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

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Summary & Purposes

This paper details the construction of a performance benchmark for Kansas State Department of Education's new postsecondary district performance measure. The new measure, the *actual* 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, describes 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 risk factors like poverty, stakeholders can better judge if districts are performing better, about the same, or worse than comparable districts.

The purposes of writing this recipe for the benchmark are:

1. to open the goals, rules, methods, and assumptions of its construction to examination, critique, and improvement by the public, technical experts, the Board, KSDE leadership and staff, districts and other stakeholders; and

2. to make the measures replicable so that KSDE's Information Technology (IT) and Research and Evaluation (R & E) staff can, if so directed, construct and publish the measures as part of KSDE's regular public reporting.

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 streams of thought:

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.[1] 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.

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.[2]

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[1] 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] 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.

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?

KSDE researchers use a statistical technique called least-squares linear regression to produce the predicted or mean effectiveness rates. The predicted mean line is 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. By comparing districts' actual effectiveness rates to their expected or predicted rates, we can separate them into at least three blurry gradations: those at some distance above the line can be described as performing above expectations, those grouped in the middle around the mean line as normal or average, and those some distance below as below expectations. Performance is measured relative to all other districts. Gradations are blurry because these performance bands run perpendicularly, in normal-curve cross-sections along the predicted line.

Regression can also account for influences that are largely environmental, like students' cumulative poverty. By quantifying and accounting for these influential factors, it allows us to assume that some of the remaining unexplained variance[3] in effectiveness rates is due to differences in districts' programming, teaching, administration, and other factors that districts do control. This too is different from NCLB. Under NCLB, the influences of factors like a community's cumulative poverty were inextricably confounded with measures of academic performance. Under NCLB, district and school staff were held accountable for the poverty of the communities they served. The model discussed here at least partially overcomes this problem.

It 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? NCLB's proficiency standards couldn't do that.

In addition to accounting for the variance that is largely beyond districts' control, more incidentally, the process can identify variables that *are* under districts' control and are predictive of higher or lower effectiveness rates. For example, this process has shown that on average, virtual programs depress postsecondary enrollment rates. Identifying and

[3] References to the amount of variance explained are to the adjusted r-squared. A model that has an adjusted r-squared of zero isn't explaining any of the variation in the dependent variable, while a model with an adjusted r-squared of one is explaining all of it.

quantifying the variables that influence effectiveness rates can help inform district and state educational decisions and policies.

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.[4]

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. This suggested that cumulative poverty might be a developmental driver of disability status as well as a driver of student mobility.

Also significant was the way the predictors of academic performance were identified: practitioners from the field worked with KSDE staff and researchers to identify the factors driving lower academic performance. Then KSDE staff constructed variables to test practitioners' hypotheses and move the conversation a step closer to possible causes.

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[4] 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 probably 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 derived from the KLN workgroup's interpretation of ESSA. The formula identified Comprehensive Support and Improvement (CSI) schools, as is required by ESSA. The identified schools were urban schools with high levels of cumulative poverty and low levels of academic achievement.

The model also served a second purpose. It 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. I standardized the residuals by dividing them by the standard error of the estimate. The results gave a measure of schools' academic achievement *after* risk factors like cumulative poverty were accounted for. They also coincided with debates in the legislature and before the State supreme court about school funding. They provided an alternative approach to more crude measures of school performance.

The First Model Predicting Effectiveness Rates

In accord with the Board and KSDE's new goals, leadership asked me to apply the risk factors developed with the KLN workgroup to a new dependent variable, the district effectiveness rates. Using the same measures 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: the proportion of Students with Disabilities, the proportion of mobile students, and cumulative poverty, which again, was strongly significant, somewhere beyond the 0.001 level. Notably, the proportion of Students with Disabilities was a significant predictor of post-secondary enrollment in addition to cumulative poverty. It was not when the dependent variable was school academic performance.

