Educational Considerations

Volume 35 | Number 2 Article 4

4-1-2008

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Explaining the Relationship Between Resources and Student Achievement: A Methodological Comparison of Production Functions and Canonical Analysis[1]

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What is the relationship between inputs to education and student achievement? The elusive answer to this seemingly self-evident question has led some to characterize the question as the "holy grail" of school finance research for the past thirty years.[2] Previous attempts to answer this important research question have relied primarily on the use of education production functions. Although the reliance on this method has led to mixed results, the literature base reveals that recent studies have shown a positive, robust relationship between inputs to schooling and measures of student achievement.[3] These studies examine not just dollar inputs to schooling, but what those dollars purchased, such as teacher characteristics, class sizes, curriculum, technology, and facilities. Monk notes that one way to combat inconsistent results in production function studies is for researchers to conduct separate studies using different data, methodological designs, and statistical techniques that may confirm previous results.[4] He postulates that the use of the education production function is flawed because this methodology only relates to education productivity in a marginal way. The use of a single output is an inadequate description of the production relation that may exist in a school given the multiple dimensions of schooling.

Toward that end, an emerging body of literature has begun to examine the relationship between resources for education and measures of student achievement by making use of multiple dependent measures. Schwartz, Stiefel and Hadj made use of cost functions to measure the performance of elementary, middle and high schools in Ohio over a three year period to discern the minimum cost of producing a bundle of outputs given a particular technology and the price of inputs.[5] Their analysis revealed a positive relationship between input prices and costs but no relationship between school-level pass rates and funding. Similarly, Rubenstein made use of multiple output variables to assess school efficiency using a methodology entitled data envelopment analysis (DEA).[6] DEA is a linear programming technique that makes use of a nonparametric efficiency frontier that includes all decision making units in the sample. Using this method of analysis, the researcher found groups of schools that were performing better than would be expected given the composition of their population (efficient schools) that he identified for further research. Although not employed in the extant research, canonical analysis is another methodology that may be used to study the relationship between two sets of variables.[7]

This study compared the results from an education production function with those found using canonical analysis. The purpose of this study was to examine the utility of canonical analysis by policymakers. By examining differing methodologies, conclusions may be drawn with regard to efficiency. Educational efficiency is concerned with the use of scarce resources. It is defined as the amount of knowledge "delivered to" and "acquired by" students given a specific set of resources.[8]

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Education Production Functions

Previous attempts to find a relationship between resources and student achievement have relied primarily on education production functions. The production function is a statistical technique that describes the maximum level of outcome possible from different combinations of inputs. The existence of a production function infers that there is something systematic about the transformation of inputs into outcomes.[9] Previous studies have made use of inputs such as resources, organizational characteristics, and student attributes while outputs have included measures of student achievement. These output measures may take the form of level scores, gain scores, or difference scores.[10] For the purpose of practice, knowledge of the process through which inputs are transformed to educational outputs would assist educational leaders and policymakers to make more accurate assessments of efficiency.

Multiple Regression

An example of a production function that utilizes a statistical technique to analyze the relationship between school resources and student learning is multiple regression analysis. This analysis includes two distinct purposes, *correlation* and *regression*, even though the terms are used interchangeably. First, regression analysis is a technique to find the relationship between one dependent variable and two or more independent variables, which is multiple correlation.[11] A second purpose is to predict future outcomes based upon analyzing an outcome measure from several independent variables. Both purposes can be utilized in interpreting the outcomes when multiple regression is used as a technique to analyze production function data.[12]

One use of multiple regression in education is to explain student learning based upon inputs found in school settings.[13] Cohen and Cohen suggest that as "the number of potential causal factors increase, their representation in measures becomes increasingly uncertain, and weak theories abound and compete."[14] Thus, explaining student learning is a difficult task, and most of the schooling variables are not well-defined. Nonetheless, one might consider years of teaching experience (EXP), amount of funds spent on instruction (FUNDS) or the number of students on free and reduced lunches (FREE) as inputs to account for the variation in student achievement. In a research design using multiple regression, student achievement (SA) can be the dependent variable (Y) and the independent variables (X_i) are the inputs to account for the variance in Y. Given the variables just mentioned, the

Published by New Prairie Press, 2017

multiple regression equation becomes:

$$Y = a + B_1X_1 + B_2X_2 + B_3X_3$$

or

$$SA = a + B_1EXP_1 + B_2FUNDS_2 + B_3FREE_3.$$

$B_1 \ldots B_3$ are regression coefficients, and when they are standardized, the relative explanatory power of the independent variables can be compared.

Another important output from multiple regression analysis is the correlation between the independent variables and the dependent variable, which is known as the squared multiple correlation coefficient (R^2) and indicates the amount of variance in the dependent measure accounted for by the independent variables. Thus, in the case in the preceding paragraph, the amount of variance in student achievement can be estimated from the effects of teaching experience, instructional funding, and number of students on free and reduced lunches.

