DOCUMENT RESUME

ED 102 197 TM 004 252

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TITLE Towards a Model of Teacher Behavior and Student Achievement.

PUB DATE [74]

NOTE 30p.

EDRS PRICE MF-$0.76 HC-$1.95 PLUS POSTAGE

DESCRIPTORS *Academic Achievement; *Educational Research; *Models; Multiple Regression Analysis; Participant Satisfaction; Prediction; *Statistical Analysis; *Teacher Behavior; Tests of Significance

IDENTIFIERS Variance Partitioning

ABSTRACT

Three procedures are examined that educational researchers can use to analyze quantitatively the extent to which modifications of specific teacher behaviors lead to changes in student achievement. The task requires decent descriptions of the behaviors, appropriate statistical tools and measures of student outcomes that are worth while examining. The data, collected in the course of an evaluation of the relationship between the organizational structure of schools and student achievement, is not entirely appropriate for the issues dealt with here. Therefore, paths are suggested that this research might take in the future: (1) it is possible, using multiple regression analysis, to construct models of teacher behavior that reflect the view that some set of teacher behaviors affect student outcomes, and (2) these models can be applied at least three distinct ways, depending on the kinds of assumptions that one is willing to make about the data and the kinds of questions that one wishes to address. (Author/RC)

TOWARDS A MODEL OF TEACHER BEHAVIOR AND STUDENT ACHIEVEMENT

by

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I. Introduction

In this paper we will examine three procedures that educational researchers can use to analyze quantitatively the extent to which modifications of specific teacher behaviors lead to changes in pupil achievement. This is not a simple task. It requires decent descriptions of the behaviors, appropriate statistical tools and measures of student outcomes that are worthwhile examining. Our data, collected in the course of an evaluation of the relationship between the organizational structure of schools and student achievement, is not entirely appropriate for the issues we wish to deal with in this paper. Therefore we can only suggest paths that this research might take in the future.

Our major arguments are as follows:

1. It is possible, using multiple regression analysis, to construct models of teacher behavior that reflect the view that some set of teacher behaviors affect student outcomes.

2. These models can be applied at least three distinct ways, depending on the kinds of assumptions that one is willing to make about the data and the kinds of questions that one wishes to address.

Following a brief description of the sample and measurement instruments we will examine each of these issues in turn.

II. Procedure

a) The Sample

The schools participating in our study are located in a suburban community. The school district is racially mixed (approximately 11% black) and represents a range of socio-economic backgrounds. As a consequence of *de facto* segregation, most of the schools are fairly homogeneous on both racial and social class indices.

A sample of 14 fifth grade classrooms was chosen from seven of the elementary schools in the district. The classes were selected to represent both a variety of social class backgrounds and the spectrum of classroom organizational styles. Questionnaires were administered to the students in these rooms on three occasions. The data for the analysis of student outcomes in year one is taken from the first two administrations of the questionnaires, September, 1971, and May, 1972. The analysis of the second year data uses the test scores collected in May, 1972, as pre-test measures and those collected in May, 1973, as post-test scores.

As with most longitudinal studies there was some attrition due to students moving out of the district, illness, etc. Our final sample (N=187) included only those students for whom there was complete data on all variables. Several equations were run with less stringent requirements, but they do not differ in any significant way from those reported in this paper.

b) The Measures[1]

i. Achievement

The achievement measure selected for use in this study was math. The arithmetic scale consists of 36 items from the CTBS tests of Computation, Concepts and Applications.

ii. Affective Outcomes

The current trend in the educational literature is to attend not only to the strictly cognitive outcomes of schooling, but to also consider

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[1]Other measures of cognitive and affective development were collected for use in the original study. They are not included in the present analysis.

outcomes that are more appropriately considered affective.

A measure of satisfaction with school, adapted from Brayfield and Rothe's (1951) Index of Job Satisfaction, was administered to the students. With appropriate modifications in the wording of the items, 8 of the original 18 items were included in the final scale. The others were deleted because of low factor loadings and/or the difficulty of translating the item from one context to another. A factor analysis indicated that the eight items loaded on a single factor.

iii. Teacher Behavior

A questionnaire, adapted from Schafer's (1965) Children's Report of Parent Behavior Inventory, was administered to the students to assess their perceptions of their teacher's behavior.[2] The adaptations consisted of deleting items that did not pertain to a classroom setting and changing the word "parent" to "teacher" in those items that were appropriate. Following a factor analysis of the first round of data, 34 items were retained for inclusion in the remaining administrations of the scale. Thirty of these items loaded on two factors that we call Carping Criticism (cf. Henry, 1963: 302ff.) and Warmth. The remaining four items constituted a third factor, Freedom or Autonomy. On the assumption that students would require some time to develop stable perceptions of their teacher's behavior, the measures of teacher behavior are derived from the May, 1972, administration of the Schafer scale year one and the May, 1973, administration for year two. Individual perceptions of teacher behavior were averaged over all students in a room; the resulting measure was used as a description of teacher behavior for that room.

