THE RETURNS TO COLLEGE EDUCATION*

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ABSTRACT

We apply grouped college-level data to estimate the returns to a college education. After comparing different econometric methods for estimating cluster samples with grouped data, we argue that there are two sets of population parameters of concern: one for estimating within-group effects, and the other for between-group effects. This leads to three major points: 1) the traditional use of fixed-effects models usually ignores the importance of between-group effects and may lead to erroneous conclusions; 2) regressions with group variables have several identifiable econometric issues; and 3) estimations of between-group estimators for between-group effects with grouped data are valid. We investigate the returns to higher education using explanatory variables representing characteristics for individuals, colleges and universities, and states with grouped data from over 500 colleges and universities. We generate a major index measuring college characteristics that are related to students' disciplines in their degree majors. We find that college majors are important determinants of post-graduation incomes; in contrast the incremental value of private schooling over publically funded colleges is relatively modest. At zero rates of interest it takes approximately 59 years for the excess earnings in starting salaries attributable to a private education to equal the extra costs of four years of private schooling.

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I. Introduction

Over fifty percent of American high school graduates seek education beyond the secondary level, with many choosing to enroll in four-year colleges that are typical of American undergraduate education. A college education is fraught with decisions and entails a large financial commitment. Among the preeminent choices that confront the college-bound are: which college to attend, what to study, and how to finance the costs of higher education. The costs of undergraduate education varies widely; some state supported schools have an annual tuition (for state residents) that is the equivalent of the purchase price of a ten-year old used car, while some private school tuitions are the equivalent of the annual purchase of a new mid-size Mercedes Benz. Graduation from highly ranked universities is widely regarded as an entrée to success and security; it supposedly opens doors, provides opportunities, and higher incomes. "Prestige" American universities attract applicants from all over the world; there is intense competition for admission with parents and students expending substantial resources to enhance the probability of admission. "Prestige" colleges and universities are the benchmark for academia; they are the comparison group that all other schools aspire to, and they drive changes in educational standards and teaching trends throughout the academic community. The empirical results of this paper are something of a challenge to the conventional wisdom, we find that the excess returns to a private school are modest; at zero interest rates the excess returns to private schooling (relative to public schools) will equal the extra costs of a private education (over in-state tuition) in about 59 years at the beginning salaries that graduates earn.[1] For mid-career salaries, using the difference that prevails between private and public school graduates, the

[1] Our data do not allow us to directly assess the returns to "prestige". The data do allow us to make public/private comparisons; still some of our explanatory variables may explain "prestige".

number of years it takes to make up the excess cost of private schooling (again at a zero rate of interest) falls to approximately 22 years.

Students acquire post-secondary education for a variety of reasons; here we examine the financial returns to undergraduate (college) education. Our analysis is simple: we hypothesize that a major motivation for the acquisition of more education is because people expect to earn increased incomes (relative to what they would have earned) subsequent to the completion of their course of studies. Certainly the decision-making process in college choice extends beyond a simple cost/benefit analysis; we focus on the salaries of college graduates after graduation because it: illuminates the economic issues, allows an investigation into the investment aspects of higher education, and provides a framework and data for further explorations. The data allow us to attempt answering a series of questions: 1) which is more important, where you study (private or public) or what you study (undergraduate major)? 2) Are the returns to high-tuition private schools greater than their costs? 3) What are the relationships between the qualities of schools and the salaries of their graduates? And 4) what factors should families and students focus upon if they are concerned with the potential earnings after graduation?

The economic costs[2] of four years of post-secondary education at many colleges and universities in the United States can exceed the median price of a home.[3] Treated as an investment, the costs of a college education are one of the largest expenditures that families will make. Parental and students' concerns about the wisdom of undertaking these substantial

[2] The costs of a college education involve both direct and indirect costs. Direct costs include tuition, fees, room and board, books, transportation, and other actual expenses. Indirect costs are the opportunity costs (what they could have done/earned) that students forsake to go to college.

[3] Average expenses (including room and board) at some of the more expensive private colleges are listed as about \$55,000 per year. Add in an opportunity cost of \$15,000 per year (minimum wage work and 2000 hours of work per year) and the present value of the cost of a four year college education discounted at a 4% (real) rate is approximately \$254,000, which was more than the median value of a house in the United States in 2010 (\$221,800; http://www.census.gov/const/uspriceann.pdf).

expenditures appear in the popular press, books (both scholarly and aimed for the general public), and journal articles.[4] Here we provide a framework and a data set that can illuminate the investment aspects of post-secondary education; this involves examining the college graduates' earnings after controlling for a variety of personal characteristics, institutional inputs, and fields of study. The major differentiating aspects of our study over other studies are: 1) we employ simple econometric procedures to analyze the economics of educational investments; 2) we use a large data set of over 500 colleges and universities instead of individual data; 3) we control for specialized knowledge acquired by students by introducing variables for fields of study (college major); and 4) our data set and procedures are available and easily replicated.

The literature on the economics of higher education is vast,[5] so our review is foreshortened by necessity; we have further pruned it to the recent literature in dealing with the returns to higher education, and the differential returns to college selectivity. Measuring the impact of college choice upon incomes after graduation is not a straight forward exercise. The native ability of students to do well in an academic environment and the measurable qualities of colleges and universities are highly correlated. In order to reveal the "full" native ability of students, Dale and Krueger (2002, 2011) control for not easily ascertained student characteristics by grouping students who were accepted and rejected by comparable schools.[6] Using this ingenious methodology, they find (2002) that measures for college selectivity, such as the average SAT for a school, have no significant effects on the salaries of graduates among those

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[4] Books in the same genre are almost as ubiquitous (Dunbar and Lichtenberger [2007]; Springer *et al*. [2009]; Hacker and Dreifus [2010]; and Ferguson [2011]).

[5] A Google search (July 21, 2012) using the phrase "economics of higher education" brought in over 90 million hits, using the Bing search engine we got over 158 million hits. When we used the same words within quotation marks (the search engines had to find all the words in that exact order) the number of hits fell to between 2,740 and 8,470.

[6] The data of Dale and Krueger (2002) came from a data set of cohort data collected in the College and Beyond Survey. These data are drawn from applications and transcripts from 34 colleges and universities. They use a subset of these data (30 institutions). Their regression models control for high school grade point averages, SAT scores, predicted parental incomes, and a variety of personal characteristics.

students who were accepted and rejected by comparable schools and who were not ethnic minorities. In their (2011) paper Dale and Krueger link survey data with Social Security earnings, and obtain similar results as in their 2002 study.

