manipulation of this reporting data can shift the benchmark, the predicted line, but to do so, either large numbers of schools would have to manipulate their data or small numbers would have to report extreme values, in which case the values become suspicious as outliers.

   The bigger danger is with certificates. Industry-recognized skill certificates can increase a school or district's effectiveness rates. If a school or district awards or reports certificates that are not of real employment value for the students then the effectiveness rates can be inflated and the students harmed when they go into the job market. This is another reason that it is desirable to get income data, preferably federal Internal Revenue Service data, to validate the employment of students and the economic value of their preparation.

6. *You are trying to identify the influence high schools have over postsecondary enrollments. Why not control for academic performance in middle school?*

   KSDE answer:

   Good idea. We think. We will add the cohorts' mean combined math and reading eighth-grade state assessment scores into the model as an independent variable. This will control for previous academic performance, but will not account for the quality of middle schools' career planning, career counseling, and hands-on curriculum and experiences. We expect these will still influence high-schools' postsecondary enrollment rates.

We aren't sure we want the high schools to think of the results as reflective of their individual schools' performances and not the result of a long effort, across the students' school lives, by the elementary and middle schools that went before, and yes, the high schools, to prepare the students for success in the larger world. The Kansas Board's vision is really to cultivate the whole student across their K-12 experience and into a successful transition into employment or postsecondary preparation.

A few additional questions are included in sections where they are pertinent.

Background & Policy Goals

Why is KSDE defining K-12 performance measures for districts and schools that run two years *after* high school graduation?

The intention is to bind district and school performance goals to the long-term interests of students and employers. By incorporating developmental measures across each child's life, from Kindergarten readiness, through social-emotional skills, individual plans of study in middle and high school, and finally, to postsecondary and career goals, the State Board expects districts and schools to cultivate the life-success of each child across the students' school life. To fully prepare youth for adulthood, the State Board is signaling the need for greater coordination between families, educators at all levels, and employers.

This re-orientation is influenced by at least three sources:

1. Labor-market studies show a mismatch and lack of coordination between the skills employers need and the skills new entrants to the labor market have. Two influential national labor market studies defined the size of this labor market / education gap for all the states.[4] The studies projected that, in order to supply the skills demanded by employers in 2020, the Kansas education system needs 71 percent of young people entering the labor market to have an associate degrees or higher. Accordingly, the Kansas State Board of Education set a long-term goal of effectiveness rates between 70 to 75 percent. KSDE's new postsecondary measure, the effectiveness rate, measures the gap between this goal and reality to be about 25 points wide.

[4] Anthony P. Carnevale, Nicole Smith, and Jeff Strohl at the Georgetown Public Policy Institute's Center on Education and the Workforce published the two studies in 2013. The first paper, *Recovery: Projections of Jobs and Education Requirements Through 2020*, made detailed national job projections. The second paper has the same name but is called the *State Report*. It made state-by-state job projections. Of its new entrants to the labor market, the Kansas economy is projected to need 11 percent master's degrees, 25 percent bachelor's degrees, and 35 percent associate degrees. International labor market studies confirm that in advanced as well as developing economies there is a global oversupply of unskilled labor which is disproportionately depressing youth's economic prospects. See Dobb, R. et al, (2012), *The world at work: Jobs, pay, and skills for 3.5 billion people*, McKinsey Global Institute. Also see Dobbs, et al, (2016), *Poorer than their parents? Flat or falling incomes in advanced economies*, McKinsey Global Institute.

2. [A Kansas study](#) that analyzed the responses of 287 focus groups in communities and business groups across the state, found that employers, educators, and participating members of the public emphasized that youth need social-emotional, character, personality, and other employability skills. Respondents cited the need for these soft skills much more frequently than traditional academic skills. Participants also strongly suggested greater collaboration, planning, and coordination between the K-12, higher education and business sectors.

   This popular assertion of the importance of social-emotional skills has been re-enforced by an increasingly strong current of economic and social research demonstrating that social-emotional, character, and personality skills are strong determinants of economic and life success.[5]

3. A reaction to the design flaws of No Child Left Behind (NCLB). NCLB set rigid proficiency standards, untempered by what was demonstrably achievable. With high frequency, districts and schools serving economically disadvantaged families were identified as failing, even when they were performing much better than comparable organizations. At the same time, many districts and schools in advantaged communities exceeded the NCLB proficiency standard, but had little incentive to enhance the skills of their advantaged students beyond basic proficiency.

How well do the new effectiveness measures address these goals and influences?

The predicted effectiveness rates are based on the districts' actual effectiveness rates. As a benchmark, it does not set goals that are unrealistically high. It draws the best-fitting line through the cloud of actual effectiveness rates.

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[5] The return for employability skills, like conscientiousness, increases constantly across all skill levels. In addition to predicting higher wages, social-emotional skills are also associated with longer lives, lower divorce rates, and higher academic achievement at all levels. Another way of saying this is: no matter what your skill level, no matter what the job, social-emotional skills matter. IQ matters little for low-skilled work, but matters a lot more for complex work. Another point made by this literature is that skills and knowledge are not separate, but intertwined, and hierarchically integrated through learning, practice, and experience. See p. 18 of *[Education for Life and Work: Developing Transferable Knowledge and Skills in the 21st Century,](#)* 2015, National Academy of Sciences. For a summary of studies showing the predictive relationship of non-academic skills to academic outcomes, see Poropat, A.E. (2009), "[A meta-analysis of the five-factor model of personality and academic performance,"](#) *Psychological bulletin, 135,* 322-338. For personality skills association with other life outcomes, see Roberts, B.W. et al (2007, December), "The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes," *Perspectives in Psychological Science 2* (4), 33-345. See also Heckman and Kautz (2013), "[Fostering and measuring skills: Interventions that improve character and cognition](#)," NBER working paper, No. 191656. Using a national sample of employers from 1996, the authors found that 69 percent of the employers had rejected applicants because they lacked soft skills—like not missing work, showing up on time, or having a strong work ethic (conscientiousness). Employers rejected less than half as many applicants due to insufficient reading and writing skills.