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[2] In addition, student observers were trained in the use of Soar's (1966) schedule of teacher behavior. The observational data is not included in this analysis.

Schafer reports on the validity and reliability of the original scale. In our own analysis, the communality estimates from factor analysis serve as lower bound estimates of reliability and construct validity. The coefficients are comparable to those obtained in other studies that have used factor analysis as a means of validating instruments (e.g., Punch, 1967).

III. Devising an Appropriate Model

In general, theories about teacher effects state that teacher behavior affects the academic performance of students. From this very general view, we feel that the appropriate test of whether or not (or to what extent) teacher behavior does affect children is to consider a mixed level analysis: individual student background measures are examined in conjunction with aggregate measures of the classroom environment (teacher behavior) in the production of individual student outcomes.

Economists refer to the problems related to changing levels of analysis as problems of aggregation (when individuals or groups are lumped together) and dis-aggregation (when they are separated). In sociology, the seminal treatment of the problem appears to be Robinson's (1950) paper on "Ecological Correlations and the Behavior of Individuals." The authors of the OEO Report (Equality of Educational Opportunity) do not deal directly with the level of analysis issue. The design of their study, however, indicated an awareness of the need to employ multi-level models in the analysis of the schooling process. Coleman et al refer to the design as a "two level" regression analysis. We found no systematic treatment of the problem in the education literature; we are fairly certain that the particular methodological issue does not play a large part in the design and reporting of studies of teacher behavior.

The appropriate model, then, should describe much more than mean differences between rooms. It should also describe the effects of various dimensions of teacher behavior on individual student outcomes while at the same time considering the characteristics of the individual student. To do this requires a modelling technique capable of handling individual and classroom level variables simultaneously. Regression analysis, which is the most general form of the analysis of variance as commonly used in educational research, meets these specifications.

There are good reasons for researchers to be concerned with the unit of analysis issue--particularly the level of aggregation on the "output" side of the equation. First, multi-level analyses of the schooling process correspond to our general impressions of what the classroom teaching process is all about. Second, to study only classroom means is to invite misleading answers.

To illustrate the latter point we draw on a paper by Rosenshine and Furst (1971), "Research on Teacher Performance Criteria." In their attempt to synthesize some of the research on teacher effectiveness, the authors utilize the rubric "process-product" studies to describe ". . . investigations which attempt to relate observed teacher behaviors to student outcome measures." These studies are _correlational_ in nature.

The correlational studies cited by Rosenshine and Furst appear to be based on classroom means. A teacher behavior is noted, mean classroom learning is computed, and correlations between the teacher behavior and _mean_ student learning are calculated over a sample of classrooms. The correlation (squared) can be interpreted as the amount of variance in "mean" learning associated with variance in teacher behavior. A correlation of .70 between teacher clarity and mean pupil achievement, indicates that 49% ($.70^2$) of the between room variance in student achievement is attributable to teacher clarity. However, if only 20% of the variance between students is attributable to rooms, then only 9.8% (.49 x .20) of the variance in individual outcome scores is attributable to teacher clarit: In correlational terms, the coefficient would drop from .70 to .31 ($\sqrt{.098}$) by changing from rooms to students as the unit of analysis. Statistically significant or not, such small relationships would probably not be regarded as important by practitioners faced with the task of improving the scores of individual students. Very simply, using classrooms as the unit of analysis will affect the value of correlations between environmental variables and student outcomes, usually resulting in over-estimates of the size of environmental effects.

IV. Uses of Regression Analysis

The choice of regression analysis does not completely resolve the methodological issues involved in modelling teacher behavior. As Coleman (1972) notes in his provocative paper, "Integration of the Social Sciences through Policy Analysis," there are at least three different ways in which the technique can be used.