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, the average district loses about 17 effectiveness points due to cumulative poverty (43 * 0.404 = 17.4).

When I removed cumulative poverty from this model, the model got weaker. The adjusted r-squared, the explained variance, 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. Cumulative poverty is a very important predictor of student outcomes, one that strongly influences several factors.

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 paper 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 non-significant independent variables. 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 general district descriptors constructed from whole district populations, to descriptors constructed from the five cohorts used to calculate 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. The two can be separated, too, by removing the mobility cases from the school transition totals.

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.[5] 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).

[5] 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.

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.

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 the independent variables used in the first model and 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 some influence, like chronic absenteeism, the percentage of new teachers, and the expulsion and suspension rates, does the model discourage districts from addressing these problems?

Should the model be applied at the school level? If so, what is the appropriate multilevel statistical model? Which variables should be regarded as having fixed and which as having random effects?

Tentative Performance Categories

The categories below are somewhat arbitrary because we are dealing with a normal curve and a continuous distribution vertical and somewhat perpendicular to the predicted effectiveness line. KSDE staff have discussed the performance levels based on the standardized residuals but no decisions have been made. For example:

- *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.

Should KSDE report these relative performance levels or leave them informally calculated by the districts themselves?

Data Preparation for the Third, Current Model

Student Longitudinal Records

I combined the audited enrollment records (ENR) from 2006 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 may be 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. In order to have more accurate estimates of mobility and chronic absence, and to have a second source to check the accuracy of student categories like Students with Disabilities, or students qualified for free lunch, I merged the ENR and EOY records by student ID, year, and the accountability school.

Before merging the EOY and ENR records, I created consistent categorical variables for students with disabilities, federal ethnic classifications, free or reduced or paid lunch status, EL classifications, including monitored, and virtual categories. I labeled each record so I could distinguish its source as ENR or EOY.

In order to merge the student records, duplicates had to be removed. When possible, I assigned responsible buildings to 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.

I then sorted records by student ID, year, accountability school, grade, and the date the records were uploaded to KSDE. I checked for duplicate records based on student ID, year, and accountability building. I then removed duplicate records, keeping the most recently uploaded record. This removed 686 records from the EOY files and 1,969 from the ENR records. Since these records spanned 2006 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.

Note that 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.

Should the audited ENR and the EOY records be merged? If so, how should student records without Accountability School Identifiers be treated?

Due to high error rates, I removed the first year of longitudinal student records, 2006.

If grade was missing from the EOY record but available in the ENR record, I assigned the record 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, I removed the records that were not graded (NG) and the pre-Kindergarten grades. After sorting the records by student

ID, year, load date, and accountability building, I assigned individual record numbers so that each student's longitudinal records had an ordered sequence number. The maximum number of records for an individual student was 32.

Independent Variables

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

Virtual Students

Though the current model and the benchmarks requested by leadership exclude virtual students as an independent variable, I anticipate that there may be subsequent questions from leadership or the Board asking to quantify the influence virtual programs have on district effectiveness rates. District leaders would also want to know if virtual programs were predictive of lower postsecondary enrollments. While it will not be included in the current model, I prepared this variable in order to make this information available.

If a student was identified as a current virtual student in the EOY or ENR records (Virtual Education Student = 1), I assigned that record a value of 1 in a new column called *virtual_r*. If the student was not a virtual student in the EOY or ENR records, but had been during the year (Virtual Education Student = 2), I assigned that record a value of 0.5 in the same column, *virtual_r*. If the records were in conflict, I selected the higher value. Records of students declared as being virtual students in at least one AP class (Virtual Education Student = 3), were ignored.

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 (Brooks-Gunn & Markman, 2005; Luby, et al., 2013; Noble, Houston, Kan, & Sowell, 2012).[6] These better measures of developmental stressors are not currently available. The

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[6] 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.,

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 was able to compare 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 year counts are truncated in the same way for all districts, so 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

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Babb, C., Nishino, T., & Barch, D., (2013). The effects of poverty on childhood brain development. *JAMA Pediatrics*, 169 (10), 938-946.