By quantifying and accounting for these influential factors that are beyond districts' control, like cumulative poverty, the model reduces the influences that are confounded with the outcome variable, district effectiveness rates.

The model also permits us to examine the relative performance of districts serving economically advantaged communities. It can answer the question, after accounting for District A's low poverty and other relative advantages, is District A performing well relative to its peers?

Precedents & Initial Requirements

A Model Predicting Academic Performance

The independent variables used in the effectiveness predictive model were first developed under the direction of a Kansas Learning Network (KLN) workgroup. In 2016, prompted by the obligations of the federal Every Student Succeeds Act (ESSA), the workgroup developed a method for identifying the neediest Title 1 schools.[6]

Practitioners from the field identified nine factors that they believed would accurately predict low-academic performance in schools:

1. chronic absence,
2. student mobility,
3. cumulative poverty,
4. higher concentrations of Students with Disabilities,
5. higher concentrations of migrant students,
6. higher proportions of English Learners,
7. the rate of suspensions and expulsions,
8. the demographic distance in gender and ethnicity between teachers and students, and
9. the percentage of new teachers.

The dependent variable was academic performance as measured by an index constructed from State assessments. Four of the nine, cumulative poverty, percentage of English Learners, the rate of suspensions and expulsions, and chronic absences, were significant predictors of lower school-level performance. They explained 58 percent of the variance in schools' academic performance.

Cumulative poverty was an especially strong detractor of school performance. When it was removed from the independent variables, the proportion of Students with Disabilities and student mobility changed from non-significant to significant predictors.

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[6] The details of the CSI model are available online on the Research and Evaluation page at the KSDE site. See Moss, T. (2016), "A method for identifying Comprehensive Support and Improvement Schools and Holes in the Every Student Succeeds Act."

The evidence also suggested that at least two variables should be removed. The demographic distance between staff and students proved to be conceptually confused and without data to appropriately measure it. Migrant students were sparsely represented across districts and insignificant in their influence on schools' academic performance. These two variables were removed from subsequent models.

The KLN model served two purposes. It generated a formula that identified Comprehensive Support and Improvement (CSI) schools. The identified schools were urban schools with high levels of cumulative poverty and low levels of academic achievement. It also generated schools' predicted academic achievement after controlling for the independent variables in the model. Similar to the procedures KSDE uses to identify Challenge grant schools that are performing well despite higher levels of student poverty, the model compared schools' actual academic performance to their predicted academic performance.

The First Model Predicting Effectiveness Rates

In accord with the Board and KSDE's new goals, leadership asked for a model that applied the risk factors developed with the KLN workgroup to a new dependent variable, the district effectiveness rates. Using the measures of the proportions of Students with Disabilities, chronic absence, English Learners, mobile students, cumulative poverty, suspensions and expulsions, and percentages of new teachers, this model explained 42 percent of districts' variance in effectiveness rates—a substantial amount but much less than the 58 percent of schools' variance in academic performance explained by a very similar model.

Only three variables were significant predictors:

1. the proportion of Students with Disabilities,
2. the proportion of mobile students, and
3. cumulative poverty, which again, was strongly significant, somewhere beyond the 0.001 level.

The proportion of Students with Disabilities was not a significant predictor when the dependent variable was school academic performance as measured by state assessments.

This first model told us that, on average, for every percentage point increase in Students with Disabilities, we could expect a district's effectiveness rate to go down 0.265 points. In the average district, 16 percent of the students are Students with Disabilities, so our model predicts that the average district loses about four effectiveness points through influences associated with SwDs (16 * 0.265 = 4.3). In comparison, according to this first model, the average district loses about 17 effectiveness points due to cumulative poverty (43 * 0.404 = 17.4).

When I removed cumulative poverty from this first model, the adjusted r-squared fell to 0.25. Students with Disabilities then became the strongest predictor, followed by the proportion of English Learners and then mobile students. The suspensions and expulsions measure also became strongly significant, even though it had not been so when cumulative poverty was included.

The Second Model

After studying the results of the first model, KSDE leadership suspected that districts with virtual school programs had lower effectiveness rates, and that district size might also be a factor. A research review reported a correlation between the total number of schools attended and lower post-secondary enrollment. All three of these variables could be created from existing data.

To test these suggestions and improve the explanatory power of the effectiveness model, I prepared a new set of independent predictors. I dropped the independent variables that were not significant in the first model. For the second model, I included the newly suggested variables and those that were significant in the first set, that is, the proportion of Students with Disabilities, the proportion of mobile students, and cumulative poverty.

I also improved the accuracy of the some of the independent variables. I changed them from being based on whole district populations, to descriptors constructed from the five cohorts used to calculate the outcome variable, the districts' effectiveness rates.

For example, I first identified all students who had been classified as having a disability at any time in the school years from 2007 through 2015. The number of school years each student was so classified were added up across all available years of data from 2007 through 2015. I also kept a cumulative total of the number of years each student had attended Kansas schools.

Next, by year and grade, I selected the approximate cohorts in the postsecondary NSC data. All ninth graders from 2008 through 2012 were selected, all tenth graders from 2009 through 2013, all eleventh graders from 2010 through 2014, and all seniors from 2011 through 2015. I then aggregated, by district, the count of the total years these students were identified as having a disability. This quantity was the numerator. The denominator was the total number of years the selected students have attended Kansas schools. I used a similar process to calculate the virtual student rate, the cumulative poverty rate, the cumulative mobility rate, and the rate that students changed schools across their school careers.

There is a subtle difference between the mobility rate and the rate that students changed schools. The mobility rate counts the number of times a student changes schools during the school year. The school transition rate counts the total number of times each student changed schools across their student lives. It includes the count of school transitions within the school year as well as those between the beginning and end of each school year. The two variables overlap, the total number of school transitions contains the total number of school changes within the school year, the mobility count.

I used the count of the five cohorts of students aggregated to each district as a measure of district size.