Coleman reviews the various approaches, with particular emphasis on the assumptions that underlie their use. Briefly, these include the use of regression analysis (1) to estimate the parameters or coefficients for a well specified model with known structures; (2) as a technique for uncovering the causal structure in a set of variables when some prior assumptions can be made about the causal relations among them (path analysis); and (3) as a procedure for partitioning the regression sum of squares in instances where no causal model can be specified and errors of measurement and colinearity are thought to be prevalent. It is apparent that each of these successive uses of regression analysis requires less stringent assumptions about the structure of the proposed model and the crudeness or sophistication of the measures employed. We will examine the use of methods one, parameter estimation, and three, variance partitioning, in the analysis of teacher behavior and student achievement.

a) Partitioning of Variance

The use of variance partitioning procedures requires relatively few assumptions about the structure of the linear regression model. In fact, all that one need assume is that the direction of "causality" is from the independent to the dependent variables. (Coleman, 1972) The crudeness of the measures generally employed in educational research is a rationale for adopting variance partitioning techniques. Mood (1971), for instance, groups the variables he works with into broad factors, on the assumption that the individual measures that he employs are first, inaccurate (measurement-wise) and second, are only proxies for the variables that he is considering. For instance, he subsumes under the general factor of "peer quality" such measures as parental expectations for higher grades, hours of homework, plans to go to college, etc. Also, for researchers concerned with the location of bases for implementing change in educational institutions, variance partitioning techniques are useful for identifying independent (orthagonal or uncorrelated) factors.

The purpose of variance partitioning is to determine what part of the explained variance can be attributed "uniquely" to each of the independent variables and that part which is due to colinearity among the independent variables. One way to conceptualize the procedure is to regard it as an attempt to first, estimate the amount of variance in a dependent variable which is attributable to an independent variables over and above the variance attributable to other variables in the set, and second, to estimate the amount of variance in the dependent variable which is shared among the predictors.

Our analysis is based on the procedures outlined by Mood (1971), although interested researchers should investigate competing techniques used by Astin (1970), Ward (1963), or Newton and Spurrell (1967). The following models are required:

(2.1) $OUT_i = f(S_{ij}+IBV_{ik})$

where: S_{ij} is 1 if student i is in room j, zero otherwise,

IBV_{ik} is the score for student i on background variable k,

OUT_i is the outcome score for student i.

(2.2) $OUT_i = f(IBV_{ik})$

(2.3) $OUT_i = f(S_{ij})$

(2.4) $OUT_i = f(MTBA_j+MTBB_j+MTBC_j)$

where: $MTBA_j$ to $MTBC_j$ are the classroom average scores on the three teacher behavior factors for the teacher in classroom j.

(2.5) $OUT_i = f(MTBA_j+MTBB_j+MTBC_j+IBV_{ik})$

Model 2.1 is referred to as a "full" model; it represents all differences that exist between rooms as well as the student background characteristics. Model 2.2 places a restriction on the full model such that differences between rooms are assumed to be zero; student outcomes are predicted solely as a function of individual background characteristics. Model 2.3 is the multiple regression analog of a one-way ANOVA. It attempts to explain differences between individual student outcomes in terms of unspecified differences between rooms. Model 2.3 signifies the upper limit on the amount of variance in the outcome that can be explained by any sort of variance in the classroom context. Assuming that this variance is large enough to be of interest, the researcher may wish to know how much of the variance in the outcome can be attributed to his particular measure of the classroom environment. This estimate is obtained by replacing the 1's in model 2.3 with measures of the classroom context, resulting in model 2.4. Any difference in the predictive efficiency (RSQ) of models 2.3 and 2.4 indicates the extent to which the replacement measures do not fully represent all differences between rooms in terms of the dependent variable. Model 2.5 predicts student outcomes from knowledge of specific teacher behaviors and individual background data. The reduction in explained variance from model 2.1 to model 2.5 is a further indication that the teacher behavior measures do not fully account for the variance attributable to the classroom context.

Results:

Table I contains the means, standard deviations and correlations for the variables employed in the study.