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) . . . ”

What is different about the chronic absence definition currently applied in the calculation of the predicted effectiveness rates? The KLN workgroup defined chronically absent students as those missing 10 days or more across all schools attended in a school year.

This definition may have an advantage over the federal definitions. Absences 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 number of lost days was 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.

Is there evidence to support absentee policies that are customized by students’ age, grade, or school level?

Absence rates are comparatively low for primary and middle schools, but higher for high school students. Across all schools and all years, the mean number of lost school days was 8 with a median of 5.5. On average, 5th graders across all years 2007 through 2016, missed 6.7 days per year (sd = 7), with a median of 5 days. Eleventh graders on average missed 11 days per year (sd = 13.7) with a median of 7 days.

It might be helpful to consider what the chronic absenteeism measure is supposed to do. If it is for early identification of problems and prevention, then a rule-making group may want to create a definition that is slightly greater than average or median absence rates at student grade or age bands. It may want to consider cumulative measures of absence. If the purpose is to identify schools or districts with the most severe levels of chronic absence, then rule-makers may want to consider district and building absence and cumulative absence distributions and how these distributions vary for elementary, middle, and high schools.

KSDE could have different chronic absence measures for different purposes—some for early warning systems, others for school or district accountability.

Whatever definition or definitions are chosen, KSDE may want to produce longitudinal versions of cumulative absence at the individual, school, and district levels. If we believe learning is hierarchical, with one skill building on another, and that missing school is like putting holes in this complex scaffolding, that chronic absence may create a cumulative deficit that should be repaired, then it makes sense to calculate chronic absenteeism as a cumulative quantity that is carried forward.

For the purposes calculating the predicted effectiveness benchmarks, how should chronic absence be calculated?

Should there be cumulative versions of absenteeism?

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 I had attached to each student record 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. In other words, 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 students. I multiplied the resulting ratios by 100, converting them into percentages. For the five cohorts, this produced these variables:

virtualrate: the percentage of students' years spent as virtual students.
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 may be improved, one that did not occur to me while I was preparing the data. 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. 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 disciplining 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 puts into the measure, 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 and hope for some improved accuracy.

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.[7] Domestic studies also note the high costs of teacher turnover and use teacher mover and leaver rates as measures.[8]

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[7] 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.

[8] 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. Recall that when we were filtering the student level data so that it contained only the five freshmen cohorts, we identified the schools the five cohorts were attending from 2008 through 2015. Before aggregating, we add dataset X to the teacher dataset and select only those schools in which the five freshmen cohorts attended.

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

We now have eight independent variables:

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.

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

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

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[9] = 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.

[9] 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.

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 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 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.

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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. They describe the average accredited district and the spread around each of the measures.

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. Some analysts would suggest that unless we have a strong theoretical reason for continuing to include them, these non-significant variables should be dropped from future models to reduce noise.

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.

The Model with Virtual Included in a Stepwise Regression

To see the relative influence the independent variables have on effectiveness rates, I ran a stepwise regression.[10] I included the measure of time as a virtual student. We are not generating the predictive benchmark in this procedure, so we can use it to quantify the influence virtual status has on district effectiveness rates.

In Table 9 below, we see that cumulative poverty explains 43 percent of the variance, the proportion of time as virtual students another 7 points, mobility a little more than 2 points, and expulsion and suspension, and chronic absence, about 1 point each. Adding the virtual measure increased the explanatory power of the model about 4 points more

[10] The stepwise criteria were: probability of F to enter < or = 0.05; probability of F to remove > or = 0.1.

than our official model. Virtual status is controlled by districts, so this is news districts with or considering a virtual program will want to have. It is also news the State Board and KSDE leadership may want to inform policies. Tables 4 and 9 also provide evidence that virtual status depresses district effectiveness rates.