The second model was a substantial improvement from the first—it explained 53 percent of districts' variance in effectiveness rates—an 11point improvement over the first model. Because of the high correlation between the mobility rate and the all-school transitions rate (see Table 1 below), I removed the latter from the model to avoid collinearity in the regression model.[7] When I removed the mobility counts from the total school transitions counts, school transitions were not significant predictors of effectiveness rates.

Table 1

Bivariate Correlations Between 8 Measures

	1	2	3	4	5	6	7	8
1. effectiveness rates	1							
2. district size	0.005	1						
3. SwD rate	-.212***	-0.084	1					
4. English Learner rate	-.213***	-.12*	-.15*	1				
5. mobile rate	-.427***	0.07	.37***	0	1			
6. all school transitions rate	-.329***	.209***	.197**	0.03	.707***	1		
7. cumulative poverty rate	-.667***	0.013	.261***	.395***	.37***	.297***	1	
8. virtual student rate	-.272***	0.07	-0.1	-0.003	.322***	.385***	0.04	1

*** Correlation is significant at the 0.001 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Which variables were significant predictors? We see in Table 2 below that only three were significant predictors: the student mobility rate, the cumulative poverty rate, and the virtual student rate.

[7] When both the mobility and the school change rate were included as independent variables in a regression procedure, the collinearity diagnostics returned some eigenvalues close to zero and a couple of conditional index values close or greater than 15. Both of these conditions indicate possible problems with collinearity; the mobility rate and school transitions rate were so similar that one could be predicted from the other.

Table 2							
Coefficients from the Linear Regression Model Predicting District Effectiveness Rates							
	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(constant)	65.057	1.634		39.814	0.000	61.84	68.273
district size	0	0	0.063	1.534	0.126	0	0.001
SwD rate	-0.038	0.12	-0.014	-0.314	0.754	-0.273	0.198
English Learner rate	0.025	0.06	0.02	0.425	0.671	-0.093	0.143
mobile rate	-0.601	0.155	-0.176	-3.879	0.000	-0.906	-0.296
cumulative poverty rate	-0.5	0.043	-0.611	-11.699	0.000	-0.584	-0.416
virtual student rate	-1.23	0.226	-0.229	-5.446	0.000	-1.675	-0.786

The second model confirmed Commissioner Watson’s impression that districts with virtual students were more likely to have lower effectiveness rates. It also demonstrated that constructing the independent variables from the student freshman cohorts being measured in the dependent variable, the effectiveness rate, improved the accuracy of the model.

After reviewing the results from the second model, KSDE leadership specified a third model. The model should include most of the independent variables used in the first model, variables that could be regarded as largely beyond the control of the districts:

1. cumulative poverty;
2. proportion of student years in which students were classified as having a disability;
3. proportion of time students were classified as English Learners;
4. proportion of student years with chronic absenteeism;
5. proportion of mobile years;
6. expulsion and suspension rates; and
7. teacher turnover (percentage of new teachers).

The model should exclude the proportion of virtual students and the new variables added to the second model. It should also produce a benchmark that would allow districts to judge their relative performance in effectiveness rates, one in which districts could have a high level of confidence, a 95-percent level of confidence.

By including variables over which districts have limited influence, like chronic absenteeism, the percentage of new teachers, and the expulsion and suspension rates, does the model discourage districts from addressing these problems?

Tentative Performance Categories

KSDE staff have discussed the performance levels based on the standardized residuals but no decisions about them have been made. Below is one example, but other performance bands have also been discussed.

- *Far above average* = ≥ 1.5 standard deviations (sd) above the mean or predicted rate
- *Above average* = > 1 sd but < 1.5 sd above the predicted rate
- *Typical or average* = ≤ 1 sd above and ≥ -1 sd below the predicted rate
- *Below average* = < -1 sd below and > -1.5 sd below the predicted rate
- *Far below average* = ≤ -1.5 sd below the predicted rate

KSDE currently reports districts' effectiveness rates based on the most recent five high school freshman cohorts available from NSC data. It reports the 95 percent confidence interval around each district's predicted rate. It does *not* report the relative performance described by the categories above, but does explain how districts can calculate their own relative performance.

Data Preparation for the Third, Current Model

Student Longitudinal Records

The student level data combines the audited enrollment records (ENR) from 2007 through 2016 and the KIDS end-of-year (EOY) records. Why?

The KLN workgroup had identified student mobility and chronic absenteeism as risk factors that were likely causes of poor academic performance. Mobile students and chronically absent students are relatively few and are more likely to have irregular school records. In order to accurately calculate rates of chronic absenteeism and mobility, we need highly accurate student records.

The EOY records should contain all the students who attended school at any time during the year. The ENR records are audited and should contain all students who were attending the school on September 20th. In comparing the two records, even after duplicate records were removed, one finds that about 1.76 percent of the ENR records are not included in the EOY records. To include those records, the ENR and EOY records were merged by student ID, year, and the accountability school.

Before merging the EOY and ENR records, consistent categorical definitions were applied for students with disabilities, ethnic classifications, free or reduced or paid lunch status, EL classifications, including monitored, and virtual categories. Each record was labeled for its source, ENR or EOY.

In order to merge the student records, duplicates had to be removed. When possible, responsible buildings' IDs were assigned to student records without one.

Separately, in the EOY and ENR records, student records without a responsible school, including those that were identified as being included in the accountability reporting for other states (Accountability School Identifier = '0001'), if they had an attending building in the record, were assigned a responsible school by making the attending building the responsible school. If no attending school was listed and the responsible school was listed as '0001' or '0002' (homeschooled), the record was removed. If the responsible school was missing and the attending building was missing, but the funding school was listed, the funding school was made the accountability building.

The records were sorted by student ID, year, accountability school, grade, and the date the records were uploaded to KSDE. Duplicates were identified based on student ID, year, and accountability building. Then duplicate records were removed, but the most recently uploaded record was kept. This removed 686 records from the EOY files and 1,969 from the ENR records. Since these records spanned 2007 through 2016, the removed records were tiny percentages of each record set. Nevertheless, adding the ENR records to the EOY records, after the duplicates were removed, added about 1.8 percent to the total merged records.
About 4,500 records that were missing an accountability building but had a resident district were still in the file. These records were included in district aggregations to create the independent variables below.