Table I

Correlations, Means and Standard Deviations
N=187

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Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Math Achievement Pre-test (Year 1)																	
Math Achievement Post-test (Year 1) and Pre-test (Year 2)	.80																
Math Achievement Post-test (Year 2)	.77	.75															
Satisfaction with School Pre-test (Year 1)	.22	.15	.12														
Satisfaction with School Post-test (Year 1) and Pre-test (Year 2)	.24	.21	.21	.53													
Satisfaction with School Post-test (Year 2)	.25	.23	.34	.26	.43												
Race (1=black)	-.38	-.41	-.44	-.12	-.24	-.24											
Sex (1=female)	.15	.07	.11	.06	.09	.11	-.07										
Number of Siblings	-.10	-.06	-.17	-.13	-.05	.00	.01	.10									
IQ Score	.45	.44	.46	.14	.13	.25	-.38	-.04	-.19								
Financial Status	-.16	-.20	-.24	.01	-.12	-.06	43	-.01	.23	-.19							
Teacher Behavior-Carping Criticism (Year 1)	-.00	-.03	-.10	-.12	-.23	-.22	.24	-.00	-.02	-.07	.11						
Teacher Behavior-Warmth (Year 1)	-.02	-.11	-.01	.12	.07	.02	-.01	.01	.03	-.02	.00	-.57					
Teacher Behavior-Autonomy (Year 1)	.08	-.01	.15	.08	.06	.09	-.05	-.01	.01	-.01	.01	-.30	.32				
Teacher Behavior-Carping Criticism (Year 2)	.01	-.03	.00	-.05	-.13	-.24	.40	-.02	-.10	-.01	.14	.42	.00	.15			
Teacher Behavior-Warmth (Year 2)	-.12	-.07	.06	-.06	.10	.30	-.26	.09	.13	-.08	-.05	-.48	.11	.24	-.72		
Teacher Behavior-Autonomy (Year 2)	.16	.13	.20	.09	.07	.20	-.24	.03	-.07	.18	-.10	-.17	.17	.55	-.12	.22	
Means	27.63	29.44	31.34	13.56	13.74	14.04	.12	.47	2.73	108.68	.09	29.03	17.11	5.24	27.43	17.65	5.36
Standard Deviations	6.73	5.20	4.36	2.23	2.11	2.17	.33	.50	2.24	11.66	.38	3.08	1.43	.46	2.53	1.29	.50

Model 2.1 (Table II), with all of the variables included, accounts for approximately 73% of the variance in math achievement. A comparison of model 2.2 with model 2.1 indicates that only 6.2% of the total variance can be attributed to differences between rooms over and above differences associated with student background characteristics. Indeed, under ideal circumstances, where student background can be assumed to be unrelated to room assignment, only 15% (model 2.3) of the variance in student achievement is associated with any differences between rooms.

Fifteen percent isn't much, six percent is even less--but these figures look like other estimates of the amount of variance in achievement that lies between school units. <u>And</u>, their size is NOT a function of inadequate measures of teacher behavior.

Finally, we note that about 58% of the variance in student achievement is associated with the student background measures, over and above differences between rooms. Some 9% of the variance is associated with joint effect of differences between rooms and student characteristics. In other words, in this sample it is impossible to disentangle a part of the background and room effects.

A second step in the analysis involves substituting measures of teacher behavior which describe the rooms for the dummy variables which simply indicate in which room a student is located. (The number of descriptors should be less than the number of rooms if degrees of freedom are not to be exceeded.) To accomplish this, we used three measures of teacher behavior: carping criticism, teacher warmth and the extent to which the teacher extends freedom and autonomy to the students. Once again, variance partitioning shows that a large amount of the variance in math achievement is associated

Table II

Partitioning of Variance in Math Achievement into Classroom and Background Related Sources - Year 1

Full Model [model 2.1]		72.98%
Unique to Background [model 2.1 - model 2.3]	57.96%*	
Unique to Classrooms [model 2.1 - model 2.2]	6.14%*	
Overlap	8.88%	

Partitioning of Variance in Math Achievement into Teacher Behavior and Background Related Sources - Year 1

Full Model [model 2.5]		68.74%
Unique to Background [model 2.5 - model 2.4]	65.82%*	
Unique to Teacher Behavior [model 2.5 - model 2.2]	1.90%**	
Overlap	1.02%	

*$p \leq .01$
**$p \leq .05$

with background, over and above the measures of teacher behavior. About 2% is associated with teacher behavior over and above room effects. Only 1% is shared between the two sets of predictors.

By comparing model 2.3 and 2.4 we see that while 15% of the variance in math achievement lies between rooms, only 3% can be attributed to teacher behavior. Either these measures of teacher behavior are not what cause the differences in the outcome--or, the measures of behavior are inadequate. For the moment we can accept either interpretation, for the finding is not as important as the fact that we have outlined an easy way to assess the adequacy of our measures of teacher behavior. Models 2.1 and 2.3 are a standard against which the measures can be evaluated; they require no assumptions about what is being measured on the independent side of the regression equation.