Table 9

Stepwise Regression Model Summaries [b]

Model	Predictors Entered in Order of Their Influence on Effectiveness Rates	Adjusted R Square	Std. Error of the Estimate
1	(Constant), proportion of years students in poverty status	0.432	7.46
2	(Constant), proportion of years students in poverty status, proportion of years students in virtual status	0.501	6.99
3	(Constant), proportion of years students in poverty status, proportion of years students in virtual status, cumulative rate of mobility	0.524	6.82
4	(Constant), proportion of years students in poverty status, proportion of years students in virtual status, cumulative rate of mobility, expulsion & suspension rate based on 2012 thru 2015 counts	0.535	6.74
5	(Constant), proportion of years students in poverty status, proportion of years students in virtual status, cumulative rate of mobility, expulsion & suspension rate based on 2012 thru 2015 counts, chronic absence rate based on total number of years attended	0.544	6.68

dependent variable: effectiveness rates

How much do virtual programs depress district effectiveness rates? The stepwise coefficients in Table 10 below quantify virtual programs' average effect.

Table 10						
Coefficients for Five Models from Stepwise Regression						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	64.069	1.313		48.778	0.000
	proportion of years students in poverty status	-0.537	0.036	-0.659	-14.756	0.000
2	(Constant)	64.896	1.238		52.402	0.000
	proportion of years students in poverty status	-0.535	0.034	-0.656	-15.678	0.000
	proportion of years students in virtual status	-1.410	0.223	-0.265	-6.330	0.000
3	(Constant)	65.833	1.233		53.411	0.000
	proportion of years students in poverty status	-0.491	0.035	-0.602	-13.921	0.000
	proportion of years students in virtual status	-1.196	0.224	-0.225	-5.333	0.000
	cumulative rate of mobility for 5 yr cohorts	-0.590	0.152	-0.173	-3.883	0.000
4	(Constant)	65.925	1.218		54.104	0.000
	proportion of years students in poverty status	-0.466	0.036	-0.571	-12.950	0.000
	proportion of years students in virtual status	-1.201	0.222	-0.226	-5.417	0.000
	cumulative rate of mobility for 5 yr cohorts	-0.587	0.150	-0.172	-3.910	0.000
	expulsion & suspension rate based on 2012 thru 2015 counts	-0.199	0.071	-0.117	-2.789	0.006
5	(Constant)	68.961	1.697		40.633	0.000
	proportion of years students in poverty status	-0.434	0.038	-0.533	-11.523	0.000
	proportion of years students in virtual status	-1.139	0.221	-0.214	-5.159	0.000
	cumulative rate of mobility for 5 yr cohorts	-0.562	0.149	-0.165	-3.774	0.000
	expulsion & suspension rate based on 2012 thru 2015 counts	-0.192	0.071	-0.113	-2.721	0.007
	chronic absence rate based on total number of years attended	-0.141	0.055	-0.111	-2.544	0.012
dependent variable: effectiveness rates						

In the fifth model at the bottom of Table 10 we see that on average, for every point increase in the virtual measure, we can expect effectiveness rates to decline a little more than a point. Very few districts have virtual programs, but for those that do, this data suggests that virtual programs are not in the best long-term interest of students.

Unresolved Problems

What criteria should decide which risks are under districts' control?

When KSDE uses factors like cumulative poverty as independent predictors of effectiveness rates, KSDE is saying that cumulative poverty is not under district control, that it should be accounted for *before* examining differences in district performance. In contrast, we know that student time spent in a virtual program is predictive of lower effectiveness rates, but KSDE excludes it from its predictive equations because virtual programs *are* under the control of districts.

What criteria does KSDE have to decide which factors to include and which to exclude? Some factors, like expulsion and suspension rates, the percentage of new teachers, and chronic absenteeism, are partially under the control of districts, but our model treats them as though they were exclusively outside the control of districts.