If grade was missing from the EOY record but available in the ENR record, the record was assigned the grade from ENR so that all records had a grade level. Based on the EOY grade, or the ENR grade if the EOY grade was missing, the records that were not graded (NG) and the pre-Kindergarten grades were removed. After sorting the records by student ID, year, load date, and accountability building, individual record numbers were assigned so that each student's longitudinal records had an ordered sequence number. The maximum number of records for an individual student was 32.

To calculate district aggregations, only public and private accredited districts were included (org_type = 2 or 5). Only districts reporting 12th graders were included.

Independent Variables

Cumulative Poverty

Why include cumulative poverty? For a long time federal and state governments have measured relative student social-economic status (SES) using students' eligibility for free or reduced lunch. Typically, they are used as cross-sectional, snapshot measures at enrollment or the end of the school year. At the school or district level, the count of students qualifying for either free or reduced lunch have the same value in the numerator. Schools that have a relatively high proportion of reduced lunch students in temporary poverty may have a poverty level comparable to those of schools with students who have lived in poverty and poor neighborhoods since birth.

A better measure would capture the influence of the developmental stressors associated with poverty, especially in early childhood when those stressors are most influential.[8] These better measures of developmental stressors are not currently available. The closest available substitute is a measure of cumulative poverty, the total number of years a school or district's students were in poverty divided by the total number of school years the students have attended state schools.

With the merged files, I compared the ENR and EOY student classifications for each school attended and each year attended. When the free-lunch qualifications were missing from the EOY, but present in the ENR, I assumed the ENR classifications were correct and used them. When records from the two sources were not in agreement for a particular year, I chose the higher value based on this scale:

free lunch = 1, reduced lunch = 0.5, paid lunch = 0.

The above were also the values I assigned for each school year the student attended Kansas schools and qualified for free lunch (1) or reduced lunch (0.5). By starting from the first year each student attended Kansas schools, and adding the maximum poverty levels from each year to the one that followed it, I carried the sum total forward as a cumulative count of total time spent in poverty. I also created a cumulative count of the number of years each student attended Kansas schools.

Using the cumulative values of student years spend in poverty as the numerator, and the cumulative count of student years spend in Kansas schools as the denominator, I aggregated the cumulative poverty levels for each district for each year. Because the cumulative poverty is attached to each individual record, when a student changes district, this quantity follows the student and is automatically carried forward to the district of present attendance.

At the district level, cumulative poverty counts and years attended are systematically truncated. Most students who were kindergarteners in 2007, the first year of student longitudinal data that I'm including here, will be tenth graders in 2017. The total number of years they could have attended Kansas schools for this calculation is eleven. Though students have not attended Kansas schools their whole student careers, the poverty and

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[8] Noble, K.G., Houston, S.M., Kan, E., & Sowell, E.R., (2012). Neural correlates of socioeconomic status in the developing human brain. *Developmental Science*, 15, 4, 516-527. See also Brooks-Gunn, J. & Markman, L. (2005). The contribution of parenting to ethnic and racial gaps in school readiness. *The Future of Children*, 15, 1, Spring, 139-168. Also Luby, J., Belden, A., Botteron, K., Marrus, N., Harms, M.P., Babb, C., Nishino, T., & Barch, D., (2013). The effects of poverty on childhood brain development. *JAMA Pediatrics*, 169 (10), 938-946. Dickerson, A., & Popli, G.K. (2016), Persistent poverty and children's cognitive development: Evidence from the UK Millennium Cohort Study. *Journal of the Royal Statistical Society A,* 179, part 2, pp. 535-558.

year counts are truncated in the same way for all districts. I'm assuming that this truncation doesn't bias the district aggregates.

Cumulative Years Students Were Classified as with Disabilities

Should the proportion of students with disabilities be calculated like cumulative poverty is calculated, as a proportion of student's time spent classified as having a disability? Intuitively, using longitudinal data to describe time spent in a particular status seems a more accurate model than a single cross-sectional snapshot of students' status. In Table 1 we saw that cumulative poverty has a strong correlation with disabilities. In the model predicting academic achievement, disability was not significant when cumulative poverty was included in the model, but became significant when cumulative poverty was removed. In the model predicting effectiveness rates, the disability measure became stronger when the cumulative poverty measure was removed. Cumulative poverty has a strong relationship with our disability measure. More time spent classified as having a disability may be indicative of the severity or persistence of impairment, and of its influence on a student's development.

If a student was identified as having a disability in either the EOY or ENR fields, for any of the schools attended in a given year, that student was counted as having a disability for that year (spednum = 1). The total number of years each student was identified as having a disability was added to each additional year attended and carried forward cumulatively.

Similar to the cumulative poverty calculation, upon aggregation at the district level, the total count of student years spent classified as having a disability was classified as the numerator, and the total count of student years in Kansas schools was classified as the denominator.

English Learner Rate

Across all available student records, from 2007 through 2016, I identified records in which the student was identified as either currently receiving English language services or was a former EL student being monitored. (An EL student enters monitored status for the two years after the student has scored at the fluent level, level 4 or above, for two years in all domains and in the total score on the English Language Proficiency Assessment. These requirements were being reconsidered as this document was being written.) I aggregated the count of years in which the student was identified as either receiving EL services or being monitored. Like cumulative poverty and disability, this variable was calculated as a proportion of students' time classified as an English Learner.

Chronic Absence

The way chronic absence was defined by the Kansas Learning Network workgroup differs from the current KSDE definitions.

There are two federal definitions. The Civil Rights Data Collection (CRDC) defines chronically absent students as those who are:

- "absent for 15 or more school days during the school year;
- not physically on school grounds and not participating in instruction or instruction-related activities at an approved off-grounds location for the school day; and
- absent for any reason (e.g., illness, suspension, the need to care for a family member)."

