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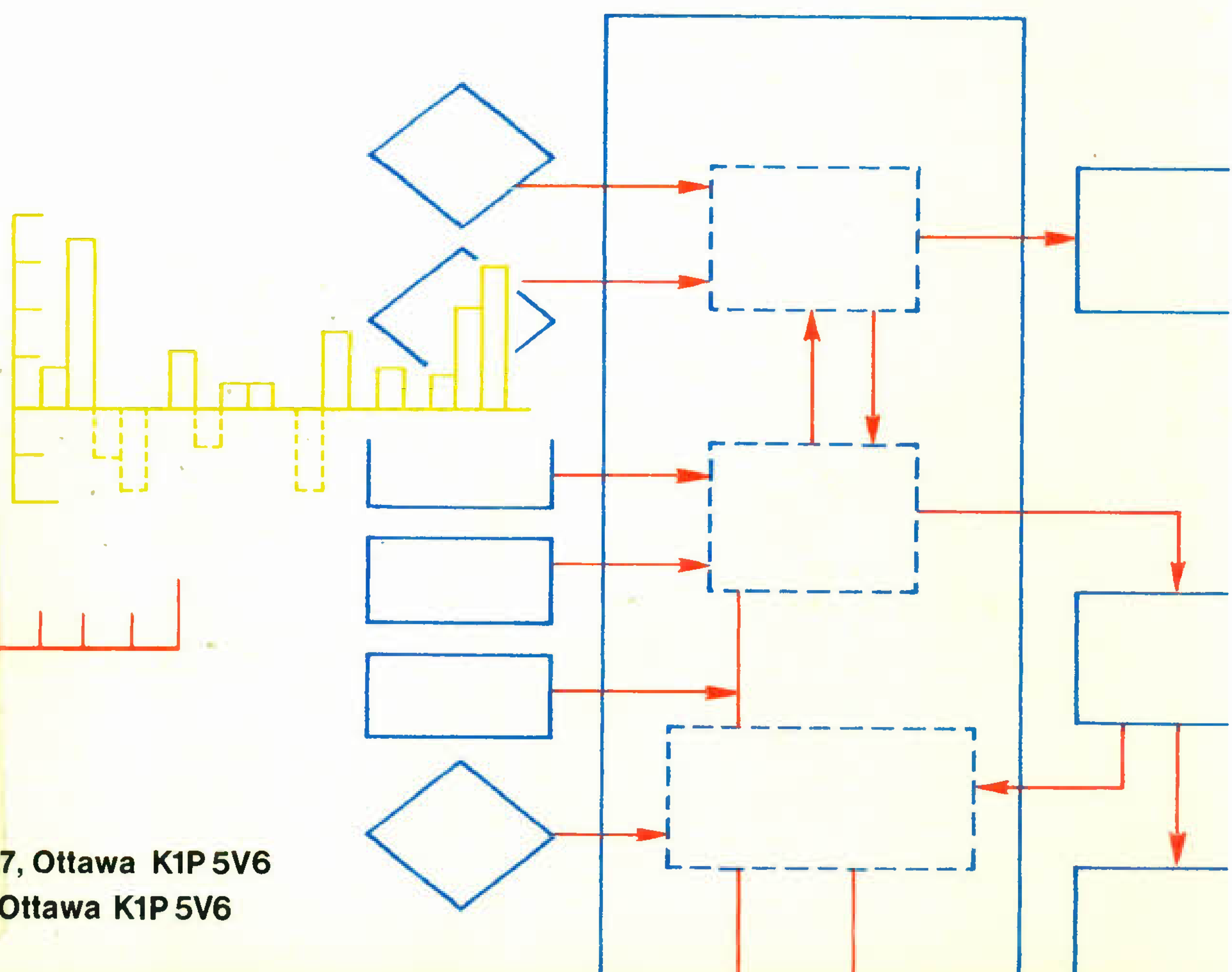

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DISCUSSION PAPER NO. 15

Social Indicators in Education:
A Case Study

Jeff Greenberg

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November 1974

ABSTRACT

Social Indicators in Education:
A Case Study

by

Jeff Greenberg

This paper represents the second stage of a research project to develop and analyse social indicators in education done in co-operation with the Ministry of Education of Ontario. Using a data set for grade one students, which has been compiled and provided for us through the co-operative efforts of the Ottawa Board of Education, two path models were estimated using ordinary least square procedures in which the relevant inputs and outputs are considered as social indicators of education.

The inputs are blocks of variables taken from four distinct sets of factors: 1) personal characteristics of the student; 2) socio-economic background; 3) teacher characteristics; and 4) peer group and class size variables. The outputs are the raw scores in three objective tests, two of which are from the cognitive domain (Reading and Mathematics) and one from the affective domain (Interest). Using the individual as the unit of observation, the final conclusions suggest that all four sets of inputs are important in determining how the student performs. The utilization of path models clearly illustrates the importance of the indirect impact that teacher and socio-economic factors had upon the outputs.

The contribution that this analysis makes to social indicator research is twofold. First, it shows the importance of explaining not only the direct impact of the inputs upon outputs but also the indirect and total impact. If this procedure were not followed in this paper, the importance of both the teacher and socio-economic factors would have been overlooked. Second, this research helps to specify the relevant inputs for two levels of disaggregation. When the level of concern is the individual, this research suggests that for the cognitive outputs only, the socio-economic, the personal and the peer group factors can be considered (along with these outputs) as social indicators of education. The teacher characteristics were also found to be relevant, but because their impact was indirect and observed through the peer group factors, their inclusion as indicators, when the individual is the level of concern, is redundant. (This should in no way be construed as meaning they are unimportant.) On the other hand, when the level of concern is the classroom, for both the cognitive and affective outputs, the teacher and class size inputs can be considered as social indicators along with the corresponding outputs.

SOCIAL INDICATORS IN EDUCATION:

A CASE STUDY*

Table of Contents

*I wish to thank Norman Leckie for his valuable technical expertise and David Henderson and Allan Maslove for their helpful comments. In particular, I wish to thank Dr. G. Halpern and Jan Lokan of the Ottawa Board of Education for their invaluable assistance and advice.

Chapter 1

INTRODUCTION

This paper is an interim report of the results of research into social indicators in education. The framework for analysis is a production function model in which the relevant inputs and outputs are considered as indicators of a social subsystem, such as education.

What we attempt to show in this paper amongst other matters is the importance of both teachers and certain socio-economic background factors in the determination of the educational outputs. In our findings, it seems that these socio-economic factors, on their own, appear to be of little importance. However, when we consider their total impact directly and indirectly through the personal characteristics of the student, these background factors become important. The influence of the teachers also appears to offer little direct impact upon the educational outputs. However, when we consider that these influences operate indirectly through peer groups to affect educational outputs of the individual, their role becomes crucial. In this vein we show that the peer group effects (as measured by average class scores) are the relevant intermediaries when discussing the role of the teacher in the grade one educational process.

Defining social indicators in education represents a problem of defining the outputs and determining the relevant inputs of an educational system. Traditionally, the outputs of an education system have been recorded in terms of the number of physical bodies that have passed through specific levels of formal schooling. Variations of this measure such as retention rates or attrition rates have also been estimated. Another view is to define the social indicators of education as the quality of the various educational services offered to the community. To quantify these types of indicators, inputs are generally used. For example, as an indicator of the effectiveness of teachers, student/teacher ratios are used. The assumption implied by the use of this proxy is that the smaller the number of students the more effective is the teaching. However, this assumption should not be taken as being absolute since it is unclear whether some optimal class size does not exist and that smaller classes may be just as debilitating as large classes. Another measure of teacher effectiveness used is the increasing academic qualifications of the teaching staff. But again, it is not clear that for all levels of education, more highly educated teachers are better teachers. Generally, any input which acts as a representative for some output may not describe what is actually produced by the educational process. As such they are relevant only to the extent that the assumptions underlying their use are relevant.

In the approach taken here, the educational system is considered to be designed to impart certain skills or characteristics to the participants in the process. These skills or characteristics become internalized and represent certain attributes which the participant then possesses. In this sense, any individual who has completed some specified level of training will then be the possessor of some combination of the elements of a set of attributes. This is akin to the approach taken by Lancaster [1966] where he attributes to any one good a bundle of characteristics which are inherent in that good. Any two goods might have the same bundle of characteristics (or attributes) but in a different combination. In terms of education, inherent in any level of schooling completed is some bundle of characteristics. This bundle of characteristics is defined as all of the elements of a set of outputs of education as described in a taxonomy of outputs in a paper by Greenberg [1974]. Different levels of education would have the same general bundle of characteristics ascribed to them, but some of the elements might take on values of zero. Also, the various quantities of each of the non-zero elements might differ. These characteristics of some specific level of education can be considered as a subset of the social indicators of education. From a theoretical viewpoint, they can be described in aggregate terms as the cognitive, affective, and psychomotor characteristics that the individual may potentially internalize during particular stages of the educational process. However, these aggregate characteristics are very general and as such display no properties for translating them "in toto" into workable definitions. In the taxonomy of educational outputs referred to earlier,[1] the cognitive and affective characteristics were disaggregated until we arrived at a collection of those attributes which we felt were conceivably quantifiable.

To proceed with the analysis, data were required concerning the results that individuals obtained on objective tests designed to measure these attributes for elementary or secondary school. We undertook a co-operative project with the Ministry of Education of Ontario, and through their assistance obtained the co-operation of certain school boards whose responsibility it is to administer, collect, and evaluate this type of material at their discretion. What follows in succeeding chapters is an analysis of the data obtained through the co-operation of one particular school board. In effect, the analysis becomes a case study in which we evaluate how the output social indicators in education are determined by relevant inputs for a given level of schooling.

Knowledge of the inputs and outputs of an education system and how these sets interact, serve as the basis for the understanding of two important issues. First, by investigating the education system in this fashion, it

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[1]Greenberg [1974], Appendix A.

serves as an inquiry into the extent to which variations in the educational outcome are due to variations in the inputs. Given such information, the policy-maker is then able to identify the resources that are most effective and are within his frame of reference. This enables him to bring about a different utilization of resources so that a more effective combination can be utilized to produce some set of desired results.

Second, such information, when the outputs are considered as a subset of social indicators, provides a preliminary step in the long-term process of building up an overall welfare index. This information can be interpreted as representing the social impact of an education system and may eventually be used to bring about changes in the outputs according to some social plan. Such a social plan would incorporate notions of which educational outputs are most desirable and the relative importance of each. It would also include the outputs of other social structures such as the health and urban systems.[2] The incorporation of all the structures, assuming a detailed weighting system exists, has been summarily discussed in another paper.[3] The first stage in this work, which is the identification of the educational outputs as a subset of social indicators in education and observing the variation in them as relevant inputs change, represents an approach different from that social indicator research which begins at a higher level of

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[2]For a discussion of urban indicators, see Maslove [1974].
[3]See Jeff Greenberg [1974].

aggregation. Our approach considers variations among individuals, groups, or geographic regions depending upon the scope and depth of the model, and then presumes that eventually a weighting system can be developed to determine an overall welfare index. Any welfare index based upon this framework has built into it the ability to consider the effect of distributional changes upon the index. However, any index which is created at a high level of aggregation must implicitly assume that either distributional aspects are relatively unimportant or that they are netted out. Indicators such as these often overestimate the welfare or well-being of the society they measure, depending upon the degree to which there are distributional disparities. The disaggregated approach taken here has the facility built in for examining distributional aspects of educational outputs.

The input-output approach (or production approach) is based upon the educational learning framework in which outputs, as defined for our purposes, are a series of standardized achievement tests in both the cognitive and affective domain. Inputs in turn, cover a broad range of factors, including teacher characteristics, the socio-economic background, peer group factors, and the student's personal characteristics. The production model to be estimated is assumed to be linear in form. In this model each continuous independent variable contributes a constant amount to the outcome of the student. In the case of the descriptive or dichotomous variables, which are the most common in this paper, they are interpreted as contributing a constant amount above or below some arbitrarily chosen norm for the variable in question. In some cases, continuous variables are converted to a dichotomous form in order to pick up the possible non-linear influences they might contribute to educational outcomes.

As has been discussed earlier, the outputs of the educational process can usually be grouped into three categories: (1) cognitive; (2) affective; and (3) psychomotor skills.* Cognitive skills, as we have defined them encompass both levels of thought and processes of thought.[4] The levels of thought deal generally with an existing body of knowledge. The processes of thought in turn deal with how this body of knowledge is internalized. These cognitive skills have conventionally been used as the outputs of the education system. However, the affective skills are receiving increasing attention for two reasons. First, there is a growing belief that these noncognitive educational outputs are a major determinant of cognitive achievement. In this way, these affective skills can be interpreted as intermediate outputs in that they are determined by a set of input variables, and, in turn, interact with all or part of them to further determine some final output. This can be expressed mathematically by a recursive model.[5]

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*No reference will be made to psychomotor skills in this paper.

[4]For a more detailed discussion see Greenberg [1974], p. 32.

[5]For a discussion of a recursive model see Greenberg [1974], Appendix E.

Second, these noncognitive skills take on greater significance in the light of some recent suggestions that the cognitive skills serve a secondary role in the determination of life success.[6] There generally appears to be a positive and high correlation between the amount of formal education and the amount of income an individual receives, but what aspects of education contribute to this income is uncertain. The thesis has been put forward by Gintis that it is the non-cognitive factors that are the relevant ones in the determination of income. Although this thesis has not been examined further by others, it does raise enough questions such that the outputs of an education system should be examined in the light of this possibility.

We shall also consider in this paper the role of peer group factors in the education process. Peer group factors include such measures as the educational attainment or general intelligence of the classmates of the student in question. Until the Coleman Report [1966], there did not appear to be any examination of these peer groups in the literature. The Coleman findings suggested that the achievement of the pupil is strongly related to the educational achievement of the other students in the school. However, Bowles and Levin [1968] in their comments on the Coleman Report suggested that a different interpretation may be placed on the facts presented. That is, the influence of the student body can be considered as a product of its socio-economic background. They suggested that in the United States there

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[6]Gintis [1971].

is sufficient homogeneity in the socio-economic status of the neighbourhoods surrounding a school that the peer group influences are merely an expression of the social status of the parents. Whether this interpretation is valid for Canada must be examined and cannot be accepted a priori as being true even if it does hold in the United States. However, a principal weakness of the Coleman Report is the fact that peer group influences from the student body of the school as a whole are used, and not the classroom influences which should be more meaningful. In this paper we will examine amongst other matters the influences of the classroom peer group upon individual student learning and the interaction of the teacher with the peer groups.

Chapter 2

SPECIFICATION OF THE MODELS

In this section, we will specify the basic conceptual model of the educational process and describe the two applications of it to be used in this paper. Consider the following equation:

$$(1) \quad y_t = f(x_{1t}, x_{2t}, x_{3t}, x_{4t}) \qquad t = (1...n)$$

where the subscript t represents each of n observations in all x and y.

y_t = a vector of raw test scores of the educational outputs for individual t;

x_{1t} = a vector of personal characteristics for individual t;

x_{2t} = a vector of socio-economic factors for individual t;

x_{3t} = a vector of peer group factors for individual t; and

x_{4t} = a vector of teacher characteristics for individual t.

Equation (1) specifies that the raw score a child receives on a specific objective test is functionally related to his own personal make-up, the socio-economic environment in which he was raised, the peer group he is associated with, and the ability of the teacher to influence the amount of the output that the child internalizes.

Many models predicting educational outputs are "value-added" models which attempt to determine the influence of the entire set of independent variables upon the educational output for one time period. The usual way of controlling for past achievement is to include the outcome score received in the previous school year or in the beginning of the corresponding year. Since we are dealing with the grade one level, we have assumed that a value-added approach is not necessary. It would seem that there is little need of controlling for past education since it is probable that most previous learning has taken place in the home and will be captured by personal and socio-economic factors.

We are using raw test scores as the outputs in our specification. The validity of these scores is often questioned on the basis of the incentive offered to the student. It is said that because there is nothing to gain from taking such tests the student will not perform as he would with incentives. However, we do not believe that this is a serious factor at the grade one level. Also, we recognize that these output scores may not always truly reflect what the child has internalized but rather reflect what the child thinks the teacher wishes of him or her. If the latter is true then we have a "Pygmalian" effect which suggests that the child attempts to become what the teacher wishes him to be. This would imply that if a teacher perceives a child to be intelligent, then the child could conceivably perform better than he or she might otherwise (within certain intellectual constraints).