Substantively, we obtain the same kind of results when student satisfaction is used as the dependent variable (Table III). Not much variance is attributable to rooms, fully 30% is explained by the background variables, and there is some, but not much, overlap between rooms and background. Much less of the total variance is attributable to variables in the full model (38% against 73% for math). However, Figure I highlights an important problem: the rooms which had high satisfaction scores are not the same as those which had high math scores. (The rank-order correlation is .1308 ($p > .05$)). It seems probable, then, that activities that might lead to high math scores might not contribute to, or even reduce, satisfaction scores. This observation represents a problem that requires extensive treatment in its own right. For now, we will proceed on the assumption that teachers are willing to maximize one output while perhaps seeking only to

Table III

Partitioning of Variance in Satisfaction with School into Classroom and Background Related Sources - Year 1

Full Model [model 2.1]		38.66%
Unique to Background [model 2.1 - model 2.3]	30.01%*	
Unique to Classroom [model 2.1 - model 2.2]	6.41%	
Overlap	2.24%	

Partitioning of Variance in Satisfaction with School into Teacher Behavior and Background Related Sources - Year 1

Full Model [model 2.5]		34.49%
Unique to Background [model 2.5 - model 2.4]	25.84%*	
Unique to Teacher Behavior [model 2.5 - model 2.2]	2.24%	
Overlap	6.41%	

*$p \leq .01$

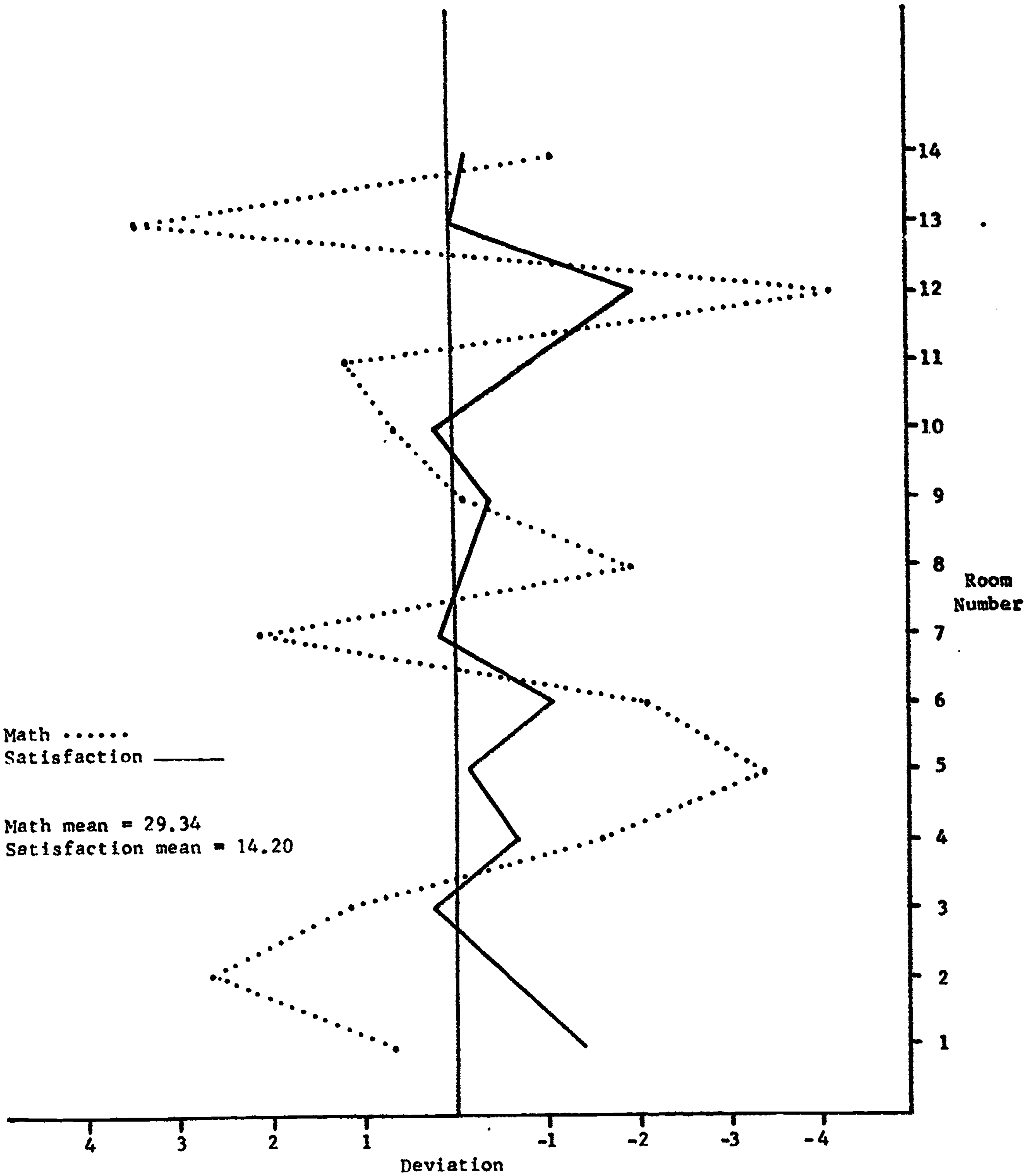

Figure I

Classroom Deviations from Mean Satisfaction and Math Scores - Year 1 avoid serious problems with other outcome(s) that might be considered. In the interest of parsimony we will confine our subsequent analyses to the math outputs.