The CRDC defines student absence in almost exactly the way KSDE's Strategic Management Plan defines a student as absent:

- "if he or she is not physically on school grounds and is not participating in instruction or instruction-related activities at an approved off grounds location for the school day."
- Absence includes "students who are absent for any reason (e.g., illness, suspension, the need to care for a family member), regardless of whether absences are excused or unexcused."
- Students who "miss 50 percent or more of a school day should be counted as absent."

KSDE, in its Strategic Plan Management Glossary, accepts the definition the federal Department of Education makes for its EDFacts data collection. The EDFacts data collection defines chronic absenteeism as the "unduplicated number of students absent 10% or more school days during the school year." Included are K-12 students "who were enrolled in the school for at least 10 school days at any time during the school year, and who missed 10% of the school days in which they were enrolled in the school."

The definitions include these rules:

- "Students should be counted once at each school he/she attends."
- "Students should be counted in the chronic absenteeism data once they have been enrolled in a school for a minimum of 10 school days."
- "States should include state institutions (juvenile justice school and department of health services schools) . . . "

At the time this model was being constructed, it wasn't clear if the chronic absenteeism definition should have been changed to the KSDE /EDFacts definition above, or kept the same. No rule-making workgroups had met. The chronic absenteeism variable currently in the model is the KLN version.

What is different about the chronic absence definition currently applied in the model? The KLN workgroup defined chronically absent students as those missing 10 days or more across all schools attended in a school year. Absences are calculated from the students' point of view: they are cumulative so that a student who attends more than one school in the year carries forward the absences from previous schools to current schools.

Here are the specific steps in the calculation as used in the predictive model described in this document:

I first calculated the number of days each student lost in each school attended by subtracting the days attended from the days in membership. For those students who attended more than one school in a year, the lost days were carried forward to each school attended within the year. If the number of lost days equaled or exceeded 10 days across the year, then the record was identified as one in which the student was chronically absent in that year. Like cumulative poverty and the proportion of time classified as having a disability, I used an accumulated proportion of years with chronic absence in the current model.

If the definition of chronic absenteeism is changed from the KLN definition to the KSDE / EDFacts definition, and the years of chronic absence are cumulative, the performance of the variable as a predictor will probably be minimal. A small number of mobile students who are chronically absent across two or more schools will not be identified as chronically absent. If the rulemaking group changes the measure from a cumulative one, to a cross-sectional one, the impact on the predictive model might be greater, but this is a comparison that could be tested if a rulemaking group or leadership wants a comparison made.

Mobile Students

Student records indicating that a student had changed accountability schools within the academic year were flagged with a one. The number of times each student had changed schools within an academic year was aggregated at the student level based on each students' ID. As with the variables above, the total number of years each student had attended Kansas schools was also aggregated, carried forward, and used to calculate a proportion of mobility years when the data were aggregated at the district level.

Cohort Selection

Once each student record had attached to it the cumulative count of years each student had:

- qualified for free or reduced lunch,
- been identified as having a disability,
- received English Language services or been in EL monitored status,

- missed more than 10 days within a year
- been a virtual student or
- changed schools within the school year

I selected an approximation of the five freshmen cohorts and their peers. I selected:

- all records of 9th graders in 2008 through 2012;
- all records of 10th graders in 2009 through 2013;
- all records of 11th graders in 2010 through 2014;
- all records of 12th graders in 2011 through 2015.

Then I placed all the information needed from individual records in each individual students' record. I selected the last available student record for each student so that there was only one record per student in the file.

Next, I aggregated the records by district. I then used the aggregated counts of five risk factors as numerators over the total counts of each district's student years. I multiplied the resulting ratios by 100, converting them into percentages. For the five cohorts, this produced these variables:

cumpovrate: the percentage of students' years spent in poverty.
spedrate: the percentage of students' years spent in disability status.
esolrate: the percentage of students' years spent in English Learner status.
chronic2: the percentage of students' years in which the student missed 10 or more days.
mobile_rate: the cumulative count of school changes during the school year over the total number of years students have attended Kansas schools.

There is another way that the accuracy of the independent variables might be improved. After approximating the five freshman cohorts, I should have aggregated the individual records to get all the building IDs of the schools the five freshmen cohorts attended from 2008 through 2015. Let's call this dataset X and set it aside. When it comes time to calculate the percentage of district teachers who are new to their schools, we should first filter the buildings by dataset X. Then when we aggregate the counts of teachers who are new to their schools, and the number of teachers in those schools, we are not aggregating across all schools in each district, but only by those schools attended by the five freshman cohorts.

Expulsion and Suspension Rates

For the five-year period the five cohorts were attending schools, KSDE does not have individual records for suspensions and expulsions.[9] For 2012 through 2017, it has building-level yearly counts of in-school and out-of-school suspensions, as well as expulsions. There are other, non-suspension and non-expulsion discipline events, and truancies, but the KLN workgroup chose not to include them in this calculation.

I removed three duplicates at the building and year levels. Unlike the other independent variables above, district suspension and expulsion rates are a general district description across all students. We cannot calculate suspension and expulsion rates from the five freshman cohorts. How much noise this makes, and whether this noise obscures the signal from this measure cannot be quantified until KSDE acquires a measure of discipline events that is tied to individual student records.

To match the time frame of the five freshman cohorts as closely as possible, I selected the 2012 through 2015 years and aggregated the counts of these discipline events at the district level. This was the numerator. The denominator was the count of students from the audited enrollment counts across the same years for each district. As with the other variables, I converted this proportion to a percentage.

It is possible to apply the same filter, the dataset X, to the expulsion and suspension data.

Teacher Turnover (Percentage of New Teachers)

This is the one independent predictor that isn't based on student-level data. There is some research identifying teacher turnover as a factor in lower student performance. Studies of international education systems have sometimes pointed to high teacher turnover in the United States as an important factor in comparatively lower student performance.[10] Domestic studies also note the high costs of teacher turnover and use teacher mover and leaver rates as measures.[11]

[9] KSDE began collecting some suspension and expulsion data tied to individual student records in 2017. KSDE does not collect all suspension, expulsions, and discipline events, only those required for federal and state reporting.