The statistical technique used in this paper is ordinary least squares procedures with the results reported as normalized regression coefficients (often called path coefficients in sociology literature). We expect a great deal of correlation among the independent variables because of the obvious relationship between many of them. We have disregarded the use of factor analysis as a method of removing this correlation because of its inability to operate when there is a predominance of dichotomous variables. Instead, in order to cope with the expected correlation, we shall utilize this correlation between the independent variables to show the direct and indirect effects of a change in any independent variable upon a dependent variable. The technique of doing this will be explained in the next few pages as we introduce the two models that are used in this study.

Model One

In the first model, we present a single equation system of which we shall make considerable use. First, we will use it to determine the direct impact of the personal, socio-economic, teacher and peer group factors upon the educational outcome variables. To do this we need simply examine the partial regression coefficients derived from the ordinary least squares estimation of a model such as follows:

$$(2) \quad y_{jt} = \sum_{i}^{g} b_{ij} x_{it} + \mu_t \qquad i = (1 \ldots a, \ldots g)$$

$$t = (1 \ldots n)$$

$$j = (1 \ldots m).$$

The subscript t signifies each of n observations on the independent variable x_i, the dependent variable y_j, and the residual term μ. Any b_{ij} represents the partial regression coefficients of x_i upon y_j.

However, by only examining the direct impact of any independent variable upon the dependent variables, a great deal of its effect will be missed if we fail to consider the indirect influences. That is, if some degree of correlation exists between two independent variables, an examination of the partial regression coefficients will not reveal all of the impact of any one of the independent variables upon the dependent variable. This will occur because some of the impact will be caught up in the other independent variable. To account for this, we must examine how the correlation between any two independent variables can be considered along with the partial regression coefficients to indicate the direct, the indirect and the total impact of any independent variable on any dependent variable. Suppose we define any simple correlation coefficient between the independent variable x_a and the dependent variable y_j as r_{aj}. This measures the degree of variation in the dependent variable associated with variations in the explanatory variable independent of any scaling. The simple correlation coefficient between any two independent variables x_a and any other member of the set x_i is defined as r_{ai}. Given this definition, we will then consider the total impact of any independent variable x_a upon a dependent variable y_j as the correlation coefficient r_{aj}. To see how r_{aj} is derived, we must first remove the scaling problems in equation (2) by transforming each variable into standardized form as follows:

$$(3) \quad Y_{jt} = \sum_{i}^{g} P_{ij} X_{it} + U_t \qquad i = (1 \ldots a, \ldots g)$$

where

$$(4) \quad Y_{jt} = \frac{y_{jt} - \bar{y}_j}{\sigma_{y_j}} \qquad (6) \quad P_{ij} = b_{ij} \frac{\sigma_{x_i}}{\sigma_{y_j}}$$

$$(5) \quad X_{it} = \frac{x_{it} - \bar{x}_i}{\sigma_{x_i}} \qquad (7) \quad U_t = \frac{\mu_t - \bar{\mu}}{\sigma_{y_j}}$$

The symbols σ_{y_j} and σ_{x_i} are the standard deviations of y_j and x_i and $\bar{y}_j$, $\bar{x}_i$ and $\bar{\mu}$ are the means of y_j, x_i and μ respectively. The coefficient P_{ij} which shall be referred to as the path coefficient may be interpreted as measuring the number of standard deviations that y_j changes if x_i changes by one standard deviation (assuming all other variables remain unchanged). To derive the correlation coefficients, consider the following transformation of equation (3):

$$(8) \quad \sum_{t}^{n} \left(\frac{Y_{jt} \cdot X_{at}}{n} \right) = P_{aj} \sum_{t}^{n} \left(\frac{X_{at} \cdot X_{at}}{n} \right) + \sum_{i'}^{g} \left[P_{i'j} \sum_{t}^{n} \left(\frac{X_{i't} \cdot X_{at}}{n} \right) \right]$$

$$+ \sum_{t}^{n} \left(\frac{U_t \cdot X_{at}}{n} \right) \qquad i' = (1 \ldots g), \quad a \neq i'$$

where X_a is not part of the set of variables defined by i'.

By definition of a simple correlation coefficient, equation (8) can be written as follows:

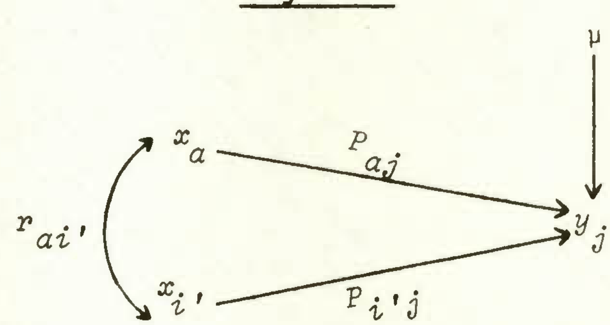
$$(9) \quad r_{aj} = P_{aj} + \sum_{i'}^{g} P_{i'j} r_{ai'}$$

(10) where $r_{aa} = 1$ and $r_{a\mu} = 0$.

Equation (9) states that the correlation coefficient (r_{aj}) for x_a and y_j is equal to the path coefficient P_{aj} plus the product of the path coefficient $P_{i'j}$ and the correlation coefficient $r_{ai'}$ for any $x_{i'}$ and x_a. We have assumed in equation (10) that the correlation of x_a with itself is equal to one and that there is zero correlation between x_a and the residual μ. Equation (9) can also be interpreted as stating that the total impact of a one standard deviation change in x_a upon y_j measured by r_{aj} is equal to the direct influence of this change upon y_j (P_{aj}), plus the sum of the indirect impact of the change working through all $x_{i'}$ upon y_j , namely, $(\sum_{i'}^{g} P_{i'j} r_{ai'})$.

It is precisely this interpretation of equation (9) we will use in this paper when we discuss the indirect impact that the socio-economic factors have on the education outcome of the student through his personal characteristics. In Figure 1 below, we illustrate how this hypothesis operates.

Figure 1



y_j individual student outcome,

$x_{i'}$ personal factors of student,

x_a socio-economic status,

μ the residual which for the purpose of this diagram captures the teacher and peer group factors.

In this figure, all straight lines which represent path coefficient are unidirectional and imply causation. The curved line, which represents correlation, is bidirectional and does not imply causation. By examining this figure it can be seen that the total relationship between the educational outcome and the socio-economic factors r_{aj} is equal to the direct effect P_{aj} plus the indirect effect $(P_{ij} \cdot r_{ai})$. This relationship suggests that all the impact of the socio-economic environment is not captured solely by regression coefficients but by the relationship between socio-economic environment and the personal factors of the student. This is a hypothesis which we shall explore in the chapter discussing the results.

Model Two

One of the principal advantages that this research project has is that we are able to include as an explanatory variable the influence of the class peer groups. Conventional wisdom suggests that peer group factors should carry a considerable influence in the direct determination of the educational outcomes of individuals. At the same time, there have been suggestions that the characteristics of the teacher bears relatively little direct impact on individual student learning. Even if both of these hypotheses were true it is unclear whether there is not some indirect influence of the characteristics of the teacher upon individual learning through the peer group as measured by the average class score on performance tests.

The view that we are hypothesizing is that learning for the class as a unit is strongly influenced by the way in which the teacher and the class perceive each other. If this is the case, then the teacher could conceivably influence the average class score without having much of an influence upon the distribution of the individual scores within the class. As such, the characteristics of the teacher would appear to bear little direct influence upon the individual's performance, but would appear to be quite important in their influence on the average class score which, in turn, directly influences the individual's performance. Generally when peer group scores of this kind have been introduced by others, the feeling is that they are merely a reflection of the socio-economic background of the family.[1] However, the data set we are using is such that when the peer group variables were measured (March-April of the school year) the students had been associated with a teacher for the largest part of a school year. Also, this was the first time many students were confronted by the formal learning process and it is most likely that the teacher influences would be strong. To test the strength of the hypothesis that the peer group scores are an endogenous variable determined by teacher inputs and in turn act as a determinant of the educational outcomes of the individual, we utilize a two-equation recursive model.

As was the case in the first model, we expect to find some collinearity among the independent variables in this model. We will attempt to sort this out by using the path coefficients as measures of the direct impact and derive relationships between these path coefficients and correlation coefficients to indicate the indirect and total impacts.

[1]See Bowles and Levin [1968].

Let us hypothesize the following two-equation recursive model:[2]

$$(11) \quad Y_{kt} = \sum_{i}^{g} P_{ik} X_{it} + V_t \qquad k = (1 \ldots r)$$

$$i = (1 \ldots a,\ g)$$

$$t = (1 \ldots n)$$

$$(12) \quad Y_{jt} = \sum_{i}^{g} P_{ij} X_{it} + P_{kj} Y_{kt} + W_t \qquad j = (1 \ldots s)$$

when t signifies each of n observations on the standardized variables X, Y, V and W. Zero correlation is assumed between the residuals V_t and W_t. Equation (11) states that the set of peer group scores, Y_k, is determined by a set of independent variables X_i and a residual V. Equation (12) states that the set of the education outcomes of an individual, Y_j, is determined by a set of independent variables, X_i, the set of peer group variables Y_k and the residual W. All path coefficients P_{ik}, P_{ij}, and P_{kj} can be considered as measures of the number of standard units that the dependent variable, with which they are associated, will change as the independent variables change by one standard unit. In effect, this is a measure of the direct impact. To obtain measures of the indirect and total impact on the dependent variables resulting from a change in any independent variable, we must first obtain the reduced-form of equations (11) and (12) and then derive the correlation coefficient relationship as was done in the first model. The reduced-form of equations (11) and (12) is as follows:

$$(13) \quad Y_{jt} = \sum_{i}^{g} (P_{ij} + P_{kj} P_{ik})\, X_{it} + P_{kj} V_t + W_t.$$

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[2]The use of capital letters to represent the variables and the residuals v_t and w_t implies that all variables have been standardized to remove scaling problems. This is the identical transformation that was performed in equations (3) to (7) in model one.

To derive the correlation coefficient between the standardized variables x_j and x_a (r_{aj}), consider the following transformation of equation (13):

$$(14)\quad \sum_t^n \frac{(Y_{jt} \cdot X_{at})}{n} = \sum_{i'}^g (P_{i'j} + P_{kj} \cdot P_{i'k}) \sum_t^n \frac{(X_{i't} \cdot X_{at})}{n}$$

$$+ (P_{aj} + P_{kj} \cdot P_{ak}) \sum_t^n \frac{(X_{at} \cdot X_{at})}{n} + P_{kj} \sum_t^n \frac{V_t \cdot X_{at}}{n}$$

$$+ \sum_t^n \frac{W_t \cdot X_{at}}{n} \qquad \begin{array}{l} i' = (1 \ldots g) \\ a \notin i' \end{array}$$

where a is not part of the set i'.

By definition, equation (14) can be written as follows:

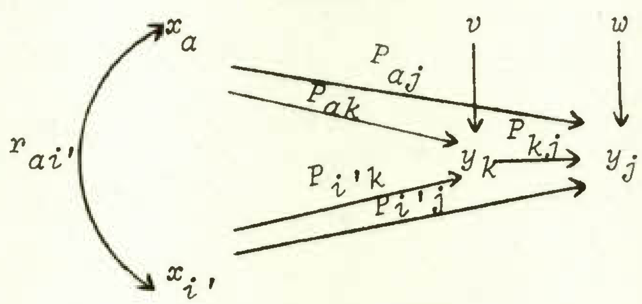
$$(15)\quad r_{aj} = (P_{aj} + P_{kj} \cdot P_{ak}) + \sum_{i'}^g (P_{i'j} + P_{kj} \cdot P_{i'k}) r_{i'a}$$

where

$$(16)\quad r_{aa} = 1;\ r_{va} = r_{wa} = 0.$$

Equation (16) states that the correlation of x_a with itself equals one and with the unstandardized residuals w and v equals zero. Equation (15) is best understood in conjunction with Figure 2.

Figure 2



In this figure, all straight lines are unidirectional and represent path coefficients while the curved line is bidirectional and represents correlation. Looking at equation (15) and Figure 2, we can see that the correlation coefficient, r_{aj}, between x_a and y_j is composed of three parts:

(1) the direct standardized effect of the variables x_a upon y_j as indicated by the path coefficient P_{aj};

(2) the indirect standardized effect of x_a upon y_j operating through y_k as indicated by the term $P_{kj} \cdot P_{ak}$;

(3) the indirect standardized effect of x_a upon y_j as a result of the correlation of x_a with $x_{i'}$, ($r_{ai'}$). This indirect effect can be considered as being composed of two parts:

   (a) the first part measures the influence of x_a through $x_{i'}$, when $x_{i'}$ influences y_j directly. This is the value $\sum_{i'}^{g} P_{i'j} \cdot r_{i'a}$;

   (b) the second part measures the influence of x_a upon y_j through $x_{i'}$, when $x_{i'}$ influences y_j indirectly through y_k. This value is expressed as $\sum_{i'}^{g} P_{kj} \cdot P_{i'k} \cdot r_{i'a}$.

   The entire indirect effect of this third point is expressed as the value $\sum_{i'}^{g} (P_{i'j} + P_{kj} \cdot P_{i'k}) r_{i'a}$ in equation (15).

These three parts combined sum up to equal r_{aj} which can be considered as the total standardized impact of the variable x_a upon y_j. In the discussion of the results in Chapter 4, we will use equation (15) and this decomposition to indicate how the teacher and class size factors influence individual learning directly and indirectly through the peer group factors.

Chapter 3

DESCRIPTION OF SAMPLE

The noncognitive and cognitive educational outputs used in this project are part of the educational outcomes measured as part of a project undertaken by the Ottawa Board of Education entitled Quality of Education Demonstration (QED). The QED project which applies only to classes where English is the language of instruction, was begun with the purpose of measuring the extent to which the objectives of education are being achieved at the grade one level at this school board. The objectives of education used by QED were originally based on those suggested by Henry Dyer in the Pennsylvania Quality Education Study[1] and modified by the research staff of the Ottawa Board of Education in conjunction with their superintendents. The tests were administered to grade one students such that half the students of any one class were administered one battery of tests and the other half were administered a second battery. They assumed that if the choice of students within a class performing a particular battery was random, then it could be assumed that half a class would have the same properties as a full class. This reasoning was necessary in order to enlarge the sample size since the level of observation for them was to be the class. Since our requirements are that the level of observation be the individual, this assumption matters only when we wish to use average class scores as proxies for peer group influences. These peer group influences should be measures of the average class performance and not the "half class" performance.

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[1] Dyer [1966].

However, since the choice of the students for each sample was done randomly, there is little loss in assuming that the "half class" peer group variables truly represent the "full class" peer groups.

Between the two samples, the only difference in the list of variables is the outputs. Because of this we will only distinguish between the output variables in the two samples (referred to as Batch A and Batch B). The data shall be described under the following system: (1) outputs; (2) personal variables (characteristics of the individual student); (3) peer group variables (classroom averages) and other classroom characteristics; (4) background variables; and (5) teacher characteristics.

(1) Output variables (Batch A)

-- Raw score in Reading; test taken at end of school year.

(Batch B)

-- Raw score in Mathematics; test taken at end of school year;

-- Raw score in Interest; test taken at end of school year.

The variable "Interest" in Batch B is the one non-cognitive test with which we deal. This variable, Interest, was claimed to be the most important aspect of learning by the committee which chose the tests. This test is designed to measure the development of interest and enthusiasm for learning. The definition used is the expression of a positive attitude by the student towards the learning environment in the areas of (1) the personnel in the school; (2) the subjects learned at school; and (3) the school, learning, and school work as general concepts.

(2) Personal Variables

- Classification ratio -- number of grade 1 half terms completed, divided by the number of half terms spent in grade 1 (recorded in April);
- Composite aptitude rating: average rating assigned by teachers for overall scholastic aptitude. This is a descriptive variable taking only three values: (1) low, (2) medium, (3) high (recorded in April);
- Disability which is known to affect work (recorded in April);
- Age in months (recorded in April).