Although outputs from regression analysis may be important, there are conditions that must be met to interpret the analysis results with some certainty. For example, most authors agree that it is important to have the appropriate cases to independent variables, absence of multicollinearity and singularity, and normality and linearity.[15] Thus, the above conditions must be analyzed before attempting to interpret the regression coefficients and multiple correlation.

Criticism of Production Function Studies

Education production formulas, also known as input-output or cost-quality analyses, were highlighted in the 1966 publication, *Equality of Educational Opportunity*, or the "Coleman" Report. This report attempted to ascertain the amount of inequality in America's schools. While attempts had been made previously to determine this information, no other studies went into as much depth as the Coleman Report nor did they have as far reaching an impact. Succinctly stated, the Coleman Report found that families, and to a lesser extent peers, are the primary determinants of variations found in student performance rather than educational inputs.[16] These results have been controversial, and some scholars have found methodological flaws in the analysis. Numerous studies have followed to attempt to find more evidence supporting the relationship between inputs to schooling and student achievement with Effective Schools research heralding a shift in thinking only to be followed by several well-designed small scale studies that found positive relations for specific resource inputs e.g. class sizes, quality preschool, and quality teachers.[17]

Although the use of education production functions has been prevalent in the research concerning the relationship between resource inputs into schooling and student performance, it has been argued that the use of this method of analysis is limited and that education production functions relate to productivity only in a marginal way.[18] The method of analysis is limited in part because it attempts to link the use of inputs to one measure of output: primarily minimum competency test scores.[19] As such, the use of this method provides a poor estimate of the efficiency with which resources are transformed in to student achievement measures. Further, researchers contend that the use of a single output measure is an inadequate description of the production relation that may exist in a school given the multiple dimensions of schooling and multiple goals and objectives.

Another issue is that the use of the education production function has led to apparently different conclusions using the same set of data. For example, Hanushek[20] and Hedges, Laine and Greenwald[21] report entirely different conclusions as to the effect of increasing funding for public education from the same set of data. Citing 187 "qualified" studies of both single and multiple districts that made use of education production functions, Hanushek concluded that there is no "systematic" relationship between expenditures and student performance.[22] As a result, he finds, educational policy should not be formulated solely on the basis of expenditures. Conversely, Hedges, Laine, and Greenwald reanalyzed the data finding fundamental flaws in the research design used by Hanushek while reaching a decidedly different conclusion.[23] The basic argument is that the method of analysis used by Hanushek, vote counting, is problematic when used as a procedure that would enable a researcher to make inferences and that Hanushek uses both significant and insignificant results to reach conclusions. Instead, Hedges, Laine, and Greenwald made use of two forms of meta-analytic techniques to ascertain the effect on student performance of a change in resources made available to schools. Their findings show strong support for resource inputs on student achievement.

Monk addresses the issue of the lack of systematic evidence from production functions. He notes that one possibility for this finding is that there may actually be multiple education production functions at work.[24] Perhaps the transformation of inputs to outputs changes based on gender, ethnicity, or subject taught. As such, regularities in the relationship between inputs to schooling and output measures of schooling will only be found when conditions are "so circumscribed that only unique events are captured."[25]

Canonical Analysis

Although not frequently employed in the extant research, another methodology that can accommodate multiple inputs and outputs of schooling that is used in this research, canonical analysis, is designed to study the relationship between two sets of variables.[26] Conceptually, canonical analysis and multiple regression are similar in terms of purpose and assumptions. The two methodologies differ in that canonical analysis enables the researcher to include multiple dependent measures. According to Thompson, a multivariate method of analysis can better simulate the reality from which the researcher is making generalizations.[27] Because researchers care about multiple outcomes, and because outcomes are the result of myriad factors, the chosen method of analysis must honor the researcher's view of reality otherwise there will be a distortion of results.[28] Canonical analysis is a multivariate method of analysis that subsumes other parametric techniques such as t-tests, analysis of variance, regression, and discriminant analysis.[29] This method of analysis prevents the researcher from discarding the variance of any variable and it allows one to portray a more accurate picture of reality.[30]

In canonical analysis, two linear combinations are formed, one of the predictor variables and one of the criteria variables, by differentially weighting them so that the maximum possible relationship between them is obtained. These linear combinations are referred to as the canonical variates, and the relationship between the canonical variates is called the canonical correlation, R_c. The square of the canonical correlation, R_c^2, is an estimate of the variance shared by the two canonical variates. It is not an estimate of the variance shared between the predictors and criteria but rather of the linear combination of these variables.[31]