Hoxby's study (2009) mirrors her earlier study (2000) showing positive returns to selectivity in higher education. Using Barron's rankings of selectivity she finds that, after controlling for some student characteristics, there are statistically and economically significant returns to students who graduate from selective institutions. Her results confirm other studies (e.g. James *et al*. [1989]; Behrman, Rosenzweig, and Taubman [1996]; Bowen and Bok [1998]; and Black and Smith [2006]) that show returns to selective institutions.

So issues remain; we believe that many of the issues can be clarified (if not settled) by a larger data set and a thoroughgoing examination of what the models should attempt to control for. Sill, as in all empirical studies, there are always questions dealing with modeling and data. In our study we analyze a sample of 553 post-secondary educational institutions, controlling for student characteristics relating to the attributes that they acquired before going to college, and those they acquired in college. We show that regressions with data aggregated at the college level are valid instruments in examining the returns to college education. We consider commonly used student attributes and school characteristics, such as SAT/ACT scores, high school rank, acceptance rate, class size, faculty salary, student-teacher ratio, percent full-time faculty, graduation rate, and freshman retention. In addition to these variables an important variable that is typically overlooked is the academic major (specialized discipline) of the graduate. We construct and include a variable to measure students' majors based on college data. Finally we include a variable for state median income. The data in our study are publicly available from PayScale, *U.S. News and World Report*, and the U.S. Department of Education's websites. The organization of the work is: Section II reviews the literature on econometric modeling with cluster samples and provides the methodology for our regression models; the detailed discussions in this section provide backing for our contention that college-level data can substitute for data on individual students. Section III introduces the regression models and data; section IV presents empirical results and some comments. Section V concludes the study.

II. Review of Econometric Modeling Returns to Education

In estimating the returns to college education many studies use individual data.[7] The regression models with individual and grouped data can be demonstrated as:

$$Y_i = \beta_0 + \beta_1 SAT_i + \beta_2 X_i + u_i, \quad (1)$$

$$Y_{gj} = \beta_0 + \beta_1 SAT_{gj} + \beta_2 X_{gj} + \alpha_g + u_{gj}, \quad (2)$$

$$Y_{gj} = \beta_0 + \beta_1 SAT_{gj} + \beta_2 X_{gj} + \gamma_1 \overline{SAT}_g + u_{gj}, \quad (3)$$

where Equation (1) is the most basic form of cross-section regression with individual data; the subscript *i* represents the *i*th individual, and Y_i represents *i*th individual's earning after graduation from college, SAT_i is *i*th individual's SAT score, X is another explanatory variable, βs are parameters, and u is a random error term. Equation (2) is an example of cluster samples. Here the subscript is gj, where g is the index for the group or cluster that contains individual j. The term α_g represents an unobservable component and is solely group-dependent. Equation (3) includes a group variable $\overline{SAT}_g$, which is the average SAT for group g. If individuals are grouped by their schools, then this group variable shows the impact of the quality of the schools, or, alternatively,

[7] See James *et al*. (1989), Hoxby (2000), Dale and Krueger (2002, 2011), and Black and Smith (2006).

college selectivity. Equation (3) is a special case of Equation (2). Suppose the unobservable component α_g in Equation (2) represents the quality of group g and:

$$\alpha_g = \gamma_0 + \gamma_1 \overline{SAT}_g + \gamma_2 \bar{X}_g + \gamma_3 Z_g + \varepsilon_g, \tag{4}$$

where $\bar{X}_g$ is the average value of *X* in group g, *Z* is an explanatory variable that does not change the value within the group, γs are parameters, and ε_g is random error. In this case, the group characteristics are represented by three variables: $\overline{SAT}_g, \bar{X}_g$, and Z_g. Combining Equations (2) and (4), we have:

$$Y_{gj} = \beta_0^* + \beta_1 SAT_{gj} + \beta_2 X_{gj} + \gamma_1 \overline{SAT}_g + \gamma_2 \bar{X}_g + \gamma_3 Z_g + u_{gj}^*, \tag{5}$$

where: $\beta_0^* = \beta_0 + \gamma_0$ and $u_{gj}^* = \varepsilon_g + u_{gj}$. Equation (3), then, is a special case of Equation (5). These models are solely for demonstration; we only use the variables *SAT* and *X* to represent individual characteristics. Our discussions focus on parameter estimation, not on the choice of variables.

The parameter estimations for Equations (1) – (3) are standard in econometrics. The main parameters in Equations (1) – (3) are all denoted by βs. Although the same notations are used in these three equations, the β parameters in the different equations may have completely different interpretations and estimated values. For example, the partial impact of *X* on earnings may be interpreted as the standard definition of the partial impact of *X* on *Y*: $\beta = \frac{\partial Y}{\partial X}$. Or, $\Delta Y = \beta \Delta X, \Delta \to 0$ while all other variables stay the same. When there are no groups, the partial effect is easily understood; the partial effect of *SAT* in Equation (1) is just β_1. The meaning of the partial impact of SAT becomes complicated in the case of cluster samples as in Equation (2). In a cluster sample the term ΔX_{gj} has two alternative meanings:

$$\Delta X_{gj} = X_{gj'} - X_{gj^0} = X_{gj'} - \bar{X}_g - (X_{gj^0} - \bar{X}_g); \text{ or} \tag{6}$$

$$\Delta X_{gj} = X_{g'j'} - X_{g^0j^0} = (X_{g'j'} - \bar{X}_{g'}) - (X_{g^0j^0} - \bar{X}_{g^0}) + \bar{X}_{g'} - \bar{X}_{g^0}\ . \tag{7}$$

Equation (6) is a within-group change; it is the change from individual j^0 to individual j' in the same group g. The second part of the equality in equation (6) means that the within-group change can be represented as the mean-deviation change in the same group. Equation (7) shows a cross-group change, a change from individual j^0 in group g^0 to another individual in a different group ($g'j'$). This includes a combination of two changes: the mean-deviation change $(X_{g'j'} - \bar{X}_{g'}) - (X_{g^0j^0} - \bar{X}_{g^0})$ across groups, and the between-group mean change $\bar{X}_{g'} - \bar{X}_{g^0}$. The mean-deviation change across groups involves the change from the mean deviation in group g^0 to the mean deviation in group g'.