The classification ratio is somewhat of an objective variable which measures the speed at which the student internalizes an existing body of knowledge. The composite aptitude rating is more of a subjective rating by the teacher of the ability of the individual to absorb the body of knowledge. The interpretation of the disability variable is not totally obvious since it does not measure disabilities of children with serious mental or physical handicaps since these children would most likely be in different schools. What it does measure is disabilities which the teacher perceives as affecting the progress of the individual.

(3) Peer Group and Other Classroom Variables

-- Average **Reading** score for the Batch A students in a particular class (taken at end of school year);

-- Average **Mathematics** score for the Batch B students in a particular class (taken at end of school year);

-- Average **Interest** score for the Batch B students in a particular class (taken at end of school year);

-- Average classification ratio for both Batch A and B students in each class (taken in April);

-- Class size (teacher/student ratio).

The only variable requiring any explanation is the teacher/student variable. This variable is based on the number of students each teacher has in his/her class. It does not include specialists or teachers not associated with a particular class.

(4) Socio-Economic Variables

-- Age of father;

-- Age of mother;

-- Education of father;

- -- Number of books in the home;
- -- Type of residence;
- -- Language spoken in the home (English, French, or other).

These variables will act as the socio-economic status factors for the students. We have some information on the conjugal status of the family but found that it offered little in the way of explaining the educational outcomes discussed in this paper.

(5) Teacher Characteristics

- -- Age of teacher;
- -- Years of experience in the present school;
- -- Possession of a college degree.

The primary weakness in this entire set of data lies in the omissions. There are no variables relating to the physical school resources. However, as Averch et al. [1972] have pointed out, school resources are seldom important determinants of student outcomes and when they are, no one school resource consistently appears in different research findings.[2] Also this data set does not contain any information on the effectiveness of teacher performance. Although we have information on the age and experience of the teacher, we have no data on the ability of teachers. Hanushek [1971] has indicated that the ability of the teachers to communicate as represented by a test in verbal fluency is a significant variable in determining student outcome.

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[2] Averch et al. [1972], pp. 44-45.

However, there are significantly strong points to this data set. The most important of these is that the unit of analysis is the individual with the corresponding classroom data on teachers. Most other studies base their results upon schools or school district observations. Where individual data do exist, it is generally not complemented by classroom information. Only Hanushek has utilized data pertaining to the individual and the classroom. The other principal advantage to such data is the ability to create peer group variables relating to the classroom of the individual which, as shall be seen later, is very important.

Chapter 4

PRESENTATION OF RESULTS

In this chapter we shall present the results of the application of the two models presented in Chapter 2. The first section will cover a discussion of model one, while the second section will cover model two. Because of the large number of variables involved, the results of the estimations shall be presented in blocks of variables which have been discussed in Chapter 3. For each block of variables, we shall discuss the influence of each of the variables in the appropriate block upon the two cognitive dependent variables -- Reading and Mathematics -- and the affective dependent variable -- Interest. Although the results are presented in separate blocks, they were estimated with ordinary least squares (O.L.S.) procedures using all of the blocks at once. The results of these full equation estimates for the three outputs, Mathematics, Reading and Interest are included in Appendix A(ii).

As was explained by equations (2) through (7) of Chapter 2, all of the results were obtained using standardized data and the coefficients are referred to as path coefficients. This technique was used to remove scaling problems and to facilitate the understanding of the relationship between path coefficients and correlation coefficients. These path coefficients are to be interpreted as measuring the number of standard deviations that the dependent variable, Mathematics, Reading or Interest, changes if one of the variables from the personal, socio-economic, peer group, class size or teacher blocks change by one standard deviation.

This interpretation is acceptable when only continuous variables are used. However, when dichotomous (or dummy) variables are used, a different interpretation is necessary. Since dichotomous variables (in this paper) take on raw values of one or zero only, the standard deviation of these dichotomous independent variables will necessarily be greater than zero and less than one. Thus, a one standard deviation change in such a variable is meaningless because, by definition, the variable must change by a value of one. For example, suppose one of the independent variables influencing Interest is the sex of the student. Further, suppose that the variable is expressed in dichotomous form and will take on raw values of one when the student is a girl and zero when the student is a boy. The coefficient for this variable derived from O.L.S. estimations should state how much higher or lower a student would perform on Interest if the child were a girl rather than a boy. Suppose that the standard deviation of this variable were equal to 0.5. If all variables are standardized, a one unit change in this standardized sex variable would be equivalent to a raw change in this variable of 0.5, which is impossible since, by definition, this variable can only change by a value of one. Thus, to make any sense of the path coefficient generated by O.L.S., this coefficient must be transformed to conform to the above rule. This can be achieved by dividing the standardized coefficient of the appropriate variable by its standard deviation. Then, assuming that the path coefficient for the sex variable upon Interest is equal to 0.2, after dividing the coefficient by its standard deviation of 0.5, we could interpret the results as stating that if a child were a girl, she would achieve a score of 0.4 standard deviation higher in Interest than a boy (assuming all other variables are unchanged).

Section One

In this section, using equation (3), we will discuss the direct impact (path coefficients) of each of the variables described in the third chapter upon the three educational outcomes -- Mathematics, Reading and Interest. Also, using equation (9) of model one, we will explain the direct, indirect, and total impact of the education of the father upon the three outcome scores. It should be pointed out that the results described in this study as a whole do not encompass all the information that could be derived from the tables that appear in the text and Appendix. We have selected what we consider some of the highlights of these results. The interested reader will certainly be able to delve deeper into the tables to obtain more than is discussed here.

Personal Variables

The personal factors are a block of variables which relate to both the learned and hereditary influences that a child has and that might influence the amount of education he or she internalizes. In Table 1, we present the path coefficients using O.L.S. procedures for these variables upon the two cognitive outputs -- Mathematics and Reading -- and the one affective output -- Interest.

Table 1

PATH COEFFICIENTS FOR PERSONAL VARIABLES UPON MATHEMATICS, READING AND INTEREST

(F statistics in brackets)

Personal Variables (X_i)	Mathematics	Mathematics* $\div \sigma_{x_i}$	Reading	Reading* $\div \sigma_{x_i}$	Interest	Interest* $\div \sigma_{x_i}$
Classification ratio	0.129 (3.52)		0.231 (21.49)		-0.024 (0.08)	
Age in months	0.135 (9.58)		0.158 (15.82)		0.096 (2.60)	
Composite aptitude† low = 1	-0.231 (18.98)	-0.569	-0.287 (44.00)	-0.664	-0.078 (1.51)	-0.192
Composite aptitude† high = 1	0.187 (14.44)	0.440	0.235 (34.86)	0.579	0.091 (2.34)	0.214
Disability† yes = 1	-0.077 (2.86)	-0.182	0.013 (0.12)	0.032	-0.129 (5.63)	-0.306
Sex: Girl = 1†	--	--	--	--	0.205 (16.92)	0.410
Interest	0.135 (9.06)		--	--	--	--
Respect for authority	--	--	0.049 (1.68)		--	--

†Dummy variable.

-- The variable is not included in this regression.

*Column of transformations of dichotomous variables is included to aid in the interpretation of the coefficients (see pages 26 and 27). All continuous variables in this column need not be transformed and so nothing appears in these cells.

It is evident from this table that the classification ratio plays an important role in the internalizing of the two cognitive skills. If the classification ratio, which is a measure of the speed of progression through a curriculum, is increased by one standard deviation (hereafter referred to as S.D.), this will increase the score in Mathematics by 0.13 S.D.'s and the score in Reading by 0.23 S.D.'s.

The composite aptitude variable is also shown in Table 1 to play a significant and consistent role in the internalizing of both cognitive skills. This composite aptitude factor is a dichotomous variable in which there are values for low, medium or high rankings. We have removed the medium value and as such we compare the low- and the high-rated students for this variable to the medium-rated students. This variable represents a subjective interpretation of the individual by the teacher and as such may be clouded by the personal feeling for the student by the teacher. With this in mind, we can nonetheless see from Table 1 that for Mathematics, a student with a low composite aptitude score will perform 0.57 S.D.'s below a medium-rated student.[1] Also, a student with a high rating in the composite aptitude will receive a score of 0.44 S.D.'s higher than the medium-rated student. Thus, if we compare the impact of a low rating in the composite aptitude upon Mathematics to the impact of a high rating, we find that there is a difference of one complete S.D. in the performance of the student.

Even more striking is the impact of this variable upon Reading. From Table 1 it is evident that a low rating in the composite aptitude generates a score which is 0.66 S.D.'s lower than a medium-rated student and 1.24 S.D.'s lower than a high-rated student. However, careful intepretation is necessary. It may be that the teacher is very perceptive and able to predict the outcome of individuals in

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[1]Note that this is a dummy variable and as such we use the transformed column for Mathematics to obtain the meaningful coefficient. This point is explained earlier in the text of this chapter on page 26 and the first half of page 27.

grade one through this ranking, but there may also be the Pygmalian effect in operation as noted earlier. That is, children attempt to perform as expected of them because they wish to react according to the expectation the teacher has of them.

In general, the strength of the direct impact of each of the personal factors upon the affective variable Interest is certainly different from their impact upon the cognitive variables. The classification ratio displays no meaningful impact upon Interest. Also the change in Interest resulting from a student having a high rating on the composite aptitude rather than a low rating, amounts to less than one half an S.D. On the other hand, other factors such as the student being a female as compared to male raises the score on Interest by 0.41 S.D.'s. The impact of this variable upon the cognitive variables was so small that after preliminary analysis it was dropped. The disability variable is also more important when comparing its impact upon the affective output to its impact on the cognitive variables.

Thus, what the material presented in Table 1 seems to suggest is that those personal factors relating to the ability of the student, such as the classification ratio and composite aptitude, are more useful in predicting the performance of the child in the cognitive domain. On the other hand, physical characteristics of the student such as sex and the existence or absence of disabilities seems to carry a greater impact upon the affective variable.[2]

[2]The age of the student is the exception.

However the above explanation and the accompanying table are not a complete interpretation of the impact of the personal characteristics of the student. Many of these variables are indicators of the preschool learning processes which in turn are a result of the background influences. To better explain this, we first require a discussion of the direct impact of these socio-economic factors, and then a further explanation of how they interact with the personal factors to influence these educational outcomes.

Socio-Economic Variables

Table 2 is a presentation of the path coefficients for the socio-economic variables which influence Mathematics, Reading and Interest directly.

Table 2

PATH COEFFICIENTS FOR SOCIO-ECONOMIC VARIABLES UPON MATHEMATICS, READING AND INTEREST

(F statistics in brackets)

Socio-Economic Variables (X_i)	Mathematics	Mathematics* $\div \sigma x_i$	Reading	Reading* $\div \sigma x_i$	Interest	Interest* $\div \sigma x_i$
Age of mother† over 35 = 1	0.003 (0.00)	0.006	-0.026 (0.33)	-0.052	0.023 (0.13)	0.047
Age of father† over 35 = 1	-0.001 (0.00)	-0.002	0.033 (0.50)	0.066	-0.114 (3.13)	0.230
Father's education† some high school or less = 1	-0.030 (0.32)	-0.061	0.005 (0.01)	0.010	-0.011 (0.03)	-0.022
Father's education† any postsecondary = 1	-0.031 (0.33)	-0.062	0.062 (1.83)	0.139	0.017 (0.07)	0.034
Books at home† of 30 to 200 = 1	0.005 (0.00)	0.011	0.113 (6.47)	0.226	-0.025 (0.154)	-0.054
Books at home† of 201 + = 1	0.130 (4.29)	0.277	0.122 (6.09)	0.279	0.037 (0.24)	0.079
Residence type† non high rise + non detached = 1	0.006 (0.02)	0.012	-0.041 (1.01)	-0.082	-0.029 (0.28)	-0.058
Residence type† high rise = 1	-0.208 (0.22)	0.897	0.061 (2.97)	0.347	0.070 (1.80)	0.306
Language spoken at home† French = 1	--	--	0.047 (1.74)	0.320	-0.100 (4.09)	-0.885
Language spoken at home† non French or English = 1	--	--	-0.020 (0.31)	-0.058	-0.052 (1.03)	-0.139

†Dummy variable.

-- The variable is not included in this regression.

*Column of transformations of dichotomous variables is included to aid in the interpretation of the coefficients (see pages 26 and 27). All continous variables in this column need not be transformed and so nothing appears in these cells.

It should be pointed out that the original data set included a much finer degree of disaggregation of the education and age variables for both parents than are presented in this table. However it was felt, after some deliberation, that only those variables included in Table 2 would be used to indicate parental age and education. The lack of impact that these variables display upon the cognitive and affective variables is very surprising. (The exception is the negative influence that older fathers have upon the affective variable when compared to younger fathers.) The possible influence of bilingualism or French unilingualism was explored but found to be fairly unsuccessful in explaining the educational outcomes at the grade one level in the cognitive domain. However, in the affective domain, if French is spoken at home, the student performs .88 S.D.'s lower than if English is the language in the home. Further, the type of residence the child is living in generally displays no strong impact in either the cognitive or affective outputs.

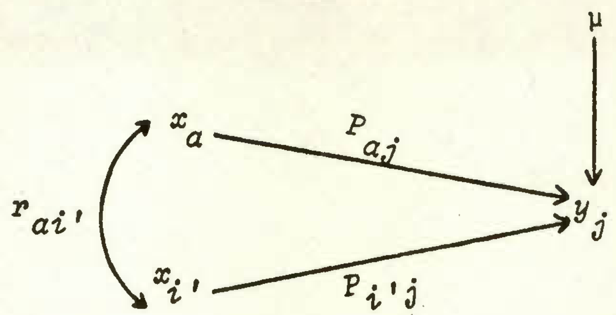
The only socio-economic factor to display any strong influence on the cognitive output is the size of the family library. For Reading, the student will generally score about 0.25 S.D.'s higher if there is least a certain number of books in the home than if there are virtually none. For Mathematics, merely the existence of a certain number of books in the home is not sufficient to influence this output. From the arbitrary division used in this paper, it seems that there must be more than 200 books at home to raise the level of Mathematics by 0.28 S.D.'s over homes with less than 30 books. One interpretation of this finding is that parents who have a considerable number of books in the home are relatively more educated and are better able to help children in Mathematics. However, to have an impact on the ability of a child to read, it is not important that there be large quantities of books in the home, but simply that there exist reading material for the child to examine. Note that these library variables have little impact on the affective variable.

Interaction of Personal and Socio-Economic Variables

The direct impact of the socio-economic variable which is displayed in Table 2 is only partly the way in which these variables influence the educational outcomes. These socio-economic variables are correlated with the personal factors of the student and as such influence the educational outcomes indirectly through these personal factors. To examine this phenomenon, we will make use of equation (9) of Model One which, as was explained earlier, indicates how the total impact of any one variable can be decomposed into its direct and indirect influences upon the educational outcomes. Specifically, what we wish to consider is the total impact of the father upon the three educational outcomes by decomposing it into direct and indirect impacts. We repeat below equation (9) and Figure 1 to aid in understanding Table 3.

$$(9) \quad r_{aj} = P_{aj} + \sum_{i'}^{g} P_{i'j} r_{ai'} \qquad i' = (1 \ldots g), \quad a \neq i'$$

Figure 1



y_j individual student outcome,

$x_{i'}$ personal factors of student,

x_a socio-economic status,

μ the residual which for the purpose of this diagram captures the teacher and peer group factors.

Table 3

DIRECT, INDIRECT AND TOTAL IMPACT OF FATHER'S EDUCATION UPON MATHEMATICS, READING AND INTEREST

	Some High School or Less Upon			Any Postsecondary Upon		
	(1) Mathematics	(2) Reading	(3) Interest	(4) Mathematics	(5) Reading	(6) Interest
1. DIRECT	0	0	0	0	0.062	0
INDIRECT VIA						
2. Classification ratio	-0.042	-0.040	0	0.047	0.060	0
3. Composite aptitude† low = 1	-0.050	-0.051	-0.017	0.045	0.039	0.015
4. Composite aptitude† high = 1	-0.045	-0.039	-0.025	0.060	0.055	0.032
5. Books at home† 30 to 200 = 1	0	-0.001	0	0	-0.015	0
6. Books at home† 201+ = 1	-0.053	-0.036	0	0.066	0.047	0
7. Interest	-0.053	--	--	0.017	--	--
8. Respect for authority	--	-0.003	--	--	0.003	--
9. Disability† yes = 1	-0.009	0	0.014	0.004	0	-0.009
10. Total (a)[1]	-0.25	-0.17	-0.03	0.24	0.25	0.04
11. Total (b)[2]	-0.51	-0.35	-0.06			
12. Total (c)[3]				0.54	0.57	0.09

†Dummy variable.