Like multiple regression, canonical analysis seeks a set of weights that will maximize a correlation coefficient. In fact, multiple regression

https://newprairiepress.org/edconsiderations/vol35/iss2/4
DOI: 10.4148/0146-9282.1188

may be considered to be subsumed under canonical analysis because when using only one dependent variable, canonical analysis is reduced to multiple regression. Unlike multiple regression, in which only the X's are differentially weighted, in canonical analysis both the X's and the Y's are differentially weighted. The formula for the linear combination of independent variables may be written as follows:

$$p=b_1y_1+b_2y_2+b_3y_3+b_4y_4+b_5y_5+b_6y_6+\ldots b_{nyn}$$

where p equals the linear combination of independent variables, b equals the standardized canonical coefficient. and y equals the variable. Similarly, the formula for the linear combination of dependent variables may be written as follows:

$$q=a_1x_1+a_2x_2+a_3x_3+a_4x_4+a_5x_5+a_6x_6+a_nxn$$

where q equals the linear combination of dependent variables, a_i equals the standardized canonical coefficient and x_i represents each of the dependent variables. Canonical correlation finds the relationship between p and q. After having obtained the maximum R_c in canonical analysis, additional R_c's are calculated, subject to the restriction that each succeeding pair of canonical variates of the X's and the Y's not be correlated with all the pairs of canonical variates that precede it. Like factor analysis and discriminant analysis, the first canonical correlation will probably not account for all of the variance in the data.[32]

In canonical analysis, the canonical correlations are calculated in descending order of magnitude, as in discriminant analysis. The first pair of linear combinations is the one that yields the highest R_c possible in a given data set. The second R_c is based on the linear combinations of predictor and criterion variables that are not correlated with the first pair and that yield the second largest R_c possible in the given data set. The same calculation follows for succeeding R_c's with the maximum number of R_c's extracted equal to the number of variables in the smaller set when $p \neq q$. A test of significance exists for each canonical correlation and for the total amount of variance accounted for in the two sets of variables. In addition to more scientific tests of significance, the literature suggests that canonical correlations that explain less than ten percent of the shared variance are considered to be not meaningful.[33]

Monk argues that chosen methodologies must accommodate for myriad contingencies.[34] Canonical correlation is most likely to be useful in situations where there is doubt that one variable can serve as a suitable criterion variable.[35] Therefore, by determining if a set of predictor variables correlates with a set of criterion variables, a clearer picture of the relationship between the X and Y variables may be found. It is for these reasons, that canonical analysis was the chosen method to examine the relationship between inputs to and outputs of schooling in this study.

Method and Results

The purpose of the study was two-fold. First, researchers sought to confirm the results from two analytic techniques, namely regression and canonical correlation. Second, by using a method of analysis that would accommodate multiple output measures, researchers sought to more fully explain the relationship between inputs to schooling and measures of student achievement. Toward that end, a comparison of results from multiple regression and canonical analysis are presented.

Table 1
Descriptive Statistics

Variable	Mean	Standard Deviation
LEP	.69	.933
FREERED	39.261	17.0040
SPED	11.257	3.5558
MAJMIN	98.07	3.79
PCTPD	98.39	8.305
MASTERS	76.93	9.419
AVE_YEARS_EXP	11.902	1.842
SPENDING	5,310.45	1,210.969
STRATIO	17.04	2.084
ST_COMP_RATIO	4.405	1.5209
CTBSLANG	50.06	10.618
KCCTWR	64.54	8.827
RETAINED	6.008	3.4737
DROUPOUT	2.973	1.693
COLLEGE	52.854	14.8040
MILITARY	2.873	1.8345
WORKFORCE	27.801	11.5170
VOCED	5.302	3.9005
PARTTIME	6.882	7.1589
FAILURE	3.769	2.9757
n =193		

Sampling and Participants

The choice of both independent and dependent variables was guided by a review of current literature. The study made use of school level data from the 2003–04 academic year. Data were collected from 193 high schools serving students in grades 9 through 12 across the Commonwealth of Kentucky. Descriptive statistics are displayed in Table 1.

Independent Variables

Stiefel, Schwartz, Rubenstein, and Zabel state that studies attempting to discern the relationship between resources and student achievement have included student demographics, resources, and organizational characteristics as independent variables.[36] By controlling for variables out of the control of the educational institution, such as student characteristics, efficiency measurements provide an opportunity to identify successful schools – especially schools where success may not be readily apparent. Measures of student attributes included in this study were, the percentage of students who received free and reduced lunch, the percentage of students who received special education services, and the percentage of students who received limited English proficiency services.

Current research has clearly identified the teacher as the single most important school-related input to improve student achievement.[37]

Researchers, economists, and policy makers have made use of education production functions in an attempt to determine the relationship between teacher quality and student achievement.[38] These studies employed measurable, policy-relevant variables to describe teacher quality such as teacher certification, performance on certification exams, years of experience, relationship of teaching assignment to college major, teacher education level and student-teacher ratio.[39] Accordingly, this study included multiple measures of teacher quality as inputs to schooling. Included in the list were percent of teachers with a major or minor in the content area taught, percent of teachers participating in professional development, education level of the teacher as measured by the percentage of teachers holding a masters degree, and average years of experience.