If the model uncovered by variance partitioning cannot be used on other sets of data, its practical significance is indeed limited. One way to examine the stability of the model is to compare equations derived from a second year of data collected with the same sample of students as they moved into the sixth grade. The relevant second year equations are 3.2, 3.4 and 3.5 in Table IV. These contain information about background, teacher behavior in the second year in all three possible combinations. (Their equivalents are models 2.2, 2.4 and 2.5 from the first year of data.) From a comparison of Tables II and IV it is evident that the results of the variance partitioning (in math achievement) between these two sets of variables does not change substantially from the first year to the second. An F-test of the statistical significance of the difference in the amount of variance attributable to teacher behavior, and the background variables reveal that the differences from year one to year two are not statistically significant at the .05 level. (See Table VI.)

Conclusion from the Variance Partitioning

From all of the above it seems that teacher behavior, as measured in this study, has a trivial effect on both math achievement and satisfaction with school. Moreover, it does not seem likely that any measure of the classroom environment can account for more than 15% of the variance in math achievement nor 8% of the variance in satisfaction with school.

Table IV

Partitioning of Variance in Math Achievement into Classroom and Background Related Sources - Year 2

Full Model [model 3.1]		70.43%
Unique to Background [model 3.1 - model 3.3]	58.26%*	
Unique to Classrooms [model 3.1 - model 3.2]	8.73%*	
Overlap	3.44%	

Partitioning of Variance in Math Achievement into Teacher Behavior and Background Related Sources - Year 2

Full Model [model 3.5]		66.95%
Unique to Background [model 3.5 - model 3.4]	62.49%*	
Unique to Teacher Behavior [model 3.5 - model 3.2]	5.25%*	
Overlap	-.0079%	

*$p \leq .01$

Table V

Partitioning of Variance in Satisfaction with School into Classroom and Background Related Sources - Year 2

Full Model /model 3.1/		35.72%
Unique to Background /model 3.1 - model 3.3/	20.35%*	
Unique to Classrooms /model 3.1 - model 3.2/	11.17%**	
Overlap	4.20%	

Partitioning of Variance in Satisfaction with School into Teacher Behavior and Background Related Sources - Year 2

Full Model /model 3.5/		32.04%
Unique to Background /model 3.5 - model 3.4/	20.51%*	
Unique to Teacher Behavior /model 3.5 - model 3.2/	7.49%*	
Overlap	4.04%	

*$p \leq .01$
**$p \leq .05$

Table VI

F Ratios Testing the Significance of the Difference between Unique Contribution of Predictor Variables in the Prediction of Math Achievement in Year 1 and Year 2

	Year 1	Year 2	F-ratio	Significance
Teacher Behavior	1.90	5.25	$F = \frac{5.25}{1.90} = 2.76$ (3,3 d.f.)	$p > .05$
Background	65.82	62.49	$F = \frac{65.82}{62.49} = 1.05$ (6,6 d.f.)	$p > .05$

b) Parameter Estimation

If we are willing to assume that our model of teacher behavior and student achievement is well specified, that the relevant variables have been included in the model and that our measures are relatively accurate, we are warranted in using regression analysis to generate the parameters of our model. A distinct advantage of using regression analysis in this manner lies in the interpretation of regression weights (the parameters or regression coefficients . For example, a regression weight of -.1790 attached to the first dimension of teacher behavior, carping criticism (Table VII, model 2.5) permits us to make the following statement: for every increase of one point in the average student perception of teacher behavior (carping criticism) there is a decrease of .18 points in the student's post-test math achievement. Beta weights, which are nothing more than standardized regression coefficients, are open to a similar interpretation, except that a change in the outcome variable due to a predictor is reported in standard (z) scores. Except for the case when the predictor variables are orthogonal, we cannot generate equivalent statements by considering the unique and overlapping parts of the partitioned variance.