[10] Auguste, B., Kihn, P. and Miller, M. (2010). Closing the talent gap: Attracting and retaining top-third graduates to careers in teaching. Washington, DC: McKinsey. http://www.mckinsey.com/App_Media/Reports/SSO/closing_the_talent_gap_september_2010.pdf.

[11] Kukla-Acevedo, S. (2009). Leavers, movers, and stayers: The role of workplace conditions in teacher mobility decisions. *The Journal of Educational Research,* 102, 6. Also see Ingersoll, R.M. (2001). Teacher turnover, teacher shortages, and the organization of schools. University of Washington: Center for the Study of Teaching and Policy. Retrieved from http://depts.washington.edu/ctpmail/PDFs/Turnover-Ing-01-2001.pdf.

The KLN workgroup chose to measure a five-year average of the percentage of new teachers in a district. They felt the five-year average would better identify systemic teacher turnover and avoid identifying small schools with the misfortune of having a high proportion of retirements in a single year.

From the Educators Assignment database, I acquired the staff ID, program year, district and building assignments, teacher codes, and teacher code descriptions. I selected only teachers and excluded administrators and school specialists (**teacher_code** = 1, 2, 3, 4, 5, or 9). I removed duplicate records (records with the same staff ID, year, and school ID). I assigned individual record numbers for each record tied to an individual staff ID. I marked the first individual teacher records as new to the building. I tagged each record that marked a teacher's first year in a school (**firstyearinbldg**). Those sequential individual records in which staff IDs were the same, and the building numbers were the same, but the year had advanced by one, I marked as a teacher continuing within the same school (**continuinginbldg**). In order to understand the records and avoid mislabeling some, I also classified and tagged the records showing teachers who rotated between buildings within the year (**rotatebldg**). Finally, I identified those sequential records where the staff IDs were the same but the school ID had changed, and the record was not marked as either a case of continuing in the building nor as a building rotation. I labeled these records as identifying teachers who were new to that building (**newtobldg**).

I also labeled records using the labels established by scholars, "movers," and "leavers." I identified six categories of movers, and two categories of leavers.

If we want to reduce the noise in the measure of teachers who are new to their buildings, we will retrieve dataset X and use it to filter the buildings used in the teacher aggregations. Dataset X identified the schools the five cohorts were attending from 2008 through 2015.

I then aggregated these counts by district and year so that I had counts of the total number of teachers, and the total number of teachers in each of the categories I had created.

With a more complete data set, we would be able to match the individual students in the five freshmen cohorts to all the teachers they have had through their school careers and identify the proportion of their teachers who were new. KSDE does not currently have the data to tie particular courses, teachers, and years to particular students. This would have given us a more accurate answer to the question, Does the proportion of new teachers influence a district's effectiveness rates?

In accord with the original specifications of the KLN workgroup, I aggregated the following district counts within the five-year time frames below:

total_teachers the count of teachers in district

newtobldg the count of teachers new to the school in which they teach
rotators the count of teachers who rotate between schools within the same year
leaver1styr the count of teachers who leave teaching in Kansas after their first year
leavertotal the count of teachers who leave teaching in Kansas
movedwi the count of teachers who moved between buildings within the district
moveddist the count of teachers who moved from one district to another
movertotal total movers from one building to another

So that questions about trends can be asked and answered, I made district aggregates within the five-year time frames below. I labeled each with the highest year included in the time frame:

2003-2007	2007
2004-2008	2008
2005-2009	2009
2006-2010	2010
2007-2011	2011
2008-2012	2012
2009-2013	2013
2010-2014	2014
2011-2015	2015.

I used only the 2011 through 2015 dataset to create the new teachers' variable. As I've explained above, it may improve the accurate of this independent variable if the data were filtered to include only the buildings the five cohorts had actually attended. It may also help to expand the time frame for the aggregation from 2008 through 2015.

Once the teacher dataset is filtered by the selected time frame, the next step is to create the district aggregations of the teacher variables. I calculated the following percentages:

pctnewtobldg = (newtobldg / total_teachers) * 100 = percent of teaching staff new to the building
pct_rotators = (rotators / total_teachers) * 100 = percent of teachers who are rotating between buildings
pct_leave1styr = (leavr1styr / total_teachers) * 100 = percent of teachers who have left after their first year
pct_leavers = (leavertotal / total_teachers) * 100 = percent of teachers who have left teaching or KS
pct_movedwi = (movedwi / total_teachers) * 100 = percent who have changed buildings within the district
pct_moveddist = (moveddist / total_teachers) * 100 = percent who what changed districts within the State
pct_movertotal = (movertotal / total_teachers) * 100 = percent who have changed schools

This produced these eight independent variables at the district level:

1. the proportion of years a district's students were virtual students;
2. the cumulative proportion of years that students' families were low income;
3. the cumulative proportion of years that students were classified as having disabilities;
4. the proportion of years students were classified as English Learners;
5. the proportion of years that students were chronically absent;
6. the proportion of years students had been mobile within the school year;
7. a measure of district's expulsion and suspension rates; and
8. a measure of the proportion of new teachers.

Dependent Variable

Effectiveness Rates

KSDE's new postsecondary measures are based on longitudinal student records. KSDE, as part of its calculation of high-school graduation rates, identifies ninth-grade student cohorts. In order to calculated graduation rates according to the required federal formula, KSDE follows the progress of these cohorts from grade to grade and through high school graduation. KSDE then sends the graduation records to the National Student Clearinghouse (NSC). NSC links the high school graduate records to college enrollment records. It then sells these records back to KSDE. KSDE uses the records to produce two postsecondary performance measures.

1. The *success rate* uses *the count of graduates* from the four-year ninth-grade cohort, adjusted for transfers in and out, as its denominator. Its numerator is the count of high-school graduates who have been enrolled in postsecondary education for two years, or, who have already completed a postsecondary degree or credential.