The input variable per pupil expenditure was included in this study. This variable is often included in input-output studies although findings are mixed.[40] The negative relationship found to exist between per pupil expenditure and student achievement is likely the result of the additional cost of educating students in underrepresented populations or those with disabilities. While the literature clearly shows that all students can learn at high levels, the cost of providing needed services may be influenced by student need, concentration of need, and school location.[41] Class size is an input variable that has been found to impact student achievement.[42] That variable was included in this study and was defined as the average number of students in each class in the school for each teacher.

Student-computer ratio was a final variable included in the study. Jones and Paolucci argue that the exponential increase in expenditures on technology in K-12 schools and institutions of higher education make this variable increasing important to researchers.[43] Further, the acquisition of skills in the use of technology is an area of focus of standards based reform as states have begun to incorporate technology in to the curriculum so that student transition from school to work may be enhanced.[44] Using data from NAEP testing, Wenglinsky examined the relationship between computer use and student achievement.[45] He found that the largest impact on student achievement was made by teachers who used technology to promote higher order thinking skills. Further, his study suggested that time spent working on school related work at home was related to student achievement thus raising the question of access to and availability of technology. This issue is important in Kentucky given the prevalence of poverty in the state and given the fact that students experiencing poverty have been shown to lag behind their more affluent peers in computer use.[46]

Dependent Variables

The 2004 Commonwealth Accountability Testing System (CATS) index was the dependent variable used in the multiple regression analysis. CATS recognizes the myriad purposes of education and makes use of multiple measures of student performance including the criterion referenced Kentucky Core Content Test (KCCT), a nationally norm-referenced test (e.g., the CTBS/5 Survey Edition), writing portfolios, and non-academic performance data (e.g., attendance, retention, and dropout rates; student transitions to next level of schooling and to adult life). Performance on each of these measures is differentially weighted to calculate a Kentucky Accountability Index for each school. Proficiency has been defined as an index score of 100. All schools are required to reach proficiency by 2014. CATS index scores are calculated yearly, although the system of sanctions and recognition operates on a biennial calendar.

To make the comparison between the multiple regression analysis and the canonical analysis unbiased, the components of the 2004 CATS index were used as the multiple dependent variables in the canonical analysis. Due to problems of multicollinearity, not all norm-referenced and criterion-referenced measures of student achievement could be used in the analysis. Researchers selected the norm-referenced test that had the smallest Pearson correlation with one of the criterion-referenced tests. This decision was made to preserve the integrity of the model because multicollinearity causes an inflated relationship in canonical analysis. The CTBS reading test was chosen as the norm-referenced test while the KCCT writing index was chosen as the criterion-referenced measure for inclusion in the canonical analysis. All non-academic measures of student achievement that comprise the CATS index were included in the canonical analysis. These measures included: percent of students retained, percent of students who were classified as dropouts, percent of students transitioning to college, percent of students entering the military, percent of students entering the workforce from high school, percent of students enrolling in vocational education, percent of students attending school part-time and working part-time, and percent of students who failed to make a successful transition following high school. Descriptive statistics appear in Table 1.

Guidelines for Interpretation

Sheskin[47] and Thompson[48] state the complexity of calculation coupled with the difficulty of interpretation of results has limited the use of canonical analysis. As such, a brief explanation of guidelines for interpretation is offered. First, the statistical significance of each canonical correlation is determined by a Wilk's test of significance. Interpretation of these results is similar to that of a Pearson correlation as one is interested in significance, size, and total variance explained by each relationship. The researcher retains any canonical correlations that are found to be statistically significant and proceeds to interpret any statistics (canonical loadings, standardized canonical coefficients, and cross loadings) that are associated with the canonical variates. Finally, the examination may include an inspection of redundancy. Unlike multiple regression which limits the interpretation of prediction to the relative importance of independent variables, three types of analysis are possible using canonical analysis. These include an interpretation of the relative importance of independent variables, an interpretation of the relative importance of dependent variables, and an interpretation of the relationship of individual variables with the linear combination of variables in the opposite set.

Both the standardized canonical coefficients and the canonical loadings provide the necessary information to discern the relative importance of independent and dependent variables. Standardized canonical coefficients are weights assigned to each variable so that the maximum possible Pearson correlation can be found between the canonical variates. The use of the standardized canonical coefficients is valuable since the coefficients are partial coefficients with the effect of the other variables removed.[49] Standardized canonical coefficients are interpreted in much the same way that one interprets a standardized regression coefficient in multiple regression.