0 States that the variable in question had an F statistic of less than one.

-- The variable in question was not included in the regression.

[1] Total of the coefficients of each column.

[2] Total of coefficients of each of columns 1 to 3 divided by standard deviation of the variable *father's education of some high school or less* is included to facilitate interpretation of the total impact of this dichotomous variable.

[3] Total of coefficients of each of columns 4 to 6 divided by standard deviation of the variable *father's education of any postsecondary training* is included to facilitate interpretation of the total impact of this dichotomous variable.

In Table 3, each of columns one, two and three contain information on the direct, indirect and total impact of the father having some high school or less upon Mathematics, Reading and Interest. Columns four, five and six refer to the same impacts resulting from the father having any amount of postsecondary education. Row one of this table refers to the direct impact of the father's education upon each of the three outcomes. It is taken directly from Table 2 and it corresponds to P_{aj} of equation (9). Rows two through nine refer to the indirect impact of the father's education upon the educational outcomes. This corresponds to each of the $P_{i'j}r_{ai'}$ of equation (9). Row ten refers to the total of each column and corresponds to r_{aj} of equation (9). Strictly speaking, r_{aj} should be equal to the actual correlation coefficient between the two variables y_j and x_a.[3] To the extent that it is not, it is due to the fact that we have assumed that the factors relating to the education of the father are correlated only with the personal factors and not with the teacher and peer group factors. Rows eleven and twelve are simply the total of row ten divided by the appropriate standard deviation to account for the problem of using standardized dummy variables. This was discussed in detail on pages 26 and 27 of this chapter.

For the two cognitive variables Mathematics and Reading, we found little or no direct impact resulting from the education of the father. However, when we include the indirect impact, the total impact represents a considerably different picture. Looking at rows eleven and twelve, we

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[3]The actual correlation coefficients appear in Appendix A(iv)2 and A(iv)3.

find that low levels of father's education can reduce the child's score in Mathematics by 0.51 S.D.'s below that of a child whose father has high school training. In turn, high levels of father's education raise the score in Mathematics by 0.54 S.D.'s. If we combine these two total impact values, we find that the child whose father has at least some postsecondary training will perform 1.05 S.D.'s higher than the child whose father has at most, some high school training. For Reading we find similar striking differences. Children whose fathers have attended postsecondary institutions generally perform 0.92 S.D.'s higher than children whose fathers have not completed high school. This striking difference is not observed in the affective domain. The direct impact of father's education is minimal, and the total impact is small for the affective output.

What we can draw from this discussion is that the education of the father is important in determining how well a child performs in the cognitive skills. The path that this impact takes is not totally obvious and would have been overlooked if we failed to examine the indirect effects. However, for the affective skills, this technique failed to reveal much further information concerning the relationship between parental education and affective skills.

Teacher Variables

In the discussion of the influence of the teacher upon the educational outcome scores, we will survey the importance of three basic factors: age, experience, and level of training. In Table 4 the direct effects of these variables in the three educational outcomes is displayed through the path coefficients. In the cognitive area of Mathematics, teachers who have been teaching in the same school for six or more years seem to have a marginally negative direct influence when compared to teachers with less than three years' experience in the same school. In Reading, teachers 45 and over appear to contribute to a favourable performance by the child when compared to teachers who are between 25 and 34 years of age. In the affective area, we do find that teachers over 45 lower the score in Interest by 0.49 S.D.'s relative to teachers between 25 and 34. Yet, overall, the direct impact of the teacher characteristics seems to be quite weak.

Table 4

PATH COEFFICIENTS OF TEACHER VARIABLES UPON MATHEMATICS, READING AND INTEREST

(F statistics in Brackets)

Variables (X_i)	Mathematics	Mathematics* $\div \sigma_{x_i}$	Reading	Reading* $\div \sigma_{x_i}$	Interest	Interest* $\div \sigma_{x_i}$
Experience in same school† of 3-5 years = 1	-0.051 (0.74)	-0.102	0.010 (0.01)	0.020	-0.021 (0.08)	-0.042
Experience in same school† of 6+ years = 1	-0.092 (2.12)	-0.185	0.033 (0.43)	0.070	0.016 (0.04)	0.032
Teacher's age† 24 or less = 1	-0.057 (0.96)	-0.148	-0.034 (0.46)	-0.085	0.060 (0.68)	0.156
Teacher's age† 35-44 = 1	-0.035 (0.31)	-0.114	0.011 (0.06)	0.035	0.073 (1.59)	0.236
Teacher's age† 45+ = 1	0.042 (0.84)	0.171	0.068 (2.90)	0.218	-0.122 (4.41)	-0.494
College degree† yes = 1	-0.038 (0.31)	-0.094	-0.072 (2.65)	-0.259	0.004 (0.01)	0.010

†Dummy variable.

-- The variable is not included in this regression.

*Column of transformations of dichotomous variables is included to aid in the interpretation of the coefficients (see pages 26 and 27). All continuous variables in this column need not be transformed and so nothing appears in these cells.

To draw the conclusion from this that the teacher variables have only a small influence on the way in which a child performs in both the cognitive and affective domains would be premature. As we shall indicate later, many of the teacher characteristics are influential in determining how well a child performs, but not via a direct route. However, we will show that these teacher characteristics do have a strong direct impact upon the performance of the class. In turn, the performance of the class, which we use as a proxy for the peer group influence, conveys a considerable direct influence in determining the educational outcome of the individual. By using this approach, we will show that teachers do matter in determining how well a child performs, but most of this impact is indirect. Before we describe the empirical evidence of this process, we must first discuss the direct role that the peer group (classroom averages) and the class size variables have in the determination of the individual scores.

Peer Group and Class Size Variables

In this section there are two distinct sets of variables to be discussed. The first is a set of variables relating to the peer group factors which are classroom averages of the educational outcome and the classroom classification ratio (with the individual score or ratio removed for each observation in each case).[4] The second is a set of variables which deal with the size of the class. Table 5 is a display of the path coefficients for the direct impact of these variables

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[4]This has been done so that we can be sure that the direction of causation is such that the class score influences the individual performance and not the other way around.

upon the three educational outcome scores. First, dealing with the class size variables, it seems that there is little difference how small or large a class is when the issue is how a child will perform in Mathematics or Interest. For Reading, there does appear to be some influence from the class size. Classes of 17 students and under and classes of 30 to 34 have a negative impact compared to classes containing 18 to 24 students. However, even this impact is relatively small.

Table 5

PATH COEFFICIENTS OF PEER GROUP AND CLASS SIZE VARIABLES UPON MATHEMATICS, READING AND INTEREST

(F statistics in brackets)

Peer Group and Class Variables (X_i)	Mathematics	Mathematics* $\div \sigma_{x_i}$	Reading	Reading* $\div \sigma_{x_i}$	Interest	Interest* $\div \sigma_{x_i}$
Class average classification ratio	0.006 (0.01)		-0.102 (6.51)		0.027 (0.12)	
Class average in mathematics	0.288 (23.97)		--		--	
Class average in reading	--		0.363 (68.01)		--	
Class average in interest	0.047 (1.00)		--		0.151 (7.27)	
Class average in respect for authority	--		-0.021 (0.33)		--	
Student/Teacher ratio† 17 or less = 1	-0.022 (0.13)	-0.065	-0.089 (2.73)	-0.246	-0.019 (0.07)	0.057
Student/Teacher ratio† 25 to 29 = 1	-0.049 (0.40)	-0.100	-0.036 (0.30)	-0.075	-0.097 (1.08)	-0.197
Student/Teacher ratio† 30 to 34 = 1	-0.102 (1.82)	-0.232	-0.110 (3.05)	-0.203	-0.092 (1.48)	-0.316
Student/Teacher ratio† 35+ = 1	-0.034 (0.31)	-0.117	0.062 (1.30)	0.203	-0.092 (1.48)	-0.316

†Dummy variable.

-- The variable is not included in this regression.

*Column of transformations of dichotomous variables is included to aid in the interpretation of the coefficients (see pages 26 and 27). All continuous variables in this column need not be transformed and so nothing appears in these cells.

When we turn our attention to the peer group influences, we find generally a very strong direct impact from the peer group factors. With respect to the average class score in Mathematics, Reading and Interest, an increase of one standard deviation in these variables leads to a 0.29 S.D. increase in Mathematics, a 0.36 S.D. increase in Reading, and a 0.15 S.D. increase in Interest. The magnitude of the influence of these average scores upon the educational outcome of the individual raises very interesting questions which are discussed in the next section.

Section Two

Interaction Between Peer Group and Teacher Variables

After examining the path coefficients of both the peer group variables and teacher variables, it appears from these direct effects that the peer group variables are relatively more important than the teacher variables. However, to conclude from this that the characteristics of the teacher have little overall influence in determining the amount of knowledge that children internalize without any further empirical investigation, would be presumptuous.

Pursuing this issue we felt that it was necessary to determine whether there was any further indirect influence from the teacher characteristics which had not been caught up by the direct influences. To do this we estimate a two-equation recursive model described in Model Two of Chapter 2 for each of the three educational outcomes. Then, utilizing equation (15) of this model, we calculate the total impart of the teacher characteristics upon the educational outcome by determining the indirect effects in addition to the previously estimated direct effects.

The first equation of each of these three two-equation models contains the peer group score as the dependent variable. The peer group score is measured as the class average in Mathematics, Reading or Interest. The second equation of each of the models is the full equation using Mathematics, Reading or Interest as the dependent variable. These latter equations are identical to the single-equation models estimated by O.L.S. procedures in the first section of this chapter and described in Tables 1, 2, 4, and 5.

In Table 6, there is a complete listing of the independent variables and their respective path coefficients for the first equation of each of the three models. These independent variables encompass the influence of the teacher, the class size and the ability of the class (which is measured by the class average classification ratio). This latter variable represents a proxy for the personal and socio-economic characteristics of the class. The path coefficients that result from these estimations are to be considered as measures of the direct impact of the independent variables upon these average class score dependent variables.

Table 6

PATH COEFFICIENTS OF PEER GROUP, TEACHER AND CLASS SIZE VARIABLES UPON CLASSROOM AVERAGE SCORE IN MATHEMATICS, READING AND INTEREST

(F statistics in brackets)

Peer Group, Teacher and Class Variables (X_i)	Mathematics Average	Mathematics Average* $\div \sigma_{x_i}$	Reading Average	Reading Average* $\div \sigma_{x_i}$	Interest Average	Interest Average* $\div \sigma_{x_i}$
Class average classification ratio	0.403 (102.26)		0.345 (71.81)		0.105 (4.52)	
Experience in same school† of 3 to 5 years = 1	0.148 (7.90)	+0.297	0.323 (35.40)	0.651	0.078 (1.44)	0.157
Experience in same school† of 6 years = 1	-0.302 (24.27)	-0.633	-0.106 (3.49)	-0.226	-0.130 (3.54)	-0.276
Teacher's age† 24 or less = 1	-0.135 (6.55)	-0.352	-0.287 (27.97)	-0.612	0.014 (0.05)	0.035
Teacher's age† 35 to 44 = 1	-0.172 (15.53)	-0.557	-0.066 (2.18)	-0.212	0.009 (0.03)	0.029
Teacher's age† 45+ = 1	-0.083 (4.24)	-0.337	-0.061 (2.04)	-0.219	-0.286 (33.07)	-1.163
College degree† yes = 1	-0.081 (2.49)	-0.401	-0.235 (24.29)	-0.588	0.011 (0.04)	0.054
Student/teacher ratio† 17 or less = 1	-0.179 (11.17)	-0.536	-0.395 (47.90)	-1.094	-0.235 (12.57)	-0.704
Student/teacher ratio† 25-29 = 1	-0.444 (43.85)	-0.904	-0.547 (64.07)	-1.144	-0.287 (12.03)	-0.859
Student/teacher ratio† 30-34 = 1	-0.486 (56.85)	-1.102	-0.518 (61.50)	-1.172	-0.202 (6.43)	-0.458
Student/teacher ratio† 35+ = 1	-0.476 (87.04)	-1.636	-0.474 (72.86)	-1.549	-0.159 (6.41)	-0.546

†Dummy variable.

*Column of transformations of dichotomous variables is included to aid in the interpretation of the coefficients (see pages 26 and 27). All continuous variables in this column need not be transformed and so nothing appears in these cells.

Looking first at the experience of the teacher, we find from Table 6 that, for Mathematics, teachers who have been teaching for three to five years in the same school (Group 2) have classes that perform about 0.3 S.D.'s higher than teachers who have spent less than three years in the same school (Group 1), and 0.93 S.D.'s higher than teachers who have been in the same school more than five years (Group 3).[5] It should also be noted that those teachers in Group 3 have classes that perform 0.63 S.D.'s lower in Mathematics than those in Group 1. In Reading, we observe that the teachers with three to five years' experience in the same school have classes that perform best. In this case, their classes score 0.65 S.D.'s higher than those of teachers in Group 1, and 0.87 S.D.'s higher than those of teachers in Group 3. Also, the classes of the teachers in Group 3 performed 0.23 S.D.'s lower in Reading than the classes of those teachers in Group 1. For the affective score, Interest, we find that those teachers with six or more years' experience in the same school have a hindering direct influence of 0.28 S.D.'s when compared to the teachers in Group 1. On the other hand, the teachers in Group 2 seem to have a small but positive impact upon the affective scores when compared to the teachers in Group 1 or Group 3.

The age of the teachers is also quite important in terms of the performance of the class in the three educational outcomes. Generally, teachers between the ages of 25 and 34

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[5]This is calculated by adding the adjusted coefficient for experience of three to five years to the adjusted coefficient for experience of 6 or more years.

have classes that perform significantly better for the two cognitive skills than those of teachers who are older or younger. However, for the affective skill, Interest, it is evident from Table 6 that only teachers who are over 44 have a negative influence upon this type of learning when compared to any younger age group of teachers.

In the determination of these classroom scores, for Mathematics, Reading and Interest, we have included a set of class size variables. As was seen in Table 5, these variables only appear to have modest importance for the individual in their direct influence upon Reading. However, when using these as determinants of classroom averages, they assume a considerable importance for all three outcomes.

In examining Table 6, what appears to be most striking is that the class size of between 18 and 24 students seems to be optimal in terms of the performance of the class in all three of the educational outcomes. All of the path coefficients indicate that there is a negative direct impact upon the class performance resulting from a class size of any value other than 18 to 24 students. In fact in the case of Reading, if any class size other than this optimal one is considered, it would lower the value of the class score by more than one standard deviation.

We have introduced these average class scores as proxies for peer group factors and have indicated the direct role that the teacher and class size factors have upon the determination of them. We have also pointed out the importance of these peer group factors in the direct determination of the individual educational outcomes for both cognitive and affective domains. (This is discussed using Table 5 in the first part of this chapter.) It remains now to show both the indirect and total impact that these teacher and class size variables have in the determination of the three individual educational outcomes.