Consider the needs of a district superintendent, faced with the problem of improving the academic achievement of the students in his various schools. He hires a consultant to advise him on the most promising course of action. The consultant collects a variety of measures pertaining to the organizational structure of the school, actual teacher behaviors, number of books per student, teacher salaries, and the number of remedial programs per x number of students in addition to data on student background characteristics. If the data is analyzed by partitioning the variance among the various factors, the results will indicate the relative importance of the variables or sets of variables. The estimation of the parameters of the model, on the other hand, will provide, in addition, an estimate of the expected increase in the outcome per standard unit increase in a particular predictor variables. The administrator is then in a position to consider simultaneously the investment (in dollars--or other terms) required to manipulate the predictor variable and the expected improvement in the outcome given that investment. It may turn out for example, that although the largest increase in the outcome measure can be expected as a result of increasing, by one, the number of books per pupil, an even larger increment can be effected, for the same cost, by increasing five-fold the number of remedial reading programs per x number of students.

There is a potential difficulty in working with regression weights which is evident even from our example. When we employ a measure such as number of books per pupil as a quality indices for the school, it is possible that the measure is nothing more than a proxy for the wealth of the schools, and by definition, the wealth (or SES) of the students. Unfortunately, by manipulating the variable number of books per pupil, we will probably not be able to effect the desired outcome. This is an issue that Mood (1971) alludes to in his defense of variance partitioning as the appropriate statistical tool for analyzing the schooling process.

An interesting and informative application of these procedures would be to run the regression equations (and estimate the parameters) separately for various groups of students. For instance, if the researcher or practitioner believed that the various dimensions of teacher behavior affected different racial groups differently, he might construct two models, one for whites and another for blacks. A comparison of the beta weights (for teacher behaviors) would indicate whether this hypothesis were, in fact, tenable.

Results

Tables VII through X present the results of the parameter estimation for years one and two for the two outcomes, math achievement and satisfaction with school.

Table VII, model 2.5, suggests that the pre-test measure is the most important predictor of post-test math achievement in year one. The other background variables make a comparatively small contribution to the outcome. (In the event that the reading pre-test measure were dropped from the equation, a variable such as IQ, which is highly correlated with the pre-test measure, would assume more importance.) The teacher behavior measures: carping criticism, teacher warmth and freedom or autonomy all make small negative contributions to the outcome. However, it is not necessary to be overly concerned with these figures (which perhaps do not correspond to our expectations). The B weights for these variables are not significant ($p > .05$), i.e., more than five times out of a hundred we would obtain B weights such as these by chance.

At this point, we are again faced with the problem of evaluating the stability of our proposed model. If we simply examine the regression weights attached to the variables in model 2.5 (year one, Table VII) and model 3.5 (year two, Table IX), we see some rather dramatic differences. While the pre-test measure is once again the most important variable in predicting the outcome in year two, the B coefficient is smaller in year two than in year one. The B weights attached to sex and number of siblings have changed

Table VII

Regression Models Predicting Level of Math Achievement - Year 1
N=187

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Variables	Model 2.1 B	Model 2.2 B	Model 2.3 B	Model 2.4 B	Model 2.5 B
Math Achievement Pre-test	.59	.57			.58
Race	-1.27	-1.26			-.94
Sex	-.76	-.40			-.42
Siblings	.06	.07			.08
IQ Score	.02	.03			.02
Finance	-.38	-.58			-.51
Teacher Behavior - Carping Criticism				-.26	-.17
Teacher Behavior - Warmth				-.74	-.47
Teacher Behavior - Autonomy				.00	-.82
Classroom 1	1.38		.67		
Classroom 2	1.06		2.60		
Classroom 3	.00		1.15		
Classroom 4	-3.06		-1.63		
Classroom 5	-.74		-3.39		
Classroom 6	.45		-2.04		
Classroom 7	2.44		2.03		
Classroom 8	-1.03		-1.94		
Classroom 9	.35		-.09		
Classroom 10	.05		.63		
Classroom 11	1.73		1.05		
Classroom 12	-1.51		-4.14		
Classroom 13	-.43		3.47		
Classroom 14	-.80		-1.01		
Constant	10.56	10.13	29.34	49.67	27.96
RSQ	.72	.66	.15	.02	.68