The correlation between the canonical variate and the variable is called the canonical loading. The cross loading is the correlation between individual variables and the linear combination of the opposite set of variables. During each of these examinations, the researcher is interested in the largest (absolute value) coefficients or correlations that

https://newprairiepress.org/edconsiderations/vol35/iss2/4
DOI: 10.4148/0146-9282.1188

are used.[50] The literature reveals that an interpretation of the results of canonical analysis is strengthened by an examination of canonical loadings and cross loadings for two reasons. First, it is assumed that there is greater stability in the correlation statistic when there are high or fairly high intercorrelations among the variables and the sample is of small or medium size. Second, the correlations provide a clearer indication of which variables are most closely aligned with the canonical variate. The researcher is interested in these correlations since the canonical variate is an unobserved trait.[51] As a rule of thumb, canonical loadings and cross loadings that are greater than .30 should be treated as meaningful.[52]

Redundancy in canonical analysis is the proportion of the variance in the X's that are predicted from, or explained by the linear combination of Y's. Redundancy is typically only calculated for canonical variates from statistically significant canonical correlations and these calculations are made based on the research design.[53] When predictor and criterion variables are used, the redundancy calculation is only made for the criterion variables since one is interested in determining the proportion of the variance that is predictable. It is important to note that redundancy is not a measure of multivariate association and that this calculation will differ from the total amount of variance explained by the linear combination of variables.

Results of the Sequential Multiple Regression

A sequential multiple regression was performed using the 2004 CATS index as the dependent variable. Independent variables were entered in two blocks. The first block included student demographic data. Input variables in model 1 included the percent of students receiving services for limited English proficiency, the percent of students qualifying for free and reduced lunch, and the percent of students receiving services for special education. The second block of input variables included variables that were identified in the literature review that have been determined to have a relationship to student achievement. Those variables included percent of teachers holding a major or minor in the content area taught, percent of teachers who participated in professional development activities, percent of teachers holding an

Table 2

Multiple Regression Results

Table 2.1

Model	Variables Entered	R	R Square	R Square Change	F Change	Significance of Change
1	LEP, FREERED, SPED	.779	.607	.607	97.386	.000
2	LEP, FREERED, SPED, ST_COMP_RATIO, PCTPD, MAJMIN, MASTERS, STRATIO, AVE_YEARS_EXP, SPENDING	.801	.642	.035	2.525	.017

Table 2.2

		Unstandardized Coefficients		Standardized Coefficients		
Model	**Variables Entered**	**B**	**Std Error**	**Beta**	**Significance**	**Tolerance**
1	Constant	91.139	1.370			
	LEP	-.070	.203	-.016	.729	.990
	FREERED	-.300	.025	-.597	.000	.821
	SPED	-.748	.121	-.311	.000	.825
2	Constant	66.551	11.974			
	LEP	-.088	.203	-.020	.667	.931
	FREERED	-.295	.026	-.587	.000	.750
	SPED	-.733	.130	-.305	.000	.671
	MAJMIN	.236	.103	.105	.023	.948
	PCTPD	.039	.046	.038	.405	.968
	MASTERS	.104	.045	.114	.023	.787
	AVE_YEARS_EXP	.038	.241	.008	.874	.732
	SPENDING	-.001	.000	-.080	.156	.625
	STRATIO	-.464	.216	-.113	.033	.711
	ST_COMP_RATIO	-.058	.259	-.010	.823	.926

Table 3
Canonical Analysis Results with Demographic Student Data Input Only

Demographic Student Data Input	First Canonical Variate			Second Canonical Variate			Total
	Loading	Coefficient	Cross Loading	Loading	Coefficient	Cross Loading	
Inputs of Schooling:							
LEP	-.151	-.100	-.118	-.794	-.852	-.261	
FREERED	-.943	-.788	-.736	.248	.551	-.062	
SPED	-.679	-.356	-.530	-.325	-.576	.184	
Outputs of Schooling:							
CTBSREAD	.973	.968	.760	.072	.391	.024	
KCCTWR	.554	.075	.433	.040	.205	.013	
RETAINED	-.363	.210	-.283	-.347	-.428	-.114	
DROUPOUT	-.454	-.172	-.354	.126	.171	.042	
COLLEGE	.505	.072	.394	-.420	.350	-.138	
MILITARY	-.114	.043	-.089	.353	.294	.116	
WORKFORCE	-.489	.021	-.382	.421	.871	.139	
VOCED	-.261	-.023	-.203	-.210	.117	-.069	
PARTTIME	-.105	.027	-.082	.246	.423	.081	
FAILURE	-.312	.029	-.244	.568	.687	.187	
Canonical Correlation	.780			.329			
Wilk's (DF)	.321 (30)			.822 (18)			
Significance	.000			.007			
Percent of Variance	60.8			10.8			71.6
Redundancy	13.9			1.1			15.0

advanced degree (masters), average years of teaching experience, spending per pupil, student-teacher ratio, and student-computer ratio. Sequential multiple regression was the chosen method of analysis so that variance explained by student demographic could be separated from the variance explained by inputs to schooling so that efficiency conclusions could be drawn.