An example demonstrates the use of Equations (6) and (7). Suppose that there are six individuals in three groups: individuals A and D are in Group 1; B and E are in Group 2; C and F are in Group 3. Table 1 shows a contrived example for individual SAT scores and average SAT score in each group. The last column in Table 1 is the mean deviation. All possible cases in changing SAT from 550 to 600 in increments of 50 points are given in Table 2. The first three cases are within-group changes as in Equation (6). Each of the other six cases includes a combination of a mean-deviation change across groups and a between-group mean change as in Equation (7). Cases (iv) and (vii) are interesting since the mean-deviation change is zero. These two cases can be considered as between-group mean changes. The nine cases show that the meaning of partial effect of SAT on *Y* is complicated. The change in SAT comes from either the within-group change, or the combined mean-deviation change across groups and the between-group mean change.

To estimate the partial impact of SAT on *Y*, we examine the sampling distribution of the data. Since the within-group change can be represented as mean-deviation change (Equation (6)), we use the data of mean deviations to measure within-group changes. Based on the data from Table 1, Table 3 shows different possible data distributions of SAT to estimate the partial impact of SAT on *Y*. The data distribution under "pooled sample" in columns 1 and 2 is used to estimate the partial impact of the SAT without considering groups. Columns 3 and 4 show the distribution of individuals' mean deviations. These data are used to estimate within-group changes. If we pool all mean deviations from all different groups for the estimation, we are making no distinction between the mean deviations in different groups, as long as the two mean deviations have the same value. For example, we pool two mean deviations of 50 from individuals A and E into the same category (one is 550 – 500 from Group 1, and the other is 600 – 550 from Group 2).

Under certain conditions the mean-deviation change across groups in Equation (7) is the same as the within-group change. If we pool the mean-deviations with the same value from different groups together, then the two mean-deviations with the same value from two different groups are treated identically. This implies that the mean-deviation changes in different groups with the same values are interchangeable, and the mean-deviation across groups can be transformed into the mean-deviation change within the sample group or the within-group change. Using case (xi) from Table 2 as an example, the mean-deviation change across groups is (600 – 550) – (550 – 600). We can replace the first deviation 600 – 550 by 650 – 600 since both have the same size of mean deviation. The deviations change (600 – 550) – (550 – 600) can be rewritten as (650 – 600) – (550 – 600), becoming the mean-deviation within the group or the within group change. All mean-deviation changes across groups in cases (iv) to (ix) can be considered as within-group changes. Equation (7) shows that the partial change in X (or SAT) includes a combination of a within-group change and a between-group mean change.

The last four columns in Table 3 show the distributions of group means in estimating the effects of between-group mean changes. There are two ways to derive the data distribution of group means. One is to use the sample mean from each group; if there are n groups, there are n data values. Since in our example there are three different groups, the total frequency is three for the "between-group sample." The second way to derive the data distribution is to consider group mean variable along with individual data. In this case, each group mean for each individual represents one observation. In the example, there are six individuals; each individual has an associated group mean $\overline{SAT}_g$ and we have six observations of group means. The value of $\overline{SAT}_g$ does not change within the group. Subsequently we use two regression equations to show two ways to include group mean variables in regression. In summary, there are four different data distributions in Table 3 to estimate the components of the partial impact of SAT.

Another important point on these data distributions is that the ways we group data (or the sampling designs of clusters) affect the estimates for the within-group and between-group mean changes. If we group individuals by schools, then $\overline{SAT}_g$ is the average SAT for school g; with these averages we are able to calculate individual mean deviations. If different methods are used to group data, then there will be different group means, mean deviations, and data distributions. This leads to different estimates for within-group and between-group mean changes.

The estimation of the partial effect without clusters in Equation (1) is done with OLS estimators; these are the best linear unbiased estimators (BLUE) for βs under the appropriate assumptions. Using Table 3 as an example, the data distribution in the first two columns is the distribution of the explanatory variable for the OLS estimation of Equation (1). If the sample data contain groups (clusters) as in Equations (2) and (3), the estimation of the partial effects of explanatory variables is standard in the analysis of panel data. In panel data analysis, the observation of each variable is usually denoted by subscripts i and t: with i is for the cross-section and t for the time series. In a cluster sample, we use the subscripts g and j; where subscript g is for the group (similar to the cross-section i in the panel data), and j represents individual j (not time) in group g. There are two fundamental differences between panel data and cluster samples: first, in panel data the data in each cross section are time series data. The time series data cannot be sorted, and are usually correlated. In cluster samples, the data in each group can be considered as a set of cross-sectional data, and they are usually not correlated. Without a time dimension, estimations with clusters have fewer econometric issues than panel data. The second fundamental difference in panel data is that observations for a given point in time form a set of cross-sectional data. In a cluster sample, there is usually only one "dimension" of clustering, even though there may be different ways to group data and we can use mixed- and multiple level clusters. Despite these differences, most econometric techniques developed for panel data analysis can be employed in studying cluster samples.

The typical estimation approaches in panel data analysis are the fixed-effects and random-effects models. The fixed-effects model for the cluster sample as in Equation (2) is

$$Y_{gj} = \beta_0 + \beta_1 SAT_{gj} + \beta_2 X_{gj} + \delta_g + u_{gj}, \tag{8}$$

where δ_g is the parameter to be estimated. The estimation is made by including a set of dummy variables for groups. The estimation of the parameters from Equation (8) is the same as:

$$Y_{gj} - \bar{Y}_g = \beta_1\left(SAT_{gj} - \overline{SAT}_g\right) + \beta_2\left(X_{gj} - \bar{X}_g\right) + error_{gj}. \tag{9}$$

The estimators for this model are the *within-group estimators* and denoted with $\hat{\beta}^W$s. The within-group estimators measure the within-group effects. The specifications of Equations (8) to (9) are embedded in Equation (6). The estimation of the βs in Equation (8) is conditional on a set of dummy variables for the groups. This is a measure of changes in explanatory variables conditional on each group; hence, it is a measure of within-group changes as the first part of Equation (6). The estimation in Equation (9) is based on the data of mean deviations, such as the data distribution in columns 3 and 4 of Table 3. This is described in the second part of Equation (6).

In panel data analysis another set of estimators for the parameters in Equation (2) is derived from the following regression:

$$\bar{Y}_g = \beta_0 + \beta_1\overline{SAT}_g + \beta_2\bar{X}_g + error_g. \tag{10}$$

where $\bar{Y}_g = \frac{\sum_j Y_{gj}}{n_g}$, $\overline{SAT}_g = \frac{\sum_j SAT_{gj}}{n_g}$, and so on. The OLS estimators from the above regression are the *between-group estimators* and denoted as $\hat{\beta}^B s$. These estimators measure the between-group effects. The data distribution in columns 5 and 6 of Table 3 is an example of this estimation. A major issue with this estimation is that $\hat{\beta}^B$ may be a biased estimator for β in Equation (2) (Wooldridge [2002]).