2. The *effectiveness rate* uses the adjusted ninth-grade cohorts, the same ones used in the high-school graduation rates, as its denominator. The numerator is the count of students from the same cohort who have been continuously enrolled in postsecondary education for two years, or have already completed a postsecondary degree or credential.

Because effectiveness rates include students who eventually will drop out of high school in its denominator, or who graduate but do not go on to postsecondary, effectiveness rates are typically eight or more points lower than success rates. Effectiveness rates offer a more complete picture of how effective institutions are in preparing and guiding youth through high school graduation and into postsecondary training.

The effectiveness rate is also sometimes described as the graduation rate multiplied by the success rate. But as Sheng Xuewen, a senior KSDE researcher points out, two of the terms cancel, so we are left with the effectiveness rate as described above.

$$\text{graduation rate} \quad * \quad \text{success rate} \quad = \quad \text{effectiveness rate}$$

$$\frac{\cancel{\text{count of graduates}}}{\text{count of freshmen}} * \frac{\text{count of h.s. graduates enrolled in postsecondary}}{\cancel{\text{count of graduates}}} = \frac{\text{count of h.s. graduates enrolled in postsecondary}}{\text{count of freshmen}}$$

The formula KSDE currently uses is below. To make it clear, I've broken it into two steps:

graduation rate = (dgsr_student_grads / dgsr_student_totals) where

> dgsr_student_grads = student count of the adjusted freshman cohort who have graduated, and
>
> dgsr_student_totals = student count of the adjusted freshman cohort.

success rate = ((ps_retained_count + ps_grad_count) / nsc_total_in_class) where

> ps_retained_count = count of students in the adjusted freshman cohort enrolled in a postsecondary institution two years after high-school graduation,
>
> ps_grad_count = count of students who have graduated from high school and a postsecondary program *or* have an industry-recognized skill certificate, and
>
> nsc_total_in_class[12] = count of high-school graduates in NSC's records;

and then, success rate * graduation rate = effectiveness rate.

As I'd done with the independent variables, I converted the effectiveness rates to percentages.

KSDE treats the combined five freshman cohorts as though they were a single cohort. It aggregates student counts from all five years. It does not calculate each year separately and then average the five effectiveness rates.

Why does KSDE aggregate the most recently available five high-school cohorts in its calculation of effectiveness rates? Kansas has many small, rural districts. In order to get

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[12] Theoretically, KSDE could use its count of high school graduates here. This would simplify the calculation to: ((ps_retained_count + ps_grad_count) / dgsr_student_totals) = effectiveness rates. When subtracting the NSC high school graduates from the KSDE graduates, there are 183 districts that do not match. The differences range from -10 to 69.

stable effectiveness rates, KSDE aggregates the graduates from the most recent five years available. As of the writing of this document, the aggregates include the high school freshman cohorts of 2011, 2012, 2013, 2014, and 2015.

Applying OLS Linear Regression

In SPSS, I ordered a frequencies table and found that some records were missing values for the disability measure. So that these cases would be included in the regression procedure, I replaced the missing values with zeros. Because of the way I had constructed the independent variables, there were no independent variables with missing values.

I ordered a correlations table and saw that the mobility measure had a high correlation (0.65) with the school change rate variable. The school change and the virtual variables were not part of the risk model leadership specified for generating the predicted effectiveness rates, so they were not included in this model.

With the variables assembled as columns in a single SPSS file with each accredited district as a row, I used linear regression with the ENTER method. It enters the independent variables as a block, all at once. I set missing values to be deleted listwise, but, as I've noted, there were no missing values except for three tiny districts without effectiveness rates. I ordered a model summary table with the adjusted r-squared and the standard error of the estimate, regression coefficients, and a collinearity diagnostics table. I saved the predicted values, the residuals (the predicted – the actual effectiveness rates), and the 95 percent confidence interval around the mean predicted effectiveness rates.

Output for Reporting & Technical Documentation

Table 3						
N, Medians, Means, Standard Errors, Standard Deviations, and Ranges of the 9 Variables						
	N	median	mean	standard error	standard deviation	range
1. effectiveness rates	286	45.1	45.81	0.585	9.89	68.2
2. proportion of student years SwD	289	12.59	12.88	0.332	5.64	83.6
3. proportion of student years English Learners	289	0.575	3.87	0.501	8.53	57.1
4. cumulative rate of mobility	289	3.89	4.52	0.195	3.32	30.2
5. proportion of student years in poverty	289	32.62	34.23	0.726	12.35	74.1
6. proportion of student years as virtual	289	0.211	0.629	0.109	1.85	17.5
7. expulsion & suspension rates 2012 - 2015	289	3.18	4.74	0.341	5.8	47.9
8. percent of new teachers	289	12.66	13.91	0.374	6.35	59.3
9. chronic absence rate based on years attended	289	29.86	30.42	0.482	8.19	60.9

Table 3 above describes the variables in the regression model, plus the virtual variable, which is not in the model but is included in Tables 3 and 4 to quantify its influence on effectiveness rates.

Table 4 below has the correlations between pairs of variables. The row numbers correspond with the column numbers—for example, column one shows the correlations between effectiveness rates and every other variable. Since a variable correlates completely with itself, the intersections where the column and row represent the same variable are ones.

Note that there are several cells without any superscript asterisks. This means there is no significant correlation between the two intersecting variables.

Table 4									
Bivariate Correlations Between the Prepared Measures									
	1	2	3	4	5	6	7	8	9
1. effectiveness rates	1								
2. proportion of student years SwD	-.240**	1							
3. proportion of student years English Learners	-.223**	-.146*	1						
4. cumulative rate of mobility	-.418**	.396**	-0.006	1					
5. proportion of student years in poverty	-.659**	.220**	.435**	.321**	1				
6. proportion of student years as virtual	-.271**	-0.086	-0.013	.191**	0.003	1			
7. expulsion & suspension rates 2012 - 2015	-.282**	-0.040	-0.083	0.047	.248**	-0.001	1		
8. percent of new teachers	-.130*	.146*	0.062	.189**	.138*	.132*	0.057	1	
9. chronic absence rate based on years attended	-.387**	0.046	0.100	.173**	.364**	0.114	0.114	.152**	1
**. Correlation is significant at the 0.01 level (2-tailed).									
*. Correlation is significant at the 0.05 level (2-tailed).									