In Tables 7, 8 and 9, we illustrate the indirect and total impact that the teacher has upon the three individual educational outcomes for Mathematics, Reading and Interest. Since the method of obtaining the information in these tables is derived from equation (15) of model two, we repeat it below with an accompanying diagram and an explanation.

$$(15) \quad r_{aj} = (P_{aj} + P_{kj} \cdot P_{ak}) + \sum_{i'}^{g} (P_{i'j} + P_{kj} \cdot P_{i'k}) r_{i'a}$$

Let us suppose that the subscripts in equation (15) refer to the following variables:

j — individual educational outcome in Mathematics;

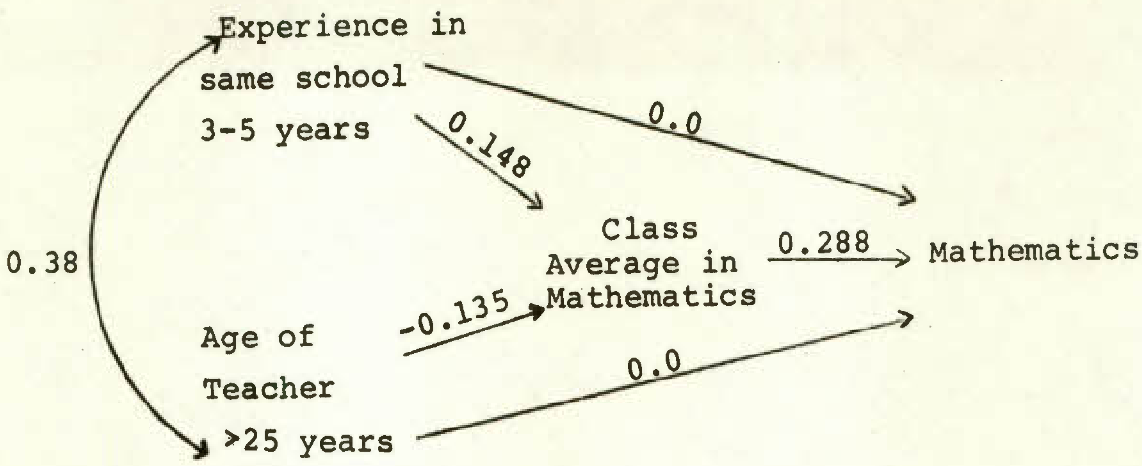
k — average class score in Mathematics (proxy for peer group factor);

a — teachers having three to five years' experience in the same school;

i' — all other teacher variables other than variable a. (For the purpose of the following figure, we will assume that i' refers to teachers who are less than 25 years old.)

Given the above definitions of the variables, equation (15) in diagramatic form appears as follows:

Figure 3*



*See Table 7 for the numbers used in this Figure.

Because this diagram corresponds directly to Figure 2 in Chapter 2, very little explanation of this figure need be given here. The only point that must be repeated is that the numerical values corresponding to unidirectional straight lines are path coefficients and the value related to the bidirectional curved line is a correlation coefficient.[6] Given this diagram, we can apply those numerical values to equation (15) as follows:

(15a) $r_{a,j} = 0.0 + 0.288 \times 0.148 + (0.0 - 0.288 \times 0.135)\ 0.38$

(15b) $= 0.043 + (-0.038)\ 0.38$

(15c) $= 0.043 - 0.014$

$= 0.029.$

Beginning with Table 7, we proceed to examine the value of 0.043 in the first row of column one which is also the value of the first term of equation (15b). This value corresponds to the direct impact of teachers with 3 to 5 years' experience in the same school upon the individual score in Mathematics,

[6]The values for the path coefficients are taken from Appendices A(ii) and A(iii), while the values for the correlation coefficients are taken from Appendix A(iv)3.

plus the indirect impact of this variable upon Mathematics operating through the class average in Mathematics. This value, which is derived under the assumption of zero correlation between this experience variable and any other independent variable, corresponds to the term $P_{aj} + P_{kj} \cdot P_{ak}$ in equation (15). Also, it corresponds to the upper half of Figure 3. The value of -0.038 in the third row of column one in Table 7 refers to the term $P_{i'j} + P_{kj} \cdot P_{i'k}$ of equation (15) and the second numerical value in equation (15b). It also corresponds to the lower half of Figure 3. Each value in the subsequent rows of column one in Table 7 refer to the term $P_{i'j} + P_{kj} \cdot P_{i'k}$ where i' represents one of the independent teacher variables not already discussed.

Table 7

DIRECT, INDIRECT AND TOTAL IMPACT OF TEACHER VARIABLES UPON MATHEMATICS USING EQUATION 15[1, 2]

	Direct Plus Indirect Impact of x_i Upon Mathematics When Correlation Between Teacher Variables = 0	Experience of Teacher in Same School				Age of Teacher						College Degree	
		3-5 years		6+ years		24 or less		35-44		45+		yes	
x_i	(1)[3]	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1. Experience in same school† 3-5 yrs = 1	0.043	1.000	0.043	--	--	0.381	0.016	0.061	0.003	-0.111	-0.005	0.142	0.006
2. Experience in same school† 6+ yrs = 1	-0.179	--	--	1.000	-0.179	-0.341	0.061	-0.146	0.026	0.117	-0.021	0.246	0.044
3. Teacher's age† 24 or less = 1	-0.038	0.381	-0.014	-0.341	0.013	1.000	-0.038	--	--	--	--	-0.236	0.009
4. Teacher's age† 35-44 = 1	-0.048	0.061	-0.003	-0.146	0.007	--	--	1.000	-0.048	--	--	-0.174	0.008
5. Teacher's age† 45+ = 1	-0.023	-0.111	0.003	0.117	-0.003	--	--	--	--	1.000	-0.023	0.261	-0.006
6. College degree† yes = 1	-0.023	0.142	-0.003	-0.246	0.006	-0.236	0.005	-0.174	0.004	-0.261	0.006	1.000	-0.023
7. Total			0.03		-0.15		0.04		-0.02		-0.04		0.04
8. Total (a)[4]			0.06		-0.33		0.13		-0.06		-0.18		0.10

†Dummy variable.

[1] Blanks occur in cells that would be illogical if a value were included. For example, the interpretation of the values of column (3) is that they measure the direct, indirect and total impact of teachers with 3 to 5 years' experience in the same school upon Mathematics when compared to teachers with less than three years' experience in the same school. Given this explanation we assume that the effect of teachers with 6 or more years' experience in the same school remains constant.

[2] Columns 2, 4, 6, 8, 10 and 12, of rows 1 to 6 are correlation coefficients. Columns 3, 5, 7, 9, 11 and 13, of rows 1 to 6 represent the direct and indirect impact of the column variable upon Mathematics operating through the appropriate row variable, assuming no correlation with other teacher variables.

[3] In the calculation of column (1), when the F-statistic for any coefficient was less than one, the value was assumed to be zero.

[4] Total (a) represents the total of the coefficients in columns 3, 5, 7, 9, 11 and 13 divided by the standard deviation of the respective column variables to facilitate interpretation of the total impact of this coefficient.

Because the values in column one are derived under the assumption that a zero correlation exists between the variable in question and all other independent variables, they do not fully measure all of the impact of the appropriate variable upon any of the educational outcomes. To account for this possible additional impact, we must utilize the correlation between each of the independent variables under consideration and the other independent variables in the model.[7] Using equation (15), which measures the total impact of any independent variable upon the educational outcome in terms of direct and indirect impact, and which can be used as seen above to determine the various elements of this impact, we are able to derive the values in the odd-numbered columns of Table 7. They measure the impact of the appropriate column variable upon Mathematics through the corresponding row variable. For example, let us consider column three of Table 7 which is an illustration of the various components which make up the total impact of teachers with 3 to 5 years' experience in the same school upon Mathematics. The value in each cell of this column measures the direct plus indirect impact of the corresponding row variable upon Mathematics operating through the variable pertaining to the experience of the teacher of 3 to 5 years in the same school. Looking specifically at the value of the first cell of the third column (a value of 0.043), we observe the direct plus indirect impact (through the class average) of teachers with 3 to 5 years' experience in the same school upon Mathematics when there is no correlation with other teacher variables. Naturally, this value is identical to the corresponding value in column one.

[7] These correlation coefficients appear in the even-numbered columns in Tables 7, 8 and 9.

If we examine the value of the third cell of this column (-0.014), we would be observing the direct plus indirect impact of teachers with 3 to 5 years' experience in the same school upon Mathematics, operating only through the variable pertaining to teachers 24 years old or less. The explanation of the first and third cell of column three is precisely akin to the example used in Figure 3 and calculated in equations (15 a, b and c).

The understanding of each cell of any of the odd-numbered columns follows directly from the explanation given for cells one and three of column three. The total (designated as row seven) at the bottom of column three represents the total impact that teachers with 3 to 5 years' experience in the same school have upon Mathematics and the total includes the indirect influences through the other teacher variables. It is to be noted that although this total should theoretically be the same as the correlation coefficient between this teacher variable and Mathematics, it is not because we have failed to consider the possible correlation of non-teacher variables with this teacher variable.[8] Row eight, designated as total (a), is a transformation of row seven and has been adjusted by dividing row seven by the appropriate standard deviation to facilitate interpretation.[9] In all, each of the odd-numbered columns (other than column one) is a numerical representation of equation (15) and the total of each of these columns represents the total impact of the appropriate teacher variable upon one of the three educational outcomes.

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[8]For the actual correlation, see Appendix A(iv)3.

[9]See text on pages 26 and 27 for an explanation of this point.

For each of Tables 7, 8 and 9, we now proceed to examine the total impact coefficients to determine whether any trend exists for the age and experience variables. Then, we will focus upon whether the total impact of the teacher variables upon Mathematics, Reading and Interest are any different from the measures of the direct impact observed in Table 4.

Beginning with Table 7, it appears that teachers with 6 or more years' experience in the same school (Group 3) have a negative total impact of 0.33 S.D.'s upon Mathematics when compared to teachers with less than 3 years' experience in the same school (Group 1). Also, when compared with this same standard group, teachers with 3 to 5 years' experience in the same school (Group 2) have a small positive total impact upon Mathematics (0.06 S.D.'s). Next, looking at the total impact of the age of teachers upon Mathematics, we observe an increasingly negative impact as the teachers become older; the teachers over 44 years have a negative total impact of 0.31 S.D.'s compared to those under 25. With these age and experience factors in mind, we can state that there is a weak but consistently negative impact upon Mathematics the longer the teacher has been in the same school. However, to argue in favour of young people in Group 1 or 2 for the teaching of Mathematics would be hasty since one of the reasons that this phenomenon could be occurring is due to the rapidly changing curricula in Mathematics. As we shall see, this same negative trend does not occur in Reading or in Interest.

Table 8

DIRECT, INDIRECT AND TOTAL IMPACT OF TEACHER VARIABLES UPON READING USING EQUATION 15[1,2]

x_i	Direct Plus Indirect Impact of x_i Upon Reading When Correlation Between Teacher Variables = 0	Experience of Teacher in Same School				Age of Teacher						College Degree	
		3-5 years		6+ years		24 or less		35-44		45+		yes	
	(1)[3]	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1. Experience in same school[†] 3-5 yrs = 1	0.132	1.000	0.132	--	--	0.411	0.054	-0.017	-0.002	-0.139	-0.018	0.080	0.011
2. Experience in same school[†] 6+ yrs = 1	-0.038	--	--	1.000	-0.038	-0.349	-0.013	-0.091	0.003	0.131	-0.005	-0.214	0.008
3. Teacher's age[†] 24 or less = 1	-0.104	0.411	-0.043	-0.349	0.036	1.000	-0.104	--	--	--	--	-0.249	0.026
4. Teacher's age[†] 35-44 = 1	-0.024	-0.017	0.000	-0.091	0.002	--	--	1.000	-0.024	--	--	-0.174	0.004
5. Teacher's age[†] 45+ = 1	0.046	-0.139	-0.006	0.131	0.006	--	--	--	--	1.000	0.046	0.230	0.011
6. College degree[†] yes = 1	-0.141	0.080	-0.011	-0.214	0.030	-0.249	0.035	-0.174	0.025	0.230	-0.032	1.000	-0.141
7. Total			0.07		0.04		-0.03		0.02		0.01		-0.08
8. Total (a)[4]			0.14		0.09		-0.07		0.06		0.04		-0.21

[†]Dummy variable.

[1, 2, 3, 4]See corresponding footnotes to Table 7.

In Table 8, we find that the variables relating to years of experience in the same school indicate that teachers in Groups 2 and 3 have a small but positive total impact upon Reading of 0.14 and 0.09 S.D.'s respectively relative to teachers in Group 1 (those having less than 3 years' experience in the same school). For the age variables, when comparing them to a standard age group of 25 to 34, we observed that a peak and positive influence upon Reading is reached for those teachers who are 35 to 44 years old and that the teachers who are 45 years old and older also have a slight positive impact upon Reading. Although the total impact coefficients are not large individually, nevertheless they do indicate that the pattern by which age and experience influence Reading is different from the way they influence Mathematics.

Table 9

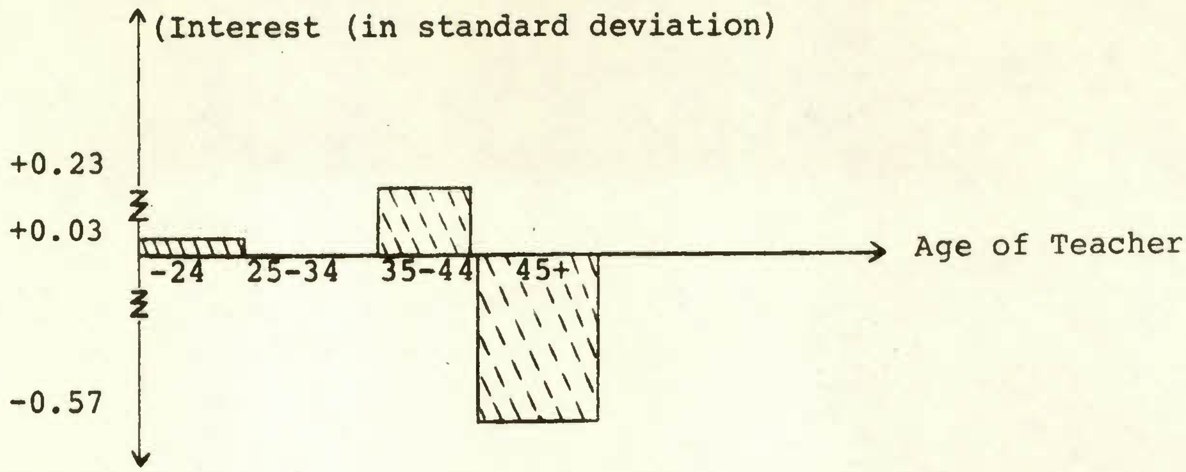
DIRECT, INDIRECT AND TOTAL IMPACT OF TEACHER VARIABLES UPON INTEREST USING EQUATION 15[1,2]

x_i	Direct Plus Indirect Impact of x_i Upon Interest When Correlation Between Teacher Variables = 0	Experience of Teacher in Same School				Age of Teacher						College Degree	
		3-5 years		6+ years		24 or less		35-44		45+		yes	
	(1)[3]	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1. Experience in same school† 3-5 yrs = 1	0.037	1.000	0.037	--	--	0.381	0.014	0.061	0.002	-0.111	-0.004	0.142	0.005
2. Experience in same school† 6+ yrs = 1	0.006	--	--	1.000	0.006	-0.341	-0.002	-0.146	-0.001	0.117	0.001	-0.246	0.001
3. Teacher's age† 24 or less = 1	0.001	0.381	0.000	-0.341	0.000	1.000	0.001	--	--	--	--	0.230	0.000
4. Teacher's age† 35-44 = 1	0.073	0.061	0.004	-0.146	-0.011	--	--	1.000	0.073	--	--	-0.174	-0.013
5. Teacher's age† 45+ = 1	-0.135	-0.111	0.015	0.117	-0.016	--	--	--	--	1.000	-0.135	0.261	-0.035
6. College degree† yes = 1	0.001	0.142	0.000	0.246	0.000	0.236	0.000	-0.174	0.000	0.261	0.000	1.000	0.001
7. Total			0.06		-0.02		0.01		0.07		-0.14		-0.04
8. Total (a)[4]			0.12		-0.04		0.03		0.23		-0.57		-0.10

†Dummy variable.

[1], [2], [3], [4]See corresponding footnotes to Table 7.

Looking at Interest next in Table 9, we generally observe that there is some total impact of the experience variables and considerable total impact of the age variables upon this affective output. With specific reference to the experience variable, we note that there is a small but positive impact of teachers with 3 to 5 years' experience in the same school when compared to teachers in Group 1. Concerning the teacher's age variables, when using the 25 to 34 age group as the standard for comparison, we find that teachers in the oldest age group have a negative impact on Interest of 0.57 S.D.'s relative to this group. On the other hand, teachers in the 35 to 44 years old age group have a positive impact on Interest of 0.23 S.D.'s relative to teachers in the 25 to 34 age group. The following graph helps to illustrate these non-linearities better.