Results from the sequential multiple regression are presented in Table 2. According to those data, student demographics significantly predict student achievement in model 1, R^2=.607, R^2_{adj}=.601, F(3, 189)=97.386, p<.000. Model 1 accounted for 60.7% of the variance in student achievement as measured by the 2004 CATS index. Table 2 also displays the unstandardized regression coefficients (B), standardized regression coefficients (β), significance level of the regression coefficients, and tolerance for each independent variable. These data enable the researcher to discern which independent variables were significant predictors of student achievement. Individually, the independent variables percent of students receiving special education services (t=-6.193, p<.000) and percent of students receiving free and reduced lunch (t=-11.859, p<.000) significantly predicted student achievement in model 1 as measured by the 2004 CATS index. Measures of tolerance calculated in the model indicated that multicollinearity was not a problem. Model 2 in the sequential multiple regression was also found to be a significant predictor of student achievement, =.642, R^2_{adj}=.622, F(7, 182)=2.525, p<.017. Model 2 accounted for an additional 3.5% of the variance. Total variance explained in the regression analysis was 64.2% of the variance in student achievement. Input variables that were found to be significant predictors of student achievement in model 2 included percent of students receiving special education services

https://newprairiepress.org/edconsiderations/vol35/iss2/4
DOI: 10.4148/0146-9282.1188

(t=-5.628, p<.000), percent of students receiving free and reduced lunch (t=-11.466, p<.000), percent of teachers with a major or minor in the content area (t=2.295, p<.023), percent of teachers with an advanced degree (masters) (t=2.287, p<.023), and student-teacher ratio (t=-2.148, p<.033). Measures of tolerance revealed that multicolinearity was not a problem in the model.

Results of the Canonical Analysis

Unlike multiple regression, canonical analysis does not allow the researcher to control for covariance. In order to compare the results of the multiple regression analysis with the results from canonical analysis, two separate canonical analyses were calculated. Similar to model 1 in the multiple regression analysis, the only input variables included in the first canonical analysis were student demographics. The second canonical analysis included all input variables to detect any changes in the explained variance for the dependent variables. Results from the second canonical analysis were compared with model 2 in the multiple regression.

Results from the first canonical analysis are displayed in Table 3. Wilk's test of significance revealed that two canonical correlations computed in the first canonical analysis were significant (R_c=.780, Wilk's (30)=.321, p<.000; R_c=.329, Wilk's (18)=.822, p<.007, respectively). The first variate pair accounted for 60.8% of the total variance. The second variate pair accounted for 10.8% of the variance. Total pooled variance for this model is 71.6%. Using the aforementioned guidelines for interpretation, researchers identified independent variables that were deemed to be of importance, dependent variables that were deemed to be of importance, and interpreted the relationship between individual variables and the linear combination of the opposite set of variables. Independent variables that were deemed important in the first canonical variate included: the percentage of students receiving services for free and reduced lunch (*canonical coefficient*=-.788) and percentage of students receiving services for special education (*canonical coefficient*=-.356). Dependent variables that were deemed important in the first canonical variate included scores on the CTBS reading test (canonical coefficient=.968). An important relationship was found to exist between the independent variables percentage of students receiving services for free and reduced lunch (*canonical loading*=.736) and percentage of students receiving services for special education (*canonical loading*=.530) and the linear combination of dependent variables in the first canonical variate. Finally, an important relationship was found to exist between the dependent variables scores on the CTBS reading test (*canonical loading*=.760), scores on the KCCT writing test (*canonical loading*=.433), percentage of dropouts (canonical loading=-.354), percentage of students enrolling in a four year college (*canonical loading*=.394), and percentage of students entering the workforce (*canonical loading*=.382).

Results from the second canonical variate identified a third measure of student demographics as an important predictor of student achievement. In addition to the percentage of students receiving services for free and reduced lunch (*canonical coefficient*=-.852) and percentage of students receiving services for special education (*canonical coefficient*=.551), the percentage of students receiving services for limited English proficiency (*canonical coefficient*=-.576) was found to be of relative importance to the relationship between student demographics and measures of student achievement. Further, the second canonical variate identified additional dependent measures of importance. In addition to scores on the CTBS reading test (*canonical coefficient*=.391), percentage of students retained (*canonical coefficient*=-.428), percentage of students enrolling in a four year college or university (*canonical coefficient*=.350), percentage of students entering the workforce (*canonical coefficient*=.871), and percentage of students classified as working part time and attending school part time (*canonical coefficient*=.423) were identified as relatively important outputs of schooling. None of the cross loadings met the criteria of <.30 in the second canonical variate. As such, no additional important relationships were identified.