When individual data are available, the between-group effect in a cluster sample is seldom estimated because of potential biases. Most empirical studies use fixed-effects models. These studies usually only report the within-group estimates and an F-test on the group of dummy variables to demonstrate the significance of grouping; the importance of between-group estimators is usually omitted or ignored. Maddala (1971) noted this over four decades ago and argued that the GLS estimator from a random-effects model is preferable to both OLS estimators from Equation (1) and within-group estimators from Equation (8) or (9). The random-effects model is:

$$Y_{gj} = \beta_0 + \beta_1 SAT_{gj} + \beta_2 X_{gj} + v_{gj}, \qquad (11)$$

where $v_{gj} = \alpha_g + u_{gj}$ is random error. Since the random error terms within each group are correlated, GLS estimators are used. We denote these GSL estimators as $\hat{\beta}^{GLS}$s. It can be shown that both OLS and GLS estimators for the βs in Equation (2) are linear combinations of $\hat{\beta}^{W}$ and $\hat{\beta}^{B}$ with different weights (Maddala [1971]; Scott and Holt [1982]). In the single explanatory variable case, $\hat{\beta}^{GLS}$ is a number between $\hat{\beta}^{OLS}$ and $\hat{\beta}^{W}$. The more $\hat{\beta}^{GLS}$ is different from $\hat{\beta}^{OLS}$, the closer $\hat{\beta}^{GLS}$ is to $\hat{\beta}^{W}$. The advantage of a GLS estimator over a within-group estimator is that it gives some weight to the between-group effects.

In addition to the traditional use of fixed-effects and random-effects models in panel data analysis, another line of research includes group variables along with individual data in regressions (Kloek [1981]; Moulton [1986, 1990]). Group variables in cluster samples are variables that do not change their values *within* a group. The examples of group variables are: aggregated means of explanatory variables, and other variables that represent the characteristics of the sampling design for the cluster. Equations (3) and (5) are examples of including group variables in a cluster sample; if we simplify Equation (5) by assuming $\gamma_3 = 0$, we obtain:

$$Y_{gj} = \beta_0^* + \beta_1 SAT_{gj} + \beta_2 X_{gj} + \gamma_1 \overline{SAT}_g + \gamma_2 \bar{X}_g + u_{gj}^*. \tag{12}$$

Equation (12) shows that the impact of the group mean variable is conditional on the values of SAT_{gj} and X_{gj}. Using the data in Table 1 as an example, the impact of group mean SAT is conditional on SAT = 550 or SAT = 600. The last two columns in Table 3 show an example of the data distribution of the group mean $\overline{SAT}_g$. Once a group variable is included in the regression, the full set of dummy variables for groups cannot be used because of mulitcollinearity. As in Equation (11), the random error terms within each group in Equation (12) are correlated when group variables are presented (Moulton, 1986, 1990). The OLS estimator is inefficient and its traditional standard error is biased; consequently GLS estimators should be used. We denote the GLS estimators for Equation (12) as $\hat{\beta}^{GLS2}$ and $\hat{\gamma}^{GLS}$. Mundlak (1978) and Scott and Holt (1982) show that the GLS estimators $\hat{\beta}^{GLS2}$ and $\hat{\gamma}^{GLS}$ are related to the within-group estimator $\hat{\beta}^{W}$ in Equation (8) and the between-group estimator $\hat{\beta}^{B}$ in Equation (10):

$$\hat{\beta}_i^{GLS2} = \hat{\beta}_i^{W} \text{ and } \hat{\gamma}_i^{GLS} = \hat{\beta}_i^{B} - \hat{\beta}_i^{W} \text{ for } i = 1, 2. \tag{13}$$

The coefficient for the group variable, γ, is the difference between the between-group estimator and the within-group estimator. This difference measures the "incremental" impact of a group mean variable. When $\gamma_i > 0$, the between-group effect is greater than the within-group effect. Where $\hat{\gamma}_i < 0$, the group mean variable has a negative impact, and, more importantly, it means that the between-group effect is smaller than the within-group effect. There are two possible implications when $\gamma_i = 0$; one is that it may mean that the between-group effect is the same as the within-group effect. The second is that it may mean that the unobservable component α_g in Equation (2) has no explanatory power ($\hat{\beta}_i^B = \hat{\beta}_i^W = \hat{\beta}_i^{GLS2} = \hat{\beta}_i^{GLS} = \hat{\beta}_i^{OLS}$). This could be caused by random clustering.

There are three econometric issues in estimation for the regressions with group variables such as in Equation (12). The first is that the GLS estimator may be biased if the random errors are correlated with the explanatory variables. This happens when some important group variables are dropped from the regression and the omitted variables are correlated with the explanatory variables. Since any regressions may suffer this omitted variables bias problem, this is not an extraordinary concern. The second econometric issue is that the degrees of freedom in the estimation may raise problems if the number of groups is small. Equation (4) illustrates the problem; it shows that group variables are used to explain the characteristics of the given sampling design of clusters in Equation (2). If there are a limited number of groups and we only use a limited number of group variables as proxies for the characteristics of the groups, then the degrees of freedom in estimation becomes a problem. The situation is illustrated in this simple example: suppose there are only two groups, and these two groups are males and females, the fixed-effects model is:

$$Y_i = \beta_0 + \beta_1 SAT_i + \beta_2 X_i + \delta_0 Female_i + u_i, \tag{14}$$

where $Female_i$ is dummy variable with the values of 1 for female and 0 for male. Note that β_1 and β_2 are parameters for within-group estimators. The parameters β_0 and δ_0 describe group characteristics. If we remove dummy variables for groups and include group variables, we can only include one group variable because of mulitcollinearity. Suppose we include the group mean variable $\overline{SAT}_g$, the mean of SAT in each group. The variable $\overline{SAT}_g$ has two possible values: one value is the average SAT for female and the other is the average SAT for male. This leads to:

$$Y_{gj} = \beta_0^* + \beta_1 SAT_{gj} + \beta_2 X_{gj} + \gamma_1 \overline{SAT}_g + u_{gj}. \quad (15)$$

As long as the value of the average SAT for female is numerically different from the average SAT for male, the statistical significance for all corresponding coefficients in Equations (14) and (15) should be identical; this could lead us to conclude incorrectly that the SAT for different gender is statistically significant.