A Comparison of Direct and Total Effects

Lastly, we now wish to make a comparison of the direct path coefficients with the total impact coefficients for the teacher variables. All of these coefficients which are found in Table 10 are reproduced from Table 4 (for the path coefficients) and Tables 7, 8 and 9 (for the total impact coefficients). There are no *F*-statistics for the total impact coefficients, but it should be pointed out that if any coefficients used in the calculation of the total impact values had an *F*-statistic of one or less, these coefficients were assigned values of zero. We shall examine the differences between the path coefficients and the total impact coefficients, these differences being interpreted as measures of the indirect impact of the teacher variable in question upon Mathematics, Reading or Interest.

Table 10

COMPARISON OF PATH AND TOTAL IMPACT COEFFICIENTS UPON MATHEMATICS, READING, AND INTEREST FOR THE TEACHER VARIABLES (x_i)[1]

(F statistics in brackets)

	Mathematics		Reading		Interest	
x_i	Path Coefficient	Total Coefficient	Path Coefficient	Total Coefficient	Path Coefficient	Total Coefficient
1. Experience in same school† 3 - 5 years = 1	- 0.10 (0.74)	0.06	0.02 (0.01)	0.14	- 0.04 (0.08)	0.12
2. Experience in same school† 6+ years = 1	- 0.19 (2.12)	- 0.33	0.07 (0.43)	0.09	0.03 (0.04)	- 0.04
3. Teacher's age† 24 or less = 1	- 0.15 (0.96)	0.13	- 0.09 (0.46)	- 0.07	0.16 (0.68)	0.03
4. Teacher's age† 35 - 44 = 1	- 0.11 (0.31)	- 0.06	0.04 (0.06)	0.06	0.24 (1.59)	0.23
5. Teacher's age† 45+ = 1	0.17 (0.84)	- 0.18	0.22 (2.90)	0.04	- 0.49 (4.41)	- 0.57
6. College degree† yes = 1	- 0.09 (0.31)	0.10	- 0.26 (2.65)	- 0.21	0.01 (0.01)	- 0.10

†Dummy variable.

[1]Path coefficients have been rounded to two places of decimal.

Beginning with Mathematics, we note that for the teachers with six or more years' experience in the same school, relative to those with less than 3 years, there is an indirect impact of -0.14 S.D.'s which reinforces the negative direct impact.[10] Because the path coefficients for the other variables in Table 10 have F statistics of one or less, implying that their impact is not different from zero, we can thus assume that for these variables the total coefficient is in fact a measure of the indirect impact of the associated teacher variable upon Mathematics relative to the impact of the related omitted variable. The greatest of these is the positive indirect impact of 0.13 S.D.'s for teachers who are 24 years old or less and the negative impact of 0.18 S.D.'s for teachers who are 45 or more, relative to teachers in the 25 to 34 age group.

[10]This is calculated as follows: Total Impact minus Path Coefficient = Indirect Impact; -0.33 - (-0.19) = -0.14

For Reading, the most striking indirect impact is a reducation of 0.18 S.D.'s in this output resulting from teachers who are 45 or older (using teachers 25 to 34 years old as the reference group). This indirect impact causes the total impact to become small which implies that the teachers from this oldest age group teach children to read only a little better than the teachers of the reference group. Relative to the reference group, teachers in the 35 to 44 age group have a small but positive indirect impact of 0.06 (the direct impact is not significant). With respect to length of experience teaching in the same school, those with 3 to 5 years and more than 6 years' experience have a positive indirect impact on Reading (0.14 S.D.'s and 0.09 S.D.'s, respectively) relative to those with less than 3 years (the direct impact again is not significant).

In the case of Interest, there is very little indirect impact from any of the teacher variables. The largest is the indirect impact of 0.12 S.D.'s of teachers with 3 to 5 years' experience in the same school when compared to teachers with less than 3 years. Also worthy of mention is the fact that, although teachers over 44 years old have a small negative indirect impact (using teachers 25 to 34 years old as the reference group), the teachers in the other age groups have a negligible indirect impact on Interest.

We have indicated in Tables 7, 8 and 9 that trends do exist when relating the age and experience of teachers to the performance of children. The trends which were based upon the total impact of the teacher variables were certainly different from the conclusions that would have been drawn if we did not consider the contributions of the indirect impact. In what follows, is a summary of those trends.

First, the teaching of Mathematics seems to be best performed by younger teachers who have been more recently exposed to the newer methods of understanding Mathematics. In fact, if the holding of a university degree acts as a proxy for a more recent exposure to the new methods in Mathematics, then our suspicions are confirmed by the college degree variable. By examining the total impact coefficient upon this variable for each of the three educational outputs, it is clear that the only case where a college degree is beneficial is with respect to Mathematics. Second, the affective output Interest appears to be positively affected by teachers who are 35 to 44 years old. Teachers who are 45 and over have a negative total impact upon Interest, relatively speaking. Whereas with Mathematics the youngest teachers performed best, the case is different for Interest where it is the teachers in the middle-age group that perform best. Third, while for Mathematics we were able to draw firm conclusions in terms of trends for the age and experience variables, the case of Reading is different where patterns are less pronounced. Nonetheless, a conclusion that can be drawn from this information on Reading is that teachers 35 years old or more and teachers having three or more years' experience in the same school appear to have an overall small to moderate total impact upon Reading relative to the appropriate reference groups (teachers aged 25 to 34 years and teachers having less than three years' experience in the same school, respectively).

Chapter 5

SUMMARY AND CONCLUSIONS

The results can be summarized by examining the cognitive and affective outputs in terms of the five sets of factors: 1) personal; 2) socio-economic; 3) teacher; 4) peer group; and 5) class size. With respect to the personal factors, the basic pattern that emerges is that those factors which act as proxies for the ability of a child generally represent strong direct determinants of the cognitive outputs (see Table 1). While these ability factors are relatively unimportant in determining the affective output, the physical personal factors such as the sex of the student and his disabilities stand out as conveying a strong direct impact upon this output.

The importance of the direct impact of socio-economic factors represented a serious dilemma since we expected those factors such as the education of the father to have a considerable influence upon learning. The only socio-economic factor that conveyed any meaningful direct impact upon the cognitive domain was the existence and size of the home library (see Table 2). In the affective domain, the only factor of importance was the negative direct impact that speaking French in the home and fathers over 35 had upon Interest. Because the education of the father indicated little direct impact upon either the cognitive or affective outputs, we proceeded to utilize a simple one-equation path model to help us determine whether the education of the father influenced learning in an indirect fashion.

Our suspicions were confirmed by our findings that the education of the father had an overall impact upon the cognitive skills which was brought about indirectly through the personal factors (higher levels of education had a relatively positive effect; see Table 3). This is quite understandable considering the personal factors of the child at the grade one level would most probably be formulated in the home under the influence of his parents. When we applied this simple path model to the affective variable, we found a small but similar indirect (and total) impact of the education of the father upon this type of learning.

Next we examined the role of the teacher in the direct determination of the cognitive and affective outputs. The results suggested that teachers generally have little direct impact upon cognitive and affective learning except for those teachers over 45 years (see Table 4). In this case it appeared that these teachers had a relatively positive direct impact upon Reading, but a relatively negative direct impact on Interest.

The direct impact of the peer group factors and the class size upon the cognitive and affective scores was next examined. Generally the impact of the class size was quite weak. However, when we examined the impact of the peer group influences (as measured by average class scores) we found that the performance of the class in any one skill was a strong determinant of the performance of the individual in that skill.[11]

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[11] It should be remembered that the performance of the individual is not a determinant of the performance of the class since the class average was calculated with the score of the individual student in question removed.

Pursuing the role of the teacher, the class size and the peer group factors, we then estimated a two-equation path model for each of the three educational outcomes. In the first equation of this model, the average class score (proxy for peer group factors) was used as the dependent variable. In the second equation, this variable was used as an independent variable determining the performance of the individual. A number of important results were derived from this exercise. First, in terms of the performance of the class in the cognitive and affective skills, there appears to be an optimal class size between 18 and 24 students (see Table 6). Second, for cognitive skills, we found that the performance of the class is strongly influenced by the age of the teacher (teachers in the age group 25 to 34 have the relatively highest positive impact) and to a lesser extent by the number of years the teacher has been in the same school (those who have spent 3 to 5 years have the relatively highest positive impact). Additionally, with respect to Interest, we found that the performance of a class is adversely affected by teachers over 44 years old and by teachers who have spent 6 or more years in the same school.

Using the above findings, we proceeded to determine the indirect and total impact of the age and experience characteristics of the teacher upon learning. Overall, we found that these factors were important in determining how well an individual performs and that this impact occurred indirectly through the influence of the performance of the class (see Tables 7, 8 and 9). The use of this two-equation model enabled us to stress the point that the total impact of the characteristics of the teacher were quite different from the direct impact of these same factors (see Table 10). These findings are summarized on pp. 55-57.

We have examined the influence of the personal, socio-economic, teacher, peer group and class size factors upon the educational outcomes in the cognitive and affective domain. However, this is by no means a complete list of the variables that should have been included. First, had we information on the ability of the teacher to communicate verbally, not only would we expect this variable to be significant, but also the explanatory power of the total equation to increase. Second, we were not able to include any variable describing the physical facilities of the school. In this case, however, we feel quite confident that such variables would add very little to the overall fit of the equations estimated. It is important that these omissions be specified because their exclusion may lead to biased estimates upon the other variables. Nonetheless, in spite of these and other omissions, the results are useful because of the uniqueness of the data set. That is, the data are disaggregated at the individual level with comparable classroom and teacher data. Also, the outputs encompass both the cognitive and affective domains.

The contribution that this analysis makes to social indicator research into education is twofold. First, it helps to specify the factors of importance when examining the determinants of social indicators in education at different levels of disaggregation. If we examine the educational indicators at the individual level, we find that the most influential factors are the socio-economic factors, personal factors and peer group influences. Of course, this is only for the cognitive outputs; we still know very little about the influence of these factors upon the varied range of affective skills (see Greenberg, 1974). On the other hand, if we consider the classroom as the important level of disaggregation, then, as we have shown for both the cognitive and affective educational indicators, the teacher and classroom variables are excellent indicators of the performance of the class.

The second contribution that this research makes is that it explores the indirect and total impact that inputs can have in determining the outputs. Normally, regression coefficients are used to indicate the direct impact that the inputs have in determining the outputs. We have used such estimates in this fashion. We have also gone one step further by utilizing them along with correlation coefficients to calculate the indirect impact of certain inputs with respect to the determination of the outputs. By combining these indirect and direct impact coefficients, we were then able to show the total impact that the socio-economic factors and teacher characteristics displayed in the determination of the performance of the child.

Appendix A

SUPPLEMENTARY TABLES

Appendix A(i)

MEANS AND STANDARD DEVIATIONS FOR ALL VARIABLES IN THE TWO SAMPLES(1)

Sample A			Sample B		
	Mean	Standard Deviation		Mean	Standard Deviation
Mathematics	36.57	8.25	Reading	60.84	10.32
Interest	15.79	3.30	Respect for Authority	10.67	1.29
Classification ratio	0.94	0.30	Classification Ratio	0.90	0.30
Age in months	74.99	5.11	Age in months	75.60	5.71
Composite aptitude (low)	0.20	0.40	Composite aptitude (low)	0.24	0.43
Composite aptitude (high)	0.23	0.42	Composite aptitude (high)	0.20	0.40
Disability (yes)	0.23	0.42	Disability (yes)	0.21	0.40
Sex (girl)	0.48	0.50	Age of mother (35+)	0.40	0.49
Age of mother (35+)	0.37	0.48	Age of father (35+)	0.56	0.49
Age of father (35+)	0.56	0.49	Father's education (some H.S.)	0.46	0.49
Father's education (some H.S.)	0.40	0.49	Father's education (some univ.)	0.27	0.44
Father's education (some univ.)	0.31	0.46	Books at home (30-200)	0.49	0.50
Books at home (30-200)	0.44	0.49	Books at home (200+)	0.25	0.43
Books at home (201+)	0.32	0.46	Residence type (non-detached)	0.48	0.50
Residence type (non-detached)	0.42	0.49	Residence type (hi-rise)	0.03	0.17
Residence type (hi-rise)	0.05	0.23	Language at home (French)	0.22	0.14
Language at home (French)	0.01	0.11	Language at home (other)	0.14	0.34
Language at home (other)	0.16	0.37	Experience in same school (3-5)	0.43	0.49
Experience in same school (3-5)	0.44	0.49	Experience in same school (6+)	0.32	0.46
Experience in same school (6+)	0.34	0.47	Teacher's age (-25)	0.20	0.40
Teacher's age (-25)	0.17	0.33	Teacher's age (35-44)	0.10	0.31
Teacher's age (35-44)	0.10	0.30	Teacher's age (45+)	0.08	0.27
Teacher's age (45+)	0.06	0.24	College degree (yes)	0.19	0.39
College degree (yes)	0.20	0.40	Class average classification ratio	0.85	0.34
Class average classification ratio	0.83	0.39	Class average in reading	57.96	6.61
Class average in mathematics	35.32	4.88	Class average in respect for authority	8.23	1.28
Class average in interest	15.30	2.29			
Student teacher ratio (-17)	0.12	0.33	Student teacher ratio (-17)	0.15	0.36
Student teacher ratio (25-29)	0.40	0.49	Student teacher ratio (25-29)	0.35	0.47
Student teacher ratio (30-34)	0.26	0.44	Student teacher ratio (30-34)	0.26	0.44
Student teacher ratio (35+)	0.09	0.29	Student teacher ratio (35+)	0.10	0.30

(1) These two samples are described in Chapter 3.

Appendix A(ii)

PATH REGRESSION COEFFICIENTS FOR x_i UPON MATHEMATICS, READING AND INTEREST

Mathematics

x_i	Path	F
Interest	0.135	9.06
Classification ratio	0.129	3.52
Age in months	0.135	9.58
Composite aptitude (low)	-0.231	18.98
Composite aptitude (high)	0.187	14.44
Disability (yes)	-0.077	2.86
Age of mother (35+)	0.003	0.00
Age of father (35+)	-0.001	0.00
Father's education(some H.S.)	-0.030	0.32
Father's education(some univ.)	-0.031	0.33
Books at home (30-200)	0.005	0.00
Books at home (201+)	0.130	4.29
Residence type (non-detached)	0.006	0.02
Residence type (hi-rise)	-0.021	0.22
Experience in same school(3-5)	-0.051	0.74
Experience in same school(6+)	-0.092	2.12
Teacher's age (-25)	-0.057	0.46
Teacher's age (35-44)	-0.035	0.31
Teacher's age (45+)	0.042	0.84
College degree (yes)	-0.038	0.31
Class average classification ratio	0.006	0.01
Class average in mathematics	0.288	23.97
Class average in interest	0.047	1.00
Student teacher ratio (-17)	-0.022	0.13
Student teacher ratio(25-29)	-0.049	0.40
Student teacher ratio(30-34)	-0.102	1.82
Student teacher ratio(35+)	-0.034	0.31
R. Square	0.48	

Reading

x_i	Path	F
Respect for authority	0.049	1.68
Classification ratio	0.231	21.49
Age in months	0.158	15.82
Composite aptitude(low)	-0.287	44.00
Composite aptitude(high)	0.235	34.86
Disability (yes)	0.013	0.12
Age of mother (35+)	-0.026	0.33
Age of father (35+)	0.033	0.50
Father's education(some H.S.)	0.005	0.01
Father's education(some univ.)	0.062	1.83
Books at home (30-200)	0.113	6.47
Books at home (201+)	0.122	6.09
Residence type(non-detached)	-0.041	1.01
Residence type(hi-rise)	0.061	2.97
Language at home(French)	0.047	1.74
Language at home(other)	-0.020	0.31
Experience in same school(3-5)	0.010	0.01
Experience in same school(6+)	0.033	0.43
Teacher's age (-25)	-0.034	0.46
Teacher's age (35-44)	0.011	0.06
Teacher's age (45+)	0.068	2.90
College degree(yes)	-0.072	2.65
Class average classification ratio	-0.102	6.51
Class average in reading	0.363	68.01
Class average in respect for authority	-0.021	0.33
Student teacher ratio(-17)	-0.089	2.73
Student teacher ratio(25-29)	-0.036	0.30
Student teacher ratio(30-34)	-0.110	3.05
Student teacher ratio(35+)	0.062	1.30
R Square	0.61	