Table VIII

Regression Models Predicting Satisfaction with School - Year 1
N=187

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Variables	Model 2.1 B	Model 2.2 B	Model 2.3 B	Model 2.4 B	Model 2.5 B
Satisfaction with School Pre-test	.53	.48			.48
Race	-.91	-.88			-.63
Sex	.14	.17			.20
Siblings	.02	.02			.02
IQ Score	-.00	.00			.00
Finance	-.37	-.43			-.40
Teacher Behavior - Carping Criticism				-.18	-.12
Teacher Behavior - Warmth				-.12	-.14
Teacher Behavior - Autonomy				.05	-.01
Classroom 1	-1.31		-1.39		
Classroom 2	.02		-.67		
Classroom 3	-.11		.23		
Classroom 4	-.83		-.73		
Classroom 5	.00		-.20		
Classroom 6	.48		-1.06		
Classroom 7	.03		.14		
Classroom 8	-.28		-.05		
Classroom 9	-.38		-.42		
Classroom 10	.20		.17		
Classroom 11	-.28		-.80		
Classroom 12	-1.04		-1.99		
Classroom 13	.00		.00		
Classroom 14	.58		-.19		
Constant	7.38	7.10	14.20	21.18	13.48
RSQ	.38	.32	.08	.05	.34

Table IX

Regression Models Predicting Level of Math Achievement - Year 2
N=187

Variables	Model 3.1 B	Model 3.2 B	Model 3.3 B	Model 3.4 B	Model 3.5 B
Math Achievement Pre-test	.54	.53			.55
Race	-2.64	-1.70			-2.06
Sex	.40	.60			.38
Siblings	-.17	-.22			-.23
IQ Score	.05	.04			.04
Finance	.19	-.05			-.11
Teacher Behavior - Carping Criticism				.14	.52
Teacher Behavior - Warmth				.26	1.04
Teacher Behavior - Autonomy				1.70	.11
Classroom 1	-.59		1.21		
Classroom 2	-2.19		-1.25		
Classroom 3	-2.07		.24		
Classroom 4	-2.33		-.55		
Classroom 5	-.20		-2.56		
Classroom 6	1.24		.27		
Classroom 7	-2.02		.41		
Classroom 8	-.81		-.54		
Classroom 9	.00		2.14		
Classroom 10	1.00		1.91		
Classroom 11	.92		-1.30		
Classroom 12	2.34		2.34		
Classroom 13	.37		4.39		
Classroom 14	.12		.97		
Constant	10.95	11.77	30.61	13.59	-22.31
RSQ	.70	.61	.12	.04	.66

Table X

Regression Models Predicting Level of Satisfaction with School - Year 2
N=187

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Variables	Model 3.1 B	Model 3.2 B	Model 3.3 B	Model 3.4 B	Model 3.5 B
Satisfaction with School Pre-test	.39	.40			.38
Race	-.29	-.62			.05
Sex	.28	.33			.27
Siblings	.03	.03			.01
IQ Score	.03	.03			.04
Finance	.23	.29			.23
Teacher Behavior - Carping Criticism				-.05	.00
Teacher Behavior - Warmth				.38	.44
Teacher Behavior - Autonomy				.64	.36
Classroom 1	-2.09		-2.31		
Classroom 2	-.69		-1.20		
Classroom 3	-.07		-.64		
Classroom 4	-.82		-1.20		
Classroom 5	-.39		-1.27		
Classroom 6	.40		-.37		
Classroom 7	-.29		-.43		
Classroom 8	.53		.16		
Classroom 9	.42		.16		
Classroom 10	.65		.29		
Classroom 11	-1.26		-2.73		
Classroom 12	.27		-1.04		
Classroom 13	-.03		.00		
Classroom 14	.40		.00		
Constant	4.27	4.55	14.64	5.39	-5.82
RSQ	.35	.24	.15	.11	.32

direction. The most noticeable changes, however, have occurred, in the parameters associated with the three dimensions of teacher behavior; the size and direction of the B weights have changed substantially for all three measures.

We applied a test (Huang, 1970) of the constancy of a subset of regression coefficients (B weights) to the measures of teacher behavior predicting math achievement. We rejected the null hypothesis (H_0: $B_1=B_2$) at the .01 level of significance ($F = 9.68$, d.f. = 3,354). We applied the same test to the background variables; the null hypothesis (H_0: $B_1=B_2$) could not be rejected ($F = 1.3363$, d.f. = 6,354).

In summary, the B weights for teacher behavior changed significantly over the period in question. The background measures, on the other hand, behaved consistently over the two samples. We acknowledge that our interpretation of these F statistics is suspect--the measurement instruments are relatively unsophisticated, making it extremely difficult to determine whether the change (<u>and</u> stability) we have verified statistically are, in fact, spurious. Regardless, we feel that the value of the procedure is that it forces educational researchers to consider the issue of the stability of their proposed models.

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