All of the independent variables have a significant correlation with effectiveness rates, the dependent variable. I have included the proportion of student years that were spent as virtual students in this table even though it will not be an independent predictor in the regression model. We can see that it has a strong correlation with lower effectiveness rates. Cumulative poverty has the largest negative correlation with effectiveness rates and strong correlations with all of the independent variables except the virtual variable.

Table 5			
Model Summary [b]			
R	R Square	Adjusted R Square	Std. Error of the Estimate
.717[a]	0.514	0.502	6.98
a. Predictors: (Constant), chronic absence rate based on total number of years attended, % of teaching staff new to the building, proportion of years students spent in SwD status, expulsion & suspension rate based on 2012 thru 2015 counts, cumulative rate of mobility for 5 yr cohorts, proportion of student years spent in EL status, proportion of years students in poverty status			
b. Dependent Variable: effectiverate2			

In Table 5, the model summary tells us that our independent variables are explaining half—0.5—of the variance between districts effectiveness rates. Explaining half is good for a beginning model, but also humbling in that there is an equal amount of the variance that the model doesn't explain.

The model also reports the standard error of the estimate as about seven (6.98). We can think of this as a measure of how districts' actual effectiveness rates are distributed around the prediction line. We will use this distance to make the tentative performance categories described on page eleven. About seven point above or below the predicted line is within one standard deviation away from the predicted line.

Below, table 6 gives us the results of our linear regression model. It tells us which variables are significant predictors of effectiveness rates.

Table 6

Coefficients from the Linear Regression Model

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	71.336	2.261		31.554	0.000
proportion of student years SwD	-0.110	0.126	-0.041	-0.870	0.385
proportion of student years English Learners	-0.031	0.064	-0.025	-0.488	0.626
cumulative rate of mobility	-0.753	0.155	-0.220	-4.856	0.000
proportion of student years in poverty	-0.390	0.049	-0.478	-7.960	0.000
expulsion & suspension rates 2012 - 2015	-0.197	0.078	-0.116	-2.536	0.012
percent of new teachers	-0.095	0.075	-0.054	-1.267	0.206
chronic absence rate based on years attended	-0.172	0.058	-0.136	-2.988	0.003

a. Dependent Variable: effectiveness rates

Table 6 gives us the coefficients or weights that optimally predict district effectiveness rates. There are many types of regression. The linear regression used here is straightforward:

$$Y' = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + b_5 x_5 + b_6 x_6 + b_7 x_7 + e$$

Where Y' = the predicted or estimated effectiveness rate

b_0 = the constant, y-intercept, or grand mean

b_1 = the coefficient or weight for the first independent variable

x_1 = the proportion of student years spent classified as having a disability

and so forth across the next six independent or predictor variables to *e*, the remaining error.

How should we interpret these results?

Looking in the column marked “Sig.” for significance, we see that, after the constant or y-intercept, four variables have significance levels at or smaller than 0.05:

1. the proportion of student years spent in poverty
2. cumulative rate of mobility
3. the chronic absence rate, and
4. the expulsion and suspension rates.

The other variables, the proportion of student years spent classified as having a disability, the proportion of student years classified as an English Learner, and the percentage of new teachers, are not significant predictors of effectiveness rates.

How do we interpret the unstandardized regression coefficients?

For the four significant predictors, we can say that for every unit change in the independent variable, the dependent variable changes by the coefficient’s units. For example, for every percentage point increase in cumulative mobility, we can expect the effectiveness rate to go down about 0.75 points. In Table 3, we see that in the average district, 4.5 percent of the student years are mobile years, so, on average, our model predicts that the average district loses a little more than three effectiveness points through the influences associated with student mobility (4.5 * 0.75 = 3.4). In comparison, the average district loses about 13 effectiveness points due to the influence of cumulative poverty (34.2 * 0.39 = 13.3), about 5 points due to chronic absenteeism (30.4 * 0.17 = 5.2), and about a point due to expulsion and suspension (4.7 * 1.97 = 0.9).

These results suggest that the largest gains in effectiveness rates may be in policies and programs that counter the effects of cumulative poverty, followed by absenteeism, mobility, and finally, expulsion and suspension.

What happens if we remove the measure of cumulative poverty?

The explained variance, the adjusted r-squared, drops to 0.39 and all our remaining measures, except for the percentage of new teaching staff, become strongly significant. Table 7 below shows the results. The evidence is again telling us how important cumulative poverty is, and how influential it is with our other measures.

Table 7					
Coefficients from the Linear Regression Model with Cumulative Poverty Removed					
	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	70.597	2.499		28.255	0.000
proportion of student years SwD	-0.548	0.126	-0.207	-4.358	0.000
proportion of student years English Learners	-0.303	0.060	-0.243	-5.082	0.000
cumulative rate of mobility	-1.140	0.163	-0.334	-7.003	0.000
expulsion & suspension rates 2012 - 2015	-0.410	0.080	-0.241	-5.097	0.000
percent of new teachers	-0.087	0.083	-0.049	-1.052	0.294
chronic absence rate based on years attended	-0.282	0.062	-0.222	-4.564	0.000
a. Dependent Variable: effectiveness rates					

What do the residuals and predicted effectiveness rates look like?

Table 8						
N, Medians, Means, Standard Errors, Standard Deviations, and Ranges of the Predicted and Residual Effectiveness Rate						
	N	median	mean	standard error	standard deviation	range
predicted effectiveness rates	289	46.02	45.55	0.438	7.45	45.39
residual rates (actual - predicted = residual)	286	-0.107	0	0.406	6.87	40.87

The residuals have a mean of zero, and standard deviations of about seven, as we would expect.