Interest

x_i	Path	F
Classification ratio	-0.024	0.08
Age in months	0.096	2.60
Composite aptitude(low)	-0.078	1.51
Composite aptitude(high)	0.091	2.34
Disability (yes)	-0.129	5.63
Sex (girl)	0.205	16.92
Age of mother (35+)	0.023	0.13
Age of father (35+)	-0.114	3.13
Father's education(some H.S.)	-0.011	0.03
Father's education(some univ.)	0.017	0.07
Books at home (30-200)	-0.025	0.15
Books at home (201+)	0.037	0.24
Residence type (non-detached)	-0.029	0.28
Residence type (hi-rise)	0.070	1.80
Language at home (French)	-0.100	4.09
Language at home (other)	-0.052	1.03
Experience in same school (3-5)	-0.021	0.08
Experience in same school(6+)	0.016	0.04
Teacher's age (-25)	0.060	0.68
Teacher's age (35-44)	0.073	1.59
Teacher's age (45+)	-0.122	4.41
College degree (yes)	0.004	0.01
Class average classification ratio	0.027	0.12
Class average in interest	0.151	7.27
Student teacher ratio(-17)	-0.019	0.07
Student teacher ratio(25-29)	-0.097	1.08
Student teacher ratio(30-34)	-0.092	1.48
Student teacher ratio(35+)	-0.092	1.48
R. Square	0.27	

Sample Size = 385

Sample Size = 404

Sample Size = 385

Appendix A(iii)

REGRESSION COEFFICIENTS FOR x_i UPON CLASS AVERAGE IN MATHEMATICS, READING AND INTEREST

	Class Average in Mathematics		Class Average in Reading		Class Average in Interest	
x_i	Path	F	Path	F	Path	F
Experience in same school(3-5)	0.148	7.90	0.323	35.40	0.028	1.44
Experience in same school(6+)	-0.302	29.27	-0.106	3.49	-0.130	3.34
Teacher's age (-25)	-0.135	6.55	-0.287	27.97	0.014	0.05
Teacher's age (35-44)	-0.172	15.53	-0.066	2.18	0.009	0.03
Teacher's age (45+)	-0.083	4.24	-0.061	2.04	-0.286	33.07
College degree (yes)	-0.081	2.49	-0.235	24.29	0.011	0.04
Class average classification ratio	0.403	102.26	0.345	71.81	0.105	4.52
Student teacher ratio (-17)	-0.179	11.17	-0.395	47.90	-0.235	12.57
Student teacher ratio (25-29)	-0.444	43.85	-0.547	64.07	-0.287	12.03
Student teacher ratio (30-34)	-0.486	56.88	-0.518	61.50	-0.202	6.43
Student teacher ratio (35+)	-0.476	87.04	-0.474	72.86	-0.159	6.40

Appendix A(iv)1

LIST OF PNEUMONICS TO ACCOMPANY APPENDIX A(iv)2 AND 3

SRDNGB	Reading
SRSPATB	Respect for Authority
SMATHA	Mathematics
SINTRSTA	Interest
CLSIFRT	Classification Ratio
AGEMNT	Age in Months
COMPSATL	Composite Aptitude (low)
COMPSATH	Composite Aptitude (high)
DISAB1	Disability (yes)
SEXG	Sex (girl)
AGEM 2	Age of Mother (35+)
AGEF2	Age of Father (35+)
EDUF1	Father's Education (some high school)
EDUF4	Father's Education (some university)
BKSLIB3	Books at Home (30 - 200)
BKLIB6	Books at Home (201+)
RESTYP2	Residence Type (non-detached)
RESTYP6	Residence Type (hi-rise)
LANGHMFF	Language at Home (French)
LANGHMFO	Language at Home (other)
YRSTPRS3	Experience in Same School (3-5)
YRSTPRS6	Experience in Same School (6+)
AGET1	Teacher's Age (-25)
AGET3	Teacher's Age (35-44)
AGET4	Teacher's Age (45+)
CLGDGY	College Degree (yes)
CLSM1	Class Average in Classification Ratio
RDGM1	Class Average in Reading
RSPM1	Class Average in Respect for Authority
MTHM1	Class Average in Mathematics
INTM1	Class Average in Interest
KIDS1	Student/Teacher Ratio (-17)
KIDS3	Student/Teacher Ratio (25-29)
KIDS4	Student/Teacher Ratio (30-34)
KIDS5	Student/Teacher Ratio (35+)

Appendix A(iv)2

CORRELATION COEFFICIENTS FOR BATCH A

	SRDNGB	SRSPATB	AGEMNT	COMPSATL	COMPSATM	DISAB1	CLSIFRT	AGEM2	AGEF2	EDUF1	EDUF4	LANGHMFF	LANGHMFD	BKSLIB6	BKSLIB3
SRDNGB	1.00000	0.18816	0.03685	-0.48088	0.43868	-0.26629	0.53327	0.07676	0.10329	-0.26714	0.31242	0.02848	-0.08105	0.26252	-0.01100
SRSPATB	0.18816	1.00000	0.03273	-0.10651	0.08618	-0.07842	0.20628	0.08833	0.10411	-0.06605	0.06277	-0.01452	0.03215	0.08741	-0.07057
AGEMNT	0.03685	0.03273	1.00000	0.14076	-0.11685	0.04219	-0.21073	0.07160	-0.01690	0.15992	-0.09362	-0.00134	0.04059	-0.07674	0.02010
COMPSATL	-0.48088	-0.10651	0.14076	1.00000	-0.29385	0.29494	-0.56121	0.03978	0.05280	0.17215	-0.13459	-0.00885	0.03116	-0.11468	0.00568
COMPSATM	0.43868	0.08618	-0.11685	-0.29385	1.00000	-0.18965	0.46363	0.03603	0.06881	-0.16732	0.24487	0.00532	-0.01492	0.15870	-0.01933
DISAB1	-0.26629	-0.07842	0.04219	0.29494	-0.18965	1.00000	-0.31241	0.04322	-0.03638	0.14458	-0.20888	-0.07792	0.05246	-0.09558	-0.01311
CLSIFRT	0.53327	0.20628	-0.21073	-0.56121	0.46363	-0.31241	1.00000	0.05486	0.01128	-0.27293	0.26363	-0.04278	0.01983	0.15903	-0.00735
AGEM2	0.07676	0.08833	0.07160	0.03978	0.03603	0.04322	0.05486	1.00000	0.62463	0.00501	0.11225	-0.05647	-0.01649	0.13583	-0.08255
AGEF2	0.10329	0.10411	-0.01690	0.05280	0.06881	-0.03638	0.01128	0.62463	1.00000	0.00030	0.16055	0.03115	-0.04543	0.22044	-0.12851
EDUF1	-0.26714	-0.06605	0.15992	0.17215	-0.16732	0.14458	-0.27293	0.00501	0.00030	1.00000	-0.56853	-0.03848	-0.04626	-0.30533	0.01908
EDUF4	0.31242	0.06277	-0.09362	-0.13459	0.24487	-0.20888	0.26363	0.11225	0.16055	-0.56853	1.00000	0.05738	-0.13796	0.39856	-0.13254
LANGHMFF	0.02848	-0.01452	-0.00134	-0.00885	0.00532	-0.07792	-0.04278	-0.05647	0.03115	-0.03848	0.05738	1.00000	-0.06118	-0.01215	0.05181
LANGHMFD	-0.08105	0.03215	0.04059	0.03116	-0.01492	0.05246	0.01983	-0.01649	-0.04543	-0.04626	-0.13796	-0.06118	1.00000	-0.15732	0.01112
BKSLIB6	0.26252	0.08741	-0.07674	-0.11468	0.15870	-0.09558	0.15903	0.13583	0.22044	-0.30533	0.39856	-0.01215	-0.15732	1.00000	-0.58298
BKSLIB3	-0.01100	-0.07057	0.02010	0.00568	-0.01933	-0.01311	-0.00735	-0.08255	-0.12851	0.01908	-0.13254	0.05181	0.01112	-0.58298	1.00000
RESTYP2	-0.20789	-0.04415	0.03674	0.04284	-0.09209	0.08474	-0.13176	-0.32438	-0.39011	0.09166	-0.19504	0.02202	0.02117	-0.21751	0.13341
RESTYP6	0.06718	0.03490	0.02496	-0.00708	-0.05686	-0.02530	-0.00422	-0.03648	-0.00952	0.02856	-0.08081	0.06752	0.04697	-0.07528	-0.01222
YRSTPRS3	0.17046	0.03549	-0.09113	-0.13099	0.10603	-0.10809	0.11056	-0.02075	0.03262	-0.03577	0.11099	-0.03041	-0.12471	0.11369	-0.07627
YRSTPRS6	-0.12070	-0.00366	-0.04550	0.06514	-0.01880	0.06769	-0.06793	0.04746	0.04795	0.07653	-0.07410	-0.10515	0.14215	-0.10840	0.04912
AGET1	0.02620	0.05712	0.10000	-0.02936	-0.02806	-0.10682	-0.00947	-0.04886	0.00358	0.03359	0.02417	0.13386	-0.06088	0.00210	0.02351
AGET3	0.12454	0.04920	-0.07629	-0.03482	0.15372	-0.00502	0.16148	0.13168	0.11487	-0.06787	0.06961	-0.05277	-0.00475	0.01224	0.01935
AGET4	-0.03391	-0.18899	0.13856	0.01207	-0.11137	0.14976	-0.15340	-0.10534	-0.07531	0.02409	-0.04677	-0.04576	0.10765	-0.07652	0.07433
CLGDGY	-0.11259	-0.20130	0.04865	0.03163	-0.00970	0.06352	-0.12092	-0.23368	-0.21482	0.03948	-0.04147	0.09334	0.01272	-0.02265	0.00492
CLSM1	0.12943	0.05238	-0.03673	0.05225	0.13936	-0.05960	0.24489	0.05960	0.09216	-0.01758	0.06720	-0.02270	-0.02780	0.08240	0.02326
KIDS1	-0.05827	0.05348	0.06332	-0.03734	-0.09969	-0.06815	0.03934	-0.04431	0.05554	-0.06262	0.06100	0.12186	0.04444	-0.03079	-0.02326
KIDS3	-0.02917	-0.04777	-0.06580	0.05828	0.05717	0.20509	0.00054	0.07767	0.06129	0.05850	-0.12793	-0.07600	-0.06009	-0.03029	-0.02382
KIDS4	-0.13301	0.02728	-0.02255	-0.00631	-0.00342	-0.00705	-0.04426	-0.01640	-0.09487	0.08708	-0.08041	-0.05259	0.12736	-0.13529	0.09009
KIDS5	0.08522	0.03969	-0.07194	-0.06382	0.00534	-0.07634	0.00297	0.01570	0.00486	-0.03802	0.06287	0.00354	-0.06816	0.11478	-0.01285
RSPM1	-0.02693	-0.13670	-0.00617	0.01328	0.07691	0.05538	-0.03816	-0.01223	-0.05886	-0.00740	0.01274	-0.02860	-0.04512	-0.03278	0.09166
RDGM1	0.41717	0.09887	-0.03954	0.01524	0.04720	-0.14576	0.16513	0.05081	0.09355	-0.17237	0.17837	-0.03741	-0.08584	0.18859	-0.05134

	RESTYP2	RESTYP6	YRSTPRS3	YRSTPRS6	AGET1	AGET3	AGET4	CLGDGY	CLSM1	KIDS1	KIDS3	KIDS4	KIDS5	RSPM1	RDGM1
SRDNGB	-0.20789	0.06718	0.17046	-0.12070	0.02620	0.12454	-0.03391	-0.11259	0.12943	-0.05827	-0.02917	-0.13301	0.08522	-0.02693	0.41717
SRSPATB	-0.04415	0.03490	0.03549	-0.00366	0.05712	0.04920	-0.18899	-0.20130	0.05238	0.05348	-0.04777	0.02728	0.03969	-0.13670	0.09887
AGEMNT	0.03674	0.02496	-0.09113	-0.04550	0.10000	-0.07629	0.13856	0.04865	-0.03673	0.06332	-0.06580	-0.02255	-0.07194	-0.00617	-0.03954
COMPSATL	0.04284	-0.00708	-0.13099	0.06514	-0.02936	-0.03482	0.01207	0.03163	0.05225	-0.03734	0.05828	-0.00631	-0.06382	0.01328	0.01524
COMPSATM	-0.09209	-0.05886	0.10603	-0.01880	-0.02806	0.15372	-0.11137	-0.00970	0.13936	-0.09969	0.05717	-0.00342	0.00534	0.07691	0.04720
DISAB1	0.08474	-0.02530	-0.10809	0.06769	-0.10682	-0.00502	0.14976	0.06352	-0.05960	-0.06815	0.20509	-0.00705	-0.07634	0.05538	-0.14576
CLSIFRT	-0.13176	-0.00422	0.11056	-0.06793	-0.00947	0.16148	-0.15340	-0.12092	0.24489	0.03934	0.00054	-0.04426	0.00297	-0.03816	0.16513
AGEM2	-0.32438	-0.03648	-0.02075	0.04746	-0.04886	0.13168	-0.10534	-0.23368	0.05960	-0.04431	0.07767	-0.01640	0.01570	-0.01223	0.05081
AGEF2	-0.39011	-0.00952	0.03262	0.04795	0.00358	0.11487	-0.07531	-0.21482	0.09216	0.05554	0.06129	-0.09487	0.00486	-0.05886	0.09355
EDUF1	0.09166	0.02856	-0.03577	0.07653	0.03359	-0.06787	0.02409	0.03948	-0.01758	-0.06262	0.05850	0.08708	-0.03802	-0.00740	-0.17237
EDUF4	-0.19504	-0.08081	0.11099	-0.07410	0.02417	0.06961	-0.04677	-0.04147	0.06720	0.06100	-0.12793	-0.08041	0.06287	0.01274	0.17837
LANGHMFF	0.02202	0.06752	-0.03041	-0.10515	0.13386	-0.05277	-0.04576	0.09334	-0.02270	0.12186	-0.07600	-0.05259	0.00354	-0.02860	-0.03741
LANGHMFD	0.02117	0.04697	-0.12471	0.14215	-0.06088	-0.00475	0.10765	0.01272	-0.02780	0.04444	-0.06009	0.12736	-0.06816	-0.04512	-0.08584
BKSLIB6	-0.21751	-0.07528	0.11369	-0.10840	0.00210	0.01224	-0.07652	-0.02265	0.08240	-0.03079	-0.03029	-0.13529	0.11478	-0.03278	0.18859
BKSLIB3	0.13341	-0.01222	-0.07627	0.04912	0.02351	0.01935	0.07433	0.00492	0.02326	-0.02326	-0.02382	0.09009	-0.01285	0.09166	-0.05134
RESTYP2	1.00000	-0.17613	-0.08465	-0.02865	0.03592	-0.22639	0.08188	0.15396	-0.04744	-0.02647	0.04628	0.08255	-0.18295	0.01678	-0.13327
RESTYP6	-0.17613	1.00000	0.01044	-0.00740	-0.05628	0.02630	-0.05527	0.01498	0.05284	0.03911	-0.07548	0.04949	0.02980	0.03499	0.09324
YRSTPRS3	-0.08465	0.01044	1.00000	-0.60898	0.41065	-0.01699	-0.13905	0.07955	-0.07590	0.05743	-0.14135	-0.11716	0.29144	0.06867	0.21198
YRSTPRS6	-0.02865	-0.00740	-0.60898	1.00000	-0.34885	-0.09108	0.13100	-0.21373	0.04317	-0.13555	0.21670	0.16792	-0.13354	0.03712	-0.22827
AGET1	0.03592	-0.05628	0.41065	-0.34885	1.00000	-0.17507	-0.15180	-0.24884	0.00033	0.26705	-0.17443	-0.30058	0.31558	-0.09024	-0.04161
AGET3	-0.22639	0.02630	-0.01699	-0.09108	-0.17507	1.00000	-0.10598	-0.17372	0.11309	0.02750	0.17532	-0.20984	0.01108	0.05695	0.07105
AGET4	0.08188	-0.05527	-0.13905	0.13100	-0.15180	-0.10598	1.00000	0.22971	-0.11469	-0.12907	-0.03642	0.12113	-0.10325	0.01704	-0.10559
CLGDGY	0.15396	0.01498	0.07955	-0.21373	-0.24884	-0.17372	0.22971	1.00000	-0.07761	-0.07371	-0.07960	0.08181	-0.16926	0.08141	-0.03427
CLSM1	-0.04744	0.05284	-0.07590	0.04317	0.00033	0.11309	-0.11469	-0.07761	1.00000	-0.01412	0.06474	-0.11545	0.05372	-0.09160	0.33822
KIDS1	-0.02647	0.03911	0.05743	-0.13555	0.26705	0.02750	-0.12907	-0.07371	-0.01412	1.00000	-0.31346	-0.25556	-0.14503	-0.22399	-0.04764
KIDS3	0.04628	-0.07548	-0.14135	0.21670	-0.17443	0.17532	-0.03642	-0.07960	0.06474	-0.31346	1.00000	-0.44188	-0.25076	0.08461	-0.06203
KIDS4	0.08255	0.04949	-0.11716	0.16792	-0.30058	-0.20984	0.12113	0.08181	-0.11545	-0.25556	-0.44188	1.00000	-0.20445	0.05897	-0.10058
KIDS5	-0.18295	0.02980	0.29144	-0.13354	0.31558	0.01108	-0.10325	-0.16926	0.05372	-0.14503	-0.25076	-0.20445	1.00000	0.09230	-0.09212
RSPM1	0.01678	0.03499	0.06867	0.03712	-0.09024	0.05695	0.01704	0.08141	-0.09160	-0.22399	0.08461	0.05897	0.09230	1.00000	-0.09806
RDGM1	-0.13327	0.09324	0.21198	-0.22827	-0.04161	0.07105	-0.10559	-0.03427	0.33822	-0.04764	-0.06203	-0.10058	-0.09212	-0.09806	1.00000