Results from the second canonical analysis are presented in Table 4. Wilk's test of significance revealed that two canonical correlations computed in the second canonical analysis were significant (R_c=.799, Wilk's (100)=.321, p<.000; R_c=.435, Wilk's (81)=.822, p<.017, respectively). The first variate pair accounted for 63.8% of the total variance. The second variate pair accounted for 18.9% of the variance. Total pooled variance for this model is 82.7%. Using the guidelines for interpretation, researchers identified independent variables that were deemed to be of importance, dependent variables that were deemed to be of importance, and interpreted the relationship between individual variables and the linear combination of the opposite set of variables. Independent variables that were deemed important in the first canonical variate included: the percentage of students receiving services for free and reduced lunch (*canonical coefficient*=.729) and percentage of students receiving services for special education (*canonical coefficient*=.352). Dependent variables that were deemed important in the first canonical variate included scores on the CTBS reading test (*canonical coefficient*=-.982). An important relationship was found to exist between the independent variables percentage of students receiving services for free and reduced lunch (*cross loading*=.703), percentage of students receiving services for special education (*cross loading*=.535), and spending per pupil (*cross loading*=.425) and the linear combination of dependent variables in the first canonical variate. Finally, an important relationship was found to exist between the dependent variables scores on the CTBS reading test (*cross loading*=-.786), scores on the KCCT writing test (*cross loading*=-.452), percentage of students retained (*cross loading*=.313), percentage of dropouts (*cross loading*=.332), percentage of students enrolling in a four year college (*cross loading*=-.385), and percentage of students entering the workforce (*cross loading*=.371).

Results from the second canonical variate identified four important input variables: percentage of students receiving services for limited English proficiency (*canonical coefficient*=-.650), percentage of teachers participating in content-focused professional development (*canonical coefficient*=.415), spending per pupil (*canonical coefficient*=-.479) and student teacher ratio (*canonical coefficient*=-.440). Further, the second canonical variate identified additional dependent measures of importance. In addition to scores on the CTBS reading test (*canonical coefficient*=.797), and percentage of students enrolling in a vocational school (*canonical coefficient*=.359) were identified as relatively important outputs of schooling. None of the cross loadings met the criteria of <.30 in the second canonical variate. As such, no additional important relationships were identified.

Discussion

The purpose of this study was to compare multiple regression with canonical analysis in order to introduce a new, policy relevant methodology to the literature on production functions. Findings from this study confirmed the results of past inquiries that found a relationship

Table 4
Canonical Analysis Results with All Input Variables

All Input Variables	First Canonical Variate			Second Canonical Variate			Total
	Loading	Coefficient	Cross Loading	Loading	Coefficient	Cross Loading	
Inputs of Schooling:							
LEP	.161	.109	.129	-.647	-.650	-.281	
FREERED	.913	.729	.703	.157	.272	.068	
SPED	.669	.352	.535	-.087	-.077	.038	
MAJMIN	-.253	-.092	-.202	-.181	-.186	-.079	
PCTPD	-.085	-.082	-.068	.337	.415	.146	
MASTERS	-.049	-.016	-.039	-.421	-.264	-.183	
AVE_YEARS_EXP	-.332	-.078	-.265	-.107	-.005	-.046	
SPENDING	.532	.140	.425	-.332	-.479	-.145	
STRATIO	-.304	.171	-.243	-.216	-.440	-.094	
ST_COMP_RATIO	-.071	-.036	-.056	-.125	-.039	-.054	
Outputs of Schooling:							
CTBSREAD	-.983	-.982	-.786	.068	.748	.030	
KCCTWR	-.566	-.100	-.452	-.196	-.059	-.085	
RETAINED	.392	-.153	.313	-.239	-.240	-.104	
DROUPOUT	.415	.103	.332	.210	.295	.091	
COLLEGE	-.482	-.058	-.385	-.668	-.169	-.291	
MILITARY	.108	-.040	.086	.243	.193	.106	
WORKFORCE	.465	-.050	.371	.628	.797	.273	
VOCED	.267	.023	.214	.149	.359	.065	
PARTTIME	.102	-.024	.081	.178	.180	.078	
FAILURE	.303	-.030	.242	.254	.284	.110	
Canonical Correlation	.799			.435			
Wilk's (DF)	.197 (100)			.544 (81)			
Significance	.000			.017			
Percent of Variance	63.8			18.9			82.7
Redundancy	14.4			2.2			16.6

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DOI: 10.4148/0146-9282.1188

between the inputs to schooling and measures of student achievement. A statistically significant relationship was found to exist through the use of canonical analysis. For the purpose of this discussion, we focus on the findings from the second canonical analysis. That model made use of ten independent variables and ten dependent measures of student achievement. Two of the ten canonical correlations calculated revealed a statistically significant relationship. Together, the pooled variance explained 82.7% of the variance between inputs to schooling and measures of student achievement. By using multiple measures of student achievement, the chosen method of analysis enabled researchers to explain a greater percentage of variance than was explained through the use of multiple regression. As suggested in the literature review, schools produce multiple outcomes; therefore the selection of a method of analysis that allowed for the interaction of all of those variables in a linear combination of output variables allowed researchers to more fully explain the relationship between inputs to schooling and measures of student achievement.