Donald and Lang (2007) address the degrees of freedom issue for the regressions with group variables. They proposed a two-step procedure in estimating the coefficients of the group variables. In the first stage, the fixed-effects model is estimated. In the second stage of the regression, the values of the dependent variable are the coefficients of the dummy variables (derived from the first stage), while the independent variables are all group variables. The number of observations for the regression is reduced from the number of individuals to the number of groups. If the number of groups is small, then the appropriate test statistic for group variables should be based upon the t-distribution rather than the normal distribution. The two-step procedure is similar to the specifications of Equations (2) and (4). In addition to handling the degrees of freedom issue, the procedure solves a major drawback in fixed-effects models and regressions with group variables—that dummy variables for the fixed effects and group variables cannot be used in the same regression because of mulitcollinearity. The two-step procedure solves this problem because the two-step procedure is itself a combination of fixed-effects models and group variables regression, with the fixed-effects model in the first stage and the regression with only group variables in the second stage.

The third econometric issue in the estimation of regression models with group variables is that the number of observations in each group or the group size should be sufficiently large. Equation (13) shows the coefficients of the group mean variables can be used to measure between-group effects. There are two alternative methods to examine the effects. One is to use between-group estimators as in Equation (10) and the other is to use the two-step procedure as in Donald and Lang (2007). Each between-group estimator in Equation (10) measures the effect of the mean of each independent variable on the mean of the dependent variable. If the group size is too small, the sample means are poor proxies for the characteristics for the groups; the between-group estimators tend to be biased and inefficient estimators for the between-group effects. In the studies of returns to college education, the group characteristics are usually not derived from the means of individual characteristics but from different data sources for college characteristics. These provide adequate proxies for the group means of independent variables. However, the mean of dependent variable still comes from a small sample and it becomes a poor proxy for the group mean dependent variable. More specific conditions for the group size are in Donald and Lang (2007). They show that the use of t-test in the two-step procedure is valid when the group size is sufficient large. When the group size is small, the two conditions for using the two-step procedure are: the number of observations should be the same for all groups, and there are no within-group varying characteristics. These two conditions usually do not hold empirically because of the nature of the data.

In summary, there are five estimators to measure the partial impacts of explanatory variables on *Y*: 1) the OLS estimators from the pooled sample; 2) the within-group estimators from fixed-effects models; 3) the between-group estimators; 4) the GLS estimators from the random-effects model; and 5) the GLS estimators from the models with group variables. All these estimators, except the OLS estimators, depend on a given sampling design of clusters; when using different grouping methods, there will be a different set of estimators. Despite the possibility of different clustering, there is usually only one population parameter considered for the partial impact of explanatory variable X on Y. With one parameter there is a trade-off problem: which estimator is the best? In the current literature the within-group estimators from fixed-effects models are deemed preferable since they are unbiased estimators in measuring within-group effects for a given sampling design of clusters. As previously discussed, fixed-effects models obscure the between-group effects in the coefficients of the dummy variables for the fixed effects. This causes a problem: if between-group effects are important, then the effects are completely ignored in the discussion.

To solve the trade-off problem of different estimators, we use two sets of population parameters for the partial impact of explanatory variables on Y for a cluster sample. These two sets of parameters are the measures of within-group and between-group effects (Scott and Holt [1982]). We denoted these parameters as β^Ws and β^Bs, respectively. The parameters for within-group effects may, or may not, be the same as the parameters for between-group effects for a given sampling designs of clusters. In general, the properties of β^Ws and β^Bs depend on the sampling designs of clusters. Any concerns about these parameters are empirical questions subject to hypothesizing and testing based on the theory.

Figure 1 shows different cases of β^W and β^B (Hsiao [1986]). Each dash circle in the graph represents a group (or cluster). The slope of the dashed line in each group is a measure of the within-group effects. In each graph, the between-group estimator is based on the sample means from each circle. The slope of the solid lines is a measure of the between-group effects.[8] In each graph, the slopes of the dashed lines are the same for all groups; but this slope is not the same as the slope of the solid line. This implies that the within-group estimator is different from the between-group estimator. In Figure 1.1, the within-group estimator is smaller than the between-group estimator; in Figure 1.2, the within-group estimator is greater than the between-group estimator; in Figure 1.3, the two estimators have opposite signs. These graphs show that β^W and β^B are parameters that have different values and meanings. We can also use these graphs to demonstrate Donald and Lang's (2007) required conditions for group size. If the numbers of individual data in each group are not the same because some groups have a large number of individuals and others have fewer, there may be estimation issues. Suppose most individual data come from the groups in the center, then the estimate of the slope for the between-group effect may not be significant, and the estimates reflecting within-group effects and between-group effects would be tangled.

We demonstrate that different sampling designs for clusters give different sets of β^W and β^B. Because there are different sets for β^W and β^B, it is not always true that $\beta^W = \beta^B = \beta$. If we assume that SAT is the sole explanatory variable in Equation (2), then a natural sampling design of clusters for our study is to group individuals by schools. Denote the within-group and between-group estimators from this sampling design as $\hat{\beta}^{W,1}$ and $\hat{\beta}^{B,1}$. Now consider other sampling designs of clusters. An extreme example is to group individuals randomly; suppose we randomly divide individuals in the sample into 100 groups sorting individuals by heights, and form groups based on the order of heights. Denote the estimators from this sampling design as $\hat{\beta}^{W,2}$ and $\hat{\beta}^{B,2}$. Because of the randomness in forming groups, α_g is not a function of SAT.

[8] Hsiao (1986) considers the slope of the solid lines as the ordinary least squares estimate.

Equation (13) implies that the between-group estimates are the same as the within-group estimates ($\hat{\beta}^{B,2} = \hat{\beta}^{W,2}$ when $\gamma_1 = 0$). In another sampling design, we can pool individuals with similar SAT scores into one group, then the difference between each individual's SAT and the average of the SAT in the group is a random error. This sampling design is similar to the studies of Dale and Krueger (2002 and 2011), where their within-group estimator is zero. Denoting the estimators from this sampling design as $\hat{\beta}^{W,3}$ and $\hat{\beta}^{B,3}$, we expect $E(\hat{\beta}^{W,3}) = 0$ and $E(\hat{\beta}^{B,3}) > 0$. In summary, it is not only that $E(\hat{\beta}^{W,1}) \neq E(\hat{\beta}^{W,2}) \neq E(\hat{\beta}^{W,3})$ and $E(\hat{\beta}^{B,1}) \neq E(\hat{\beta}^{B,2}) \neq E(\hat{\beta}^{B,3})$, but note that $\beta^{W} = \beta^{B} = \beta$ is not always true for each possible sampling design of clusters.