Appendix A(iv)3

CORRELATION COEFFICIENTS FOR BATCH B

	SMATHA	CLSIFRT	SINTRSTA	SEXG	AGEMNT	COMPSATL	COMPSATH	DISABI	AGEM2	AGEF2	EDUF1	EDUF4	LANGHMFF	LANGHMFD	BKSLIB6	BKSLIB3
SMATHA	1.00000	0.42319	0.34889	0.09826	0.09324	-0.39502	0.36556	-0.21645	0.04219	0.02024	-0.26055	0.22371	-0.09481	0.04652	0.28074	-0.12620
CLSIFRT	0.42319	1.00000	0.19419	0.12346	-0.18914	-0.60347	0.48767	-0.29023	-0.00635	-0.02200	-0.31594	0.33310	0.03600	-0.06729	0.25223	-0.05495
SINTRSTA	0.34889	0.19419	1.00000	0.23826	0.05006	-0.19137	0.15873	-0.19394	0.00394	-0.05030	-0.15066	0.12432	-0.14264	-0.03408	0.15921	-0.08023
SEXG	0.09826	0.12346	0.23826	1.00000	0.02059	-0.11345	0.10765	-0.11376	-0.04750	-0.00419	-0.00272	0.03045	-0.06557	0.06860	0.00858	0.01015
AGEMNT	0.09324	-0.18914	0.05006	0.02059	1.00000	0.14972	-0.06363	0.07044	-0.01085	0.00741	0.18636	-0.12562	0.03628	0.07341	-0.14209	-0.00424
COMPSATL	-0.39502	-0.60347	-0.19137	-0.11345	0.14972	1.00000	-0.28493	0.26584	0.01150	0.02464	0.21334	-0.19260	-0.00220	0.01206	-0.16120	0.00067
COMPSATH	0.36556	0.48767	0.15873	0.10765	-0.06363	-0.28493	1.00000	-0.02953	0.07226	0.02107	-0.25017	0.32518	-0.00982	0.08002	0.23147	-0.09698
DISABI	-0.21645	-0.29023	-0.19394	-0.11376	0.07044	0.26584	-0.02953	1.00000	-0.05747	-0.06415	0.10916	-0.06305	-0.06290	0.05304	-0.03514	-0.07422
AGEM2	0.04219	-0.00635	0.00394	-0.04750	-0.01085	0.01150	0.07226	-0.05747	1.00000	0.59744	-0.07777	0.18292	0.00553	-0.03029	0.16404	-0.06634
AGEF2	0.02024	-0.02200	-0.05030	-0.00419	0.00741	0.02464	0.02107	-0.06415	0.59744	1.00000	0.06937	0.16242	0.00841	-0.08543	0.10210	-0.03695
EDUF1	-0.26055	-0.31594	-0.15066	-0.00272	0.18636	0.21334	-0.25017	0.10916	-0.07777	0.06937	1.00000	-0.55841	0.04487	0.02699	-0.41361	0.14293
EDUF4	0.22371	0.33310	0.12432	0.03045	-0.12562	-0.19260	0.32518	-0.06305	0.18292	0.16242	-0.55841	1.00000	0.02187	-0.13478	0.50825	-0.22459
LANGHMFF	-0.09481	0.03600	-0.14264	-0.06557	0.03628	-0.00220	-0.00982	-0.06290	0.00553	0.00841	0.04487	0.02187	1.00000	-0.05122	-0.07906	0.12698
LANGHMFD	0.04652	-0.06729	-0.03408	0.06860	0.07341	0.01206	0.08002	0.05304	-0.03029	-0.08543	0.02699	-0.13478	-0.05122	1.00000	-0.15846	0.03144
BKSLIB6	0.28074	0.25223	0.15921	0.00858	-0.14209	-0.16120	0.23147	-0.03514	0.16404	0.10210	-0.41361	0.50825	-0.07906	-0.15846	1.00000	-0.62265
BKSLIB3	-0.12620	-0.05495	-0.08023	0.01015	-0.00424	0.00067	-0.09698	-0.07422	-0.06634	-0.03695	0.14293	-0.22459	0.12698	0.03144	-0.62265	1.00000
RESTYP2	-0.05202	-0.06844	-0.06259	0.03489	0.03428	0.00438	-0.04075	-0.01809	-0.21731	-0.24728	0.20275	-0.22143	0.04164	-0.08380	-0.22718	0.10794
RESTYP6	-0.08134	-0.03430	0.02612	-0.10491	0.06336	0.03940	-0.03161	0.02427	-0.16826	-0.18954	0.06896	-0.06903	-0.02824	0.10048	-0.12179	0.07006
YRSTPRS3	0.14232	0.08977	0.12742	-0.02119	-0.03838	-0.11516	0.00134	-0.04945	0.05220	-0.02642	-0.08020	0.03470	-0.10362	-0.05272	0.11488	-0.04973
YRSTPRS6	-0.19915	-0.02787	-0.13285	0.04270	-0.07403	0.02897	0.02987	0.05204	0.02850	0.09316	0.01504	0.07339	0.06067	-0.01868	0.03316	-0.00233
AGET1	0.05526	-0.10634	0.13656	0.03368	0.09000	-0.02233	-0.06869	-0.17591	0.02813	-0.01217	0.05323	-0.08051	-0.05360	-0.02674	0.01126	-0.02730
AGET3	0.03356	0.09632	0.08200	-0.06595	-0.05335	-0.09380	-0.03351	0.07035	0.02708	0.03211	-0.02946	0.04037	0.03477	-0.06368	-0.00370	0.00976
AGET4	-0.16638	-0.21361	-0.26117	-0.08737	0.09767	0.17680	-0.12180	0.15554	-0.11781	-0.08695	0.12452	-0.10906	-0.03023	0.05221	-0.11396	-0.00495
CLGDGY	-0.01173	-0.02725	-0.05562	0.00148	0.04043	0.10818	0.05421	0.12215	-0.05837	-0.09074	0.00253	-0.00435	-0.05782	0.13945	-0.04318	-0.02662
CLSM1	0.26462	0.36431	0.11269	0.03569	0.04822	-0.10372	0.14505	-0.02678	0.07754	0.09168	-0.17671	0.15252	-0.00427	-0.02258	0.18001	-0.05199
KIDS1	0.03528	0.04798	0.06297	-0.07485	-0.00116	-0.00349	-0.08405	-0.06151	0.02486	-0.04114	0.01615	-0.00459	-0.04380	-0.02398	0.05368	-0.09429
KIDS3	-0.03060	-0.05109	-0.06422	-0.00303	-0.04442	-0.02882	-0.00793	0.15288	-0.06970	0.04951	0.00854	0.03074	0.09295	-0.02513	-0.02179	0.07826
KIDS4	-0.10639	0.08197	-0.11750	-0.02430	-0.06234	0.04385	0.11295	-0.01888	0.01171	-0.03485	0.03380	-0.04437	-0.01625	0.06678	-0.05724	-0.02830
KIDS5	-0.07463	-0.04248	0.02865	0.08058	-0.04539	-0.03255	-0.05269	-0.07030	0.10019	0.03075	-0.01235	-0.02351	-0.03684	-0.04755	-0.01136	0.06857
MTHM1	0.42129	0.05616	0.21561	-0.00371	0.10597	0.01743	0.06339	-0.05137	0.04869	0.06726	-0.16790	0.07945	-0.11273	0.05690	0.13429	-0.08020
INTM1	0.21659	0.05804	0.25935	-0.03186	0.02339	0.01672	-0.00499	-0.05999	0.11302	0.10143	-0.13644	0.04149	-0.12222	-0.03092	0.10874	-0.03077

	RESTYP2	RESTYP6	YRSTPRS3	YRSTPRS6	AGET1	AGET3	AGET4	CLGDGY	CLSM1	KIDS1	KIDS3	KIDS4	KIDS5	MTHM1	INTM1
SMATHA	-0.05202	-0.08134	0.14232	-0.19915	0.05526	0.03356	-0.16638	-0.01173	0.26462	0.03528	-0.03060	-0.10639	-0.07463	0.42129	0.21659
CLSIFRT	-0.06844	-0.03430	0.08977	-0.02787	-0.10634	0.09632	-0.21361	-0.02725	0.36431	0.04798	-0.05109	0.08197	-0.04248	0.05616	0.05804
SINTRSTA	-0.06259	0.02612	0.12742	-0.13285	0.13656	0.08200	-0.26117	-0.05562	0.11269	0.06297	-0.06422	-0.11750	0.02865	0.21561	0.25935
SEXG	0.03489	-0.10491	-0.02119	0.04270	0.03368	-0.06595	-0.08737	0.00148	0.03569	-0.07485	-0.00303	-0.02430	0.08058	-0.00371	-0.03186
AGEMNT	0.03428	0.06336	-0.03838	-0.07403	0.09000	-0.05335	0.09767	0.04043	0.04822	-0.00116	-0.04442	-0.06234	-0.04539	0.10597	0.02339
COMPSATL	0.00438	0.03940	-0.11516	0.02897	-0.02233	-0.09380	0.17680	0.10818	-0.10372	-0.00349	-0.02882	0.04385	-0.03255	0.01743	0.01672
COMPSATH	-0.04075	-0.03161	0.00134	0.02987	-0.06869	-0.03351	-0.12180	0.05421	0.14505	-0.08405	-0.00793	0.11295	-0.05269	0.06339	-0.00499
DISABI	-0.01809	0.02427	-0.04945	0.05204	-0.17591	0.07035	0.15554	0.12215	-0.02678	-0.06151	0.15288	-0.01888	-0.07030	-0.05137	-0.05999
AGEM2	-0.21731	-0.16826	0.05220	0.02850	0.02813	0.02708	-0.11781	-0.05837	0.07754	0.02486	-0.06970	0.01171	0.10019	0.04869	0.11302
AGEF2	-0.24728	-0.18954	-0.02642	0.09316	-0.01217	0.03211	-0.08695	-0.09074	0.09168	-0.04114	0.04951	-0.03485	0.03075	0.06726	0.10143
EDUF1	0.20275	0.06896	-0.08020	0.01504	0.05323	-0.02946	0.12452	0.00253	-0.17671	0.01615	0.00854	0.03380	-0.01235	-0.16790	-0.13644
EDUF4	-0.22143	-0.06903	0.03470	0.07339	-0.08051	0.04037	-0.10906	-0.00435	0.15252	-0.00459	0.03074	-0.04437	-0.02351	0.07945	0.04149
LANGHMFF	0.04164	-0.02824	-0.10362	0.06067	-0.05360	0.03477	-0.03023	-0.05782	-0.00427	-0.04380	0.09295	-0.01625	-0.03684	-0.11273	-0.12222
LANGHMFD	-0.08380	0.10048	-0.05272	-0.01868	-0.02674	-0.06368	0.05221	0.13945	-0.02258	-0.02398	-0.02513	0.06678	-0.04755	0.05690	-0.03092
BKSLIB6	-0.22718	-0.12179	0.11488	0.03316	0.01126	-0.00370	-0.11396	-0.04318	0.18001	0.05368	-0.02179	-0.05724	-0.01136	0.13429	0.10874
BKSLIB3	0.10794	0.07006	-0.04973	-0.00233	-0.02730	0.00976	-0.00495	-0.02662	-0.05199	-0.09429	0.07826	-0.02830	0.06857	-0.08020	-0.03077
RESTYP2	1.00000	-0.20983	-0.01898	-0.09260	0.01325	-0.10663	0.03161	0.09397	-0.04790	-0.04133	0.05127	0.00600	-0.03882	-0.06939	-0.09086
RESTYP6	-0.20983	1.00000	-0.01993	0.00805	-0.05669	-0.01244	0.07136	0.09864	-0.08979	-0.06044	-0.04238	0.10756	-0.00220	-0.10364	-0.01181
YRSTPRS3	-0.01698	-0.01993	1.00000	-0.66004	0.38114	0.06054	-0.11091	0.14226	-0.05528	0.09372	-0.16662	-0.11139	0.22999	0.26327	0.20885
YRSTPRS6	-0.09260	0.00805	-0.66004	1.00000	-0.34143	-0.14619	0.11725	-0.24620	0.02359	-0.13178	0.20071	0.13445	-0.10357	-0.39059	-0.25845
AGET1	0.01325	-0.05669	0.38114	-0.34143	1.00000	-0.16132	-0.12314	-0.23554	0.02964	0.30923	-0.20409	-0.27867	0.26862	0.13693	0.12167
AGET3	-0.10663	-0.01244	0.06054	-0.14619	-0.16132	1.00000	-0.09098	-0.17402	0.14028	0.04502	0.04281	-0.20588	0.09157	0.01035	0.07342
AGET4	0.03161	0.07136	-0.11091	0.11725	-0.12314	-0.09098	1.00000	0.26055	-0.12163	-0.10063	-0.02289	0.10643	-0.08464	-0.15594	-0.29973
CLGDGY	0.09397	0.09864	0.14226	-0.24620	-0.23554	-0.17402	0.26055	1.00000	-0.18855	-0.05676	-0.09754	0.14011	-0.16189	0.04078	-0.00609
CLSM1	-0.04790	-0.08979	-0.05528	0.02359	0.02964	0.14028	-0.12163	-0.18855	1.00000	-0.18599	0.06971	-0.02820	0.05680	0.37454	0.15211
KIDS1	-0.04133	-0.06044	0.09372	-0.13178	0.30923	0.04502	-0.10063	-0.05676	-0.18599	1.00000	-0.31349	-0.22774	-0.12265	0.07092	-0.04189
KIDS3	0.05127	-0.04238	-0.16662	0.20071	-0.20409	0.04281	-0.02289	-0.09754	0.06971	-0.31349	1.00000	-0.48956	-0.26366	-0.05170	-0.10139
KIDS4	0.00600	0.10756	-0.11139	0.13445	-0.27867	-0.20588	0.10643	0.14011	-0.02820	-0.22774	-0.48956	1.00000	-0.19153	-0.15255	-0.04094
KIDS5	-0.03882	-0.00220	0.22999	-0.10357	0.26862	0.09157	-0.08464	-0.16189	0.05680	-0.12265	-0.26366	-0.19153	1.00000	-0.18676	0.04836
MTHM1	-0.06939	-0.10364	0.26327	-0.39059	0.13693	0.01035	-0.15594	0.04078	0.37454	0.07092	-0.05170	-0.15255	-0.18676	1.00000	0.37174
INTM1	-0.09086	-0.01181	0.20885	-0.25845	0.12167	0.07342	-0.29973	-0.00609	0.15211	-0.04189	-0.10139	-0.04094	0.04836	0.37174	1.00000

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