The use of canonical analysis confirmed that student demographics, as identified in the multiple regression, are significant predictors of student achievement. Because interpretations of canonical loadings, standardized canonical coefficients, and cross loadings make use of absolute values conclusions with regard to the direction of the relationship are not possible. The method of analysis enabled the identification of all three measures of student demographics as important. Through the use of multiple regression, limited English proficiency (LEP) was not identified as a significant predictor of student achievement even though policy implications about LEP abound. Given the small percentage of students identified as limited English proficiency in the Commonwealth of Kentucky, the finding of a relationship is significant and has policy implications. The use of canonical analysis has allowed for the interaction of multiple outputs of schooling and therefore aided in the identification of an area for further research and intervention.

Aside from measures of student demographics, multiple input resources were found to be significant predictors of student achievement through the use of canonical analysis. The multiple regression analysis identified the variables major or minor in the content area, education level of teachers (master's degree) and student teacher ratio as significant predictors of student achievement. By using canonical analysis, researchers found that spending per pupil, student-teacher ratio, and percent of teachers participating in content focused professional development were significant predictors of student achievement. Professional development is not a variable that has been found to be a significant predictor of student achievement in the literature. This study has identified that variable as are area of future inquiry. Most importantly, this study clearly links the input resources with measures of student achievement making this method of analysis a viable method for the study of resource efficiency.

The main difference between multiple regression and canonical analysis is that the researcher may make use of multiple dependent measures. Because schools produce multiple outputs, it has been postulated that this method of analysis better enables the researcher to simulate reality. The use of multiple output measures eliminates researcher bias. This methodology does not require the researcher to choose one independent measure. Results from this study indicated that the most important output of schooling, given the ten dependent measures, was reading. The identification of literacy as the predominant output of schools has tremendous policy implications when one considers state and national goals with regard to access to and completion rates of higher education to drive the economy. Further, the identification of workforce entry and percentage of students enrolling in vocational schools as important outputs of schooling is noteworthy in a time of standards based reform. Without casting dispersions on the current movement of educational reform, it is undeniable that the focus on standards and student achievement as measured by standardized testing may have disillusioned students from pursuing these interests. The production of academic skills has been the priority of public schools of late. As such, schools have had to cut back on programs such as vocational education and tech prep. These findings suggest that schools produce more than just academic results and that a focus on vocational programs has merit in our high schools so long as the proper counseling is provided to students with regard to life opportunity and so that students are not categorized and tracked based on ethnicity or socioeconomic status. All children must be afforded the equal opportunity to pursue their own educational and occupational goals.

Results from this study are important for both policymakers and practitioners because they suggest the need for an alignment of educational practice. Schools make use of a variety of resources to achieve multiple goals. The realization of these sometimes competing goals requires an educational leader with the vision, knowledge dispositions, and leadership skills to align the school mission with research based educational best practice in order to maximize student achievement, however that is defined. Schools cannot afford to focus their energies on one specific goal or one subpopulation in the entire student body. Current educational policy that requires proficiency for all coupled with the realities of globalization and increased international competition necessitate a rethinking of the focus and leadership of schools. Empirical research must include these multiple contingencies to help inform practice. Canonical analysis is one method with the potential to do that.

A limitation of this study was that data were aggregated to the school level and included merely one year's worth of data. While acknowledging the limitations of this data set, this study has identified canonical analysis as a methodology that more fully explains the relationship between input resources to schooling and multiple output measures. We envision an extension of this study wherein a canonical correlation is calculated for each individual school. The myriad of ways by which results from canonical analysis may be interpreted enable the researcher to examine not just important inputs to schooling but also to identify the outputs of importance at each school and the interaction of all variables. The ability to examine the outputs of schools has merit given current educational policy. With proficiency goals looming by 2014 for both state and national education policy, canonical analysis may identify the need to change both focus and practice at the school level so that policy goals of social justice may be obtained. We envision the these results being useful by policymakers and educational leaders who must confront the belief systems of practitioners with regard to what and how much students from different socioeconomic and ethnic groups can learn.

The redundancy statistic is included in the analysis to temper the size of the relationship that was found in this study. The research clearly states that the redundancy statistic is not to be used as an analytical technique. For the purposes of this study, the redundancy statistic demonstrates that the predictive model presented in this study can be used to discern the relationship between inputs to schooling and measures of student achievement. Total redundancy in the model was 16.6% which suggests that the inputs utilized in this study are predictors of student achievement. Moreover, it suggests that the model has not accounted for all factors that are present in the relationship between inputs to schooling and measures of student achievement. In examining the relationship between measures of teacher quality and student achievement, Rice notes that the research has been limited to policy relevant, measurable variables.[54] Results from this study suggest the need for more and better variables at the classroom level that more fully capture the process of teaching and learning. Not only do we as researchers need better sets of data that disaggregate data at the classroom level, we need to develop better tools to measure student-teacher interaction, communication, teacher reflection, and the use of assessment measures in the educational process. By more fully capturing the ability to measure the educational process, research becomes more relevant for educational leaders who seek to maximize student achievement.

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DOI: 10.4148/0146-9282.1188