If the within-group and between-group estimators are estimating different population parameters for a given cluster sampling design, we should denote these parameters explicitly in regression models. For example, we could rewrite Equation (2) as:

$$Y_{gj} = \beta_0^W + \beta_1^W SAT_{gj} + \beta_2^W X_{gj} + \alpha_g + u_{gj}, \tag{16}$$

where the β^Ws are parameters estimating within-group effects conditional on group characteristics (α_g). The βs parameters in fixed-effects models (Equation 8) should be denoted as β^Ws. Subsequently the within-group regression of Equation (9) could be rewritten as:

$$Y_{gj} - \bar{Y}_g = \beta_1^W \left(SAT_{gj} - \overline{SAT}_g\right) + \beta_2^W \left(X_{gj} - \bar{X}_g\right) + error_{gj}. \tag{17}$$

Substituting Equation (4) with $\gamma_3 = 0$ into Equation (16) and taking sample average over the group, gives the between-group regression:

$$\bar{Y}_g = \beta_0^W + \gamma_0 + (\beta_1^W + \gamma_1)\overline{SAT}_g + (\beta_2^W + \gamma_2)\bar{X}_g + \varepsilon_g + u_{gj}$$

$$= \beta_0^B + \beta_1^B \, \overline{SAT}_g + \beta_2^B \, \bar{X}_g + \varepsilon_g^*, \tag{18}$$

where β^Bs are the parameters estimating between-group effects. The use of two different superscripts (W, B) for the parameters means that $\beta^W s$ may not be the same as $\beta^B s$. These parameters are related to the regressions with group variables by substituting $\bar{Y}_g$ from Equation (18) into Equation (17):

$$Y_{gj} = \beta_0^B + \beta_1^W \left(SAT_{gj} - \overline{SAT}_g\right) + \beta_2^W (X_{gj} - \bar{X}_g) + \beta_1^B \overline{SAT}_g + \beta_2^B \bar{X}_g + error_{gj}. \tag{19}$$

$$Y_{gj} = \beta_0^B + \beta_1^W SAT_{gj} + \beta_2^W X_{gj} + (\beta_1^B - \beta_1^W)\overline{SAT}_g + (\beta_2^B - \beta_2^W)\bar{X}_g + error_{gj}. \tag{20}$$

These two equations show different ways to include group mean variables in the estimation. The data distribution in the last two columns of Table 3 is an example of using group mean variable in the estimation. Both equations give the within-group estimators and between-group estimators directly and indirectly. The explanatory variables in Equation (19) include the mean deviations. The partial impacts of the group mean variables are conditional on mean deviations. The estimated coefficients are within-group and between-group estimators. This equation decomposes the partial effect into a combination of a mean-deviation change across groups and a between-group mean change (as in Equation (7)). Equation (20) estimates the partial impact of the group mean variables conditioned on SAT and X, not their mean deviations. It gives within-group estimators directly and between-group estimators indirectly. This equation is the same as the traditional specification of regression models with group mean variables (Equation (12)). This is also the specification by Mundlak (1978), and Equation (13) follows automatically.

Equations (17) – (20) demonstrate that there may be two different sets of population parameters to measure the partial effect of an explanatory variable: the first set measures within-group effects, and the second measures between-group effects. The separation of the two sets of parameters has four implications. 1) The contention that the between-group estimator is biased is based on the assumption of a single parameter. If we relax this assumption, then we can consider the parameter estimation for between-group effects with grouped data. The econometric modeling for the data with all group means (as in Equation (18)) is still valid. 2) The second implication is that either Equation (19) or (20) can be used to estimate both within-group and between-group effects simultaneously. Equation (19) provides intuitive meanings of the two estimators. Equation (20) is similar to the current practice of including group variables along with individual data. All group mean variables must be included in the model to derive the within-group estimators.

3) The third implication is on the interpretation of the significance of an explanatory variable. If the explanatory variable is significant in a regression with a cluster sample, we have to ask if the significance is for the within-group effect, or, alternatively, for the between-group effect. The estimated coefficients from a fixed-effect model like Equation (17) only give the measures of within-group effects. These measures may not the same as the partial effects of explanatory variables; consequently it is important to examine between-group effects. Still a significant between-group estimate from a regression such as Equation (18) does not necessarily mean that the grouping is important, it may simply imply that the variable itself is important. If the coefficient for a group variable is significant, we should ask what does the significance indicate? If the school mean SAT is used as a group mean variable and its coefficient is significant in explaining the salary of graduates, does this imply that the individual SAT is important, or, that college selectivity is important, or are both individual SAT and college selectivity important? Equations (19) and (20) directly address these questions. If the coefficient

of SAT_g is significant either in Equation (19) or (20), the individual's SAT is important only for the within-group effects. If the coefficient of $\overline{SAT}_g$ is significant in Equation (19), this implies that SAT is important for the between-group effects. This does not necessarily mean that the grouping is important since random groupings may create significant coefficients of $\overline{SAT}_g$. If the coefficient of $\overline{SAT}_g$ is significant in Equation (20), then the between-group estimate is different from the within-group estimate. This implies that the grouping is important and it can be explained by the group mean SAT. Since the group mean SAT comes from the average of the individual SATs, then the individual SATs are also important. If individuals cannot move from one group to another group easily, and the characteristics of groups are important, then between-group estimates can be different from the within-group estimates and the group mean variables in Equation (20) can be used to describe the characteristics of groups. Finally 4) the separation of the two sets of parameters provides a methodology to study the properties of aggregating data. The formation of groups is basically to aggregate the data with a rule. If aggregation plays an important role, we expect that the between-group parameter is different from the within-group parameter. Since data aggregation is possible and common (as in panel data, and time series data with different frequencies) the approach of separation of within-group and between-group parameters should have wide variety of applications for regressions with both individual and grouped data. In this paper, the separation of the parameters provides the methodology for our empirical estimation of returns to college education in the absence of individual data.

III. Regression Model and Data

Our estimations of the returns to education are based on grouped data, rather than individual data; the data are aggregated for each college. The basic regression model is:

$$\bar{Y}_i = \beta_0 + \beta_1 \bar{X}_i + \beta_2 Z_i + u_i, \qquad (21)$$

where $\bar{Y}_i$ is a group mean of the dependent variable, $\bar{X}_i$ is a vector of group mean independent variables, and Z_i represents a vector of group variables for college i. The estimated parameters are between-group estimators. For simplicity we denoted these parameters by βs rather than by$\beta^B s$. We hypothesize that the appropriate measure of a return to an education is the salaries graduates earn which is the dependent variable, $\bar{Y}_i$, it is the average salaries for college i's graduates. The explanatory variables are a variety of measurable individual, institutional, and environmental characteristics. In our estimations individual attributes are aggregated by averaging individual values into group mean variables, and the other institutional characteristics are also group variables. Let vector X represents individual characteristics, such as SAT scores and high school rank. We take the average of these variables in each college and it provides the group mean variables $\bar{X}_i$. Although high school rank is an individual characteristic, we use the percentage of students at the aggregate level; thus for each college we may have the percentage of the student body who were in the top 10% of their graduating high school class. Since the data are collected at the aggregate (college) level, some information pertaining to individuals such as parents' education and income are not used in our estimations. Vector Z contains group variables that represent institutional and environmental characteristics. For institutional characteristics, we use some of the quality measures in school rankings contained in *U.S. News and World Report (Report)*. The *Report* uses seven major indicators to measure academic quality. They (and their weights in parentheses) are: peer assessment (25%), graduation and retention (20%), faculty resources (20%), student selectivity (15%), financial resources (10%), alumni giving rate (5%), and graduation rate performance (5%). Table 4 lists these measures. This study includes the measures: SAT/ACT, high school standing in top 10%, acceptance rate, class size, faculty salary, student-teacher ratio, percent full-time faculty, expenditure per full-time-equivalent (FTE) student, graduation rate, freshman retention rate, peer assessment, and alumni giving rate. Most of these variables have been used in other studies. Increases in the variables: SAT/ACT score, high school standing in top 10%, faculty salary, percent full-time faculty, expenditure per FTE, graduation rate, freshman retention rate, peer assessment, and alumni giving rate are all hypothesized to have positive impact on college graduates' salary. Conversely increases in the acceptance rate, class size, and student-teacher ratio are hypothesized to have negative impacts. Since the impact of class size may be affected by the school size, we include total enrollment as one of the independent variables. Peer assessment and alumni giving rate are two variables from the *Report* that deserve attention; both are a type of external evaluation of the quality of schools. Peer assessment is subjective since it depends on the type of assessment instruments and the body of reviewers; the donation of alumni is also subjective to alumni's viewpoint, but the data collection of alumni giving rate is objective. We consider these two measures as proxies for the reputation of schools. The alumni giving rate variable may be endogenous to salaries earned by the colleges' graduates; in addition to ordinary least squares we utilize two-stage least square estimations with college graduates' salary and alumni giving rate as endogenous variables.

An essential explanatory variable in our analysis is the choice of academic major. This variable is frequently omitted in the literature, yet it is well known that the course of studies pursued has a substantial impact upon labor incomes (Black, Sanders, and Taylor [2003]; Black, Smith, and Daniel [2005]); still this variable is typically not included in studies on the returns to higher education because of the difficulty of acquiring data. Nevertheless omitting the variable for college major has serious consequences if academic specializations affect income and/or college choice. Since all labor market studies show different returns to different skills, we believe that there are meaningful omitted variable problems in studies on the returns to higher education that abstract from majors. In comparisons between schools, if students in one school disproportionately choose majors that are highly paid (engineering or finance) compared to another school whose students disproportionately choose lower paid majors (social work or elementary education), then much of the differences in the incomes of graduates would reflect the effects of the choice of a major rather than the effects of the choice of school. Additionally, students may have expectations on what their future salaries will be in their chosen career paths, and these expectations are closely linked to their academic majors. Expectations may affect their school choice. Students who anticipate high incomes may disproportionately choose schools that are selective and expensive because of physical amenities (recreational facilities, living and dining accommodations, the beauty of the buildings and grounds, and location) and a collegial atmosphere that is reflective of a lower student-faculty ratio and a more personal approach to higher education. Students (and their parents) will pay more for these amenities if they anticipate relatively high future incomes they may well wish to smooth their consumption patterns; somewhat higher living standards in college paid out of anticipated large future earnings. Conversely students who expect to enter relatively low-income occupations (elementary education), will be less likely to borrow now to support a life-style they will find difficult to pay for out of post-graduation wages; these students will disproportionately choose schools that charge lower tuitions, even if they have fewer amenities. Additionally, if there are financial benefits to attending a selective school, and attending a selective school results in a higher wages across all majors, then we would expect students who plan to enter high-paying occupations to choose to attend high-cost, prestige institutions disproportionately more than students who expect to enter low paying occupations. Reinforcing these tendencies, if students attend selective universities without clear career goals, then the choice of major may be influenced by the higher cost of attendance and the burden of student loans. Under these circumstances, financing student education may be a significant factor in the choosing majors and careers that are relatively high-paying. If students have to generate sufficient post-graduation income to repay educational loans, then this requirement disproportionately affects both choices of major and career for students attending high-priced institutions. Omitting academic major variable creates an additional estimation issue. Choosing a major is not only related to students' interests, but also their abilities; the engineering disciplines students generally have high mathematical SAT scores. Because the SAT and majors are correlated, the omitted variable bias problem occurs if majors are not included in estimation procedures.

Another relatively uncommon variable that we use is the median income of the state in which the college is located. This variable has several possible impacts upon college education and college graduates' earnings. The funding of college education comes from both private individuals and governments. In states with higher median incomes, parents are better able to afford college education, including private schools. Additionally states with higher median incomes will typically have higher state appropriations for public colleges. Combining the effects from private individuals and governments, higher state incomes increase the likelihood of better funded state colleges, and more, and better-funded private colleges. There is another possible effect of state median income. States with high median incomes usually have higher market salaries for college graduates. If college graduates accept employment in states where schools are located, then the higher salaries are reflective of state effects rather than that of college and/or major.

The data in this study primarily came from three sources: PayScale, *U.S. News and World Report* (*Report*), and Integrated Postsecondary Education Data System (IPEDS) from the U.S. Department of Education's National Center for Education Statistics.[9] Our salary data (the dependent variable) are derived from PayScale's website. The data source from PayScale contains starting median salary and mid-career median salary for 598 universities and colleges in the United States.[10] The data of SAT/ACT scores, high school standing in top 10%, acceptance rate, class size, percent full-time faculty, graduation rate, freshman retention rate, peer assessment, and alumni giving rate are derived from the *Report*; faculty salaries, student-faculty ratios, expenditure per FTE, and enrollment data are from IPEDS; state median income data are from the U.S. Census Bureau.[11]

We generate a *major index* for each college using salary data for different majors to measure the impact of academic major on salaries; the major index is created by weighting the median nation-wide salary of college graduates in each discipline by the percentage of each college's graduates in the various disciplines. The salary data for college graduates in each discipline are from PayScale. Table 5 lists the salaries for 75 college degrees from PayScale. In 2009 the top five majors that had the highest mid-career salaries were aerospace engineering, chemical engineering, computer engineering, electronic engineering, and economics. We match

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[9] The salary data are from *PayScale 2009 College Salary Report.* The data from *U.S. News and World Report* are from the *2010 edition of America's Best Colleges* by *U.S. News and World Report*. Both reports are based on the survey data in 2009. The data from IPEDS contains school data for the 2008-2009 academic year. The data are available on the authors' websites.

[10] The median salaries are good proxy for the mean salaries for a normal distribution with a large sample data.

[11] State income is the average state median income between 2006 and 2008 in 2007 dollars.

the 75 degrees majors from PayScale with the majors of students who graduated from each school. The weights used in the major index are the percentages of graduates in each major in each school; the data for majors for each school come from the IPEDS. To illustrate how the index was derived using mid-career salaries, consider the following example: there are three schools, each with different distributions of majors. The major index is 109,000 for a school when 100 percent of the graduates chose aerospace engineering as a major (the 109,000 is identical to the dollar salary of the median mid-career aerospace engineer). If a school had 100 percent of its graduates in social work then the major index would be 41,600 (identical to the dollar earnings of mid-career social worker). And a school that had 70% of its students graduating in aerospace engineering and 30% in social work would have a major index of 88,780, the weighted (by percentage of graduates majoring in each discipline) average of mid-career earnings.[12] A school with a high major index had more students graduating in disciplines that led to higher paid jobs. Holding all other factors constant, increases in the major index should have positive impact on the returns to college education.[13]

The descriptive statistics for all variables are in Table 6. It shows the summary statistics for all schools, additionally the bottom three rows have descriptive statistics for the salaries based on the 75 academic degrees listed in Table 5. After matching the schools from PayScale, the *Report*, and IPEDS, we have a total of 564 schools with a total of 4,640,332 students enrolled in these schools. Among these schools, 300 of them are public schools and 264 are private schools. Table 6B shows the summary data for public schools; 6C shows the summary data for private schools. A dummy variable for private schools is included in our regressions to indicate

[12] The starting-salary major index uses the same procedure except that it uses PayScale's starting salary data. The major index for the salary increment regressions is derived by weighting the salary increment in each major.

[13] An alternative measure for the impact of academic specialization in regression analysis is to use dummy variables to represent different majors as in James *et al.* (1989). In this case, only a small number of dummy variables are used for different majors. In our major index, we include 75 different majors.

selectivity for private school education. Tables 6B and 6C show the public schools' mean in-state tuition and fees per year is $22,355 lower than the mean of private schools'. Tables 7 and 8 show the correlation between variables. The correlations between the dependent variable and the independent variables in Table 7 show that all correlations have the expected signs, except that of class size. We expected to see a negative impact on earnings when the percentage of large classes (equal to or greater than 50 students) increased; the positive correlation (19%) between large classes and starting salaries contradicts that expectation. We had no prior on the sign of the correlation between enrollment and starting salary; it has the smallest correlation (10%) of all. The five highest correlations between starting salary and the independent variables are: major index, SAT/ACT, high school standing, faculty salary, and expenditure per FTE (58% to 70%). The five independent variables that have the highest correlations with the dependent variable either mid-career salary or salary increment are: major index, SAT/ACT, high school standing, faculty salary, and freshman retention. There are several pairs of high correlations between independent variables in Table 8. The SAT/ACT score is highly correlated to high school standing, with a correlation of 87%. These two variables are also highly correlated to faculty salary, expenditure per FTE, graduation rate, freshman retention, peer assessment and alumni giving rate, with correlations ranging from 69% to 87%. The highest correlation among all pairs of independent variables is between graduation rate and freshman retention (92%). Because of the high correlations of several independent variables, regressions may have mulitcollinearity problems. The major index based on starting salary is not highly correlated to other variables; the highest value is 26% with faculty salary. In contrast, the major index based on mid-career salary or salary increment has higher correlations with other independent variables; most are greater than 26%.

IV. Empirical Results

The dependent variables for our regressions are: 1) the college graduates' starting salary, 2) the mid-career salary, 3) the salary increment (the difference between mid-career salary and starting salary), and 4) the alumni giving rate. We place somewhat more emphasis on the starting salary models. The alumni giving rate is included as a dependent variable because it may be a function of post graduation salaries. Table 9 shows the regression results for the four dependent variables. When the starting salary is used as the dependent variable, the coefficients for state income, major index, private school dummy, acceptance rate, faculty salary, and peer assessment are all significant at the 1% level. The partial effect of state income is about 13 cents for an additional dollar increase in state income. The coefficient of major index is close to one, meaning that each extra dollar earned in the major is reflected as one extra dollar of income. An extra dollar of faculty salary is associated with an increase of about ten cents in starting salaries. The dollar amount of additional earnings that a private school education generates is $1,516. The mean difference between the annual cost of private school tuition and in-state tuition is $22,355; at a zero interest rate it takes just under 59 years of the extra income that accrues to a private education to pay for the extra costs of four years of at a private school.[14] Peer assessment as a measure of reputation has a positive impact on starting salary.

[14] The data for the mean costs of education come from Table 6. If we compare tuition and fees of private schools to out-of-state education tuition and fees, then the annual excess costs of a private education is $12,608 ($28,871-$16,263). The premium that a private school graduate receives ($1,516) at a zero rate of interest will equal the excess costs of four years at private school in just over 33 years. Any interest rate greater than 3 percent will not lead to a solution because above 3 percent the annual interest payments due to the excess capital costs of four years of private schooling ($50,432) are greater than the premium to private schooling ($1,516). The critical interest rate for the excess costs of private versus in-state tuition is just under 1.7 percent due the four years of the higher excess costs of private versus in-state schooling ($89,420).

Neither the SAT/ACT score, nor the high school rank variables are significant. The institutional acceptance rate captures a number of individual characteristics that if looked at individually are statistically significant, but, because they are highly co-linear, as a group they are much less significant. The use of the institutional acceptance rates reduces the problem of co-linearity; further it captures the individual characteristics that admission officers focus on when selecting students. The other institutional characteristics, including percent of small class size, student-faculty ratio, percent full-time faculty, expenditure per FTE, graduation rate, freshman retention, and alumni giving rate, are not significant. We found that the percent of large class and the total enrollment have positive and significant impact. The percent