Frequently Asked Questions

How does regression distinguish between poverty and other factors when we are using them as explanatory variables?

The answer has to do with how multiple regression works.

Let's use our the district effectiveness rates as an example. We have several variables that district personnel identified as risk factors to academic performance, and other student outcomes like postsecondary enrollment.

Among the risk factors the field identified were these:

1. The proportion of Students with Disabilities
2. The proportion of English Learners
3. The student mobility rate
4. The cumulative poverty of students
5. Expulsion and Suspension Rates
6. The percentage of new teachers
7. Chronic absenteeism

Multiple regression measures how much districts vary in their effectiveness rates. Our goal is to explain what factors best explain that variation in effectiveness rates.

When we enter our independent variables, the risk factors above, all at once into a simple, linear multiple regression procedure, each of the independent variables is assessed as though it had been entered last, after all the other variables. The goal is to explain as much of the variation in districts' effectiveness rates as possible. Cumulative poverty explains the largest portion of districts' variation in effectiveness rates, about 43 percent.

It is a very powerful predictor. Once cumulative poverty has explained this 43 percent of the variance in effectiveness rates, the next most powerful variable is student mobility (we've excluded the virtual measure from this procedure), followed by chronic absenteeism, and finally expulsion and suspension rates. Together, they explain 50 percent of districts' variation in effectiveness rates. Once these stronger variables are entered into the equation, the other variables have no power to explain any more of the variation in effectiveness rates. The proportions of Students with Disabilities, of students who are English Learners, the percentage of new teachers, are not significant.

If we remove cumulative poverty from the equation, however, the situation changes. First, our explanatory power goes down. The remaining variables only explain 39 percent of districts' variation in effectiveness rates, so our equation is weaker. But all the remaining variables, except the percentage of new teachers, become strongly significant. We can think of them as proxies or substitutes for the missing measure of cumulative poverty or as confounded with it. This picture fits with what we know about the developmental risks associated with poverty, especially poverty in early childhood and the risks it poses to optimum brain and language development.

Why use the proportion of time students spend in poverty rather than if they are low-income when they graduated?

By using proportions of students' time in one condition or another, we get measures that more closely approximate students' developmental risks. More time spent in poverty or with a disability means more exposure to the risks associated with poverty and disability. If we were only to measure exposure to poverty or disability at a single point in time, we hide these differences in exposures to developmental risks. Students who, at the time of the data snapshot, were briefly classified as low-income or having a disability, are given weight equal to other students who may have been exposed to the risks associated with poverty or disability for their entire lives.

Does your model assume that half the variation in district effectiveness rates is under the control of the districts?

No, but it does assume that some unknown amount of the unexplained variance is under the control of districts. It also assumes that there are things districts and schools can do to improve effectiveness rates despite the factors, like community and family poverty, that districts don't control. Rather than confound community and family poverty with school performance, like No Child Left Behind did, our models account for poverty and other risk factors largely beyond district control. It's not perfect, but the unexplained variation in effectiveness rates is more likely to reflect things districts do control.

We also know that despite poverty, programs like high-quality early child care can greatly reduce the damaging impact and risks associated with poverty. We also believe and hope to prove, that strong programs in Individual Plans of Study, and collaboration with higher education and business communities, and integrated, hands-on curricula will also improve students' postsecondary enrollments and employment, despite high poverty.

Will KSDE add other factors to its model in the future?

Eventually, KSDE hopes to measure the influence district programs and interventions are having on effectiveness rates. Those that are under the control of districts, like the quality of districts' Individual Plans of Instruction, we hope to quantify, and identify which IPS configurations are most effective, and how effective they are. But factors that are under district control probably won't be used in the regression equations that generate the benchmark, the predicted effectiveness rates. We want the factors that are under district control to show the differences they make after other factors, like cumulative poverty, are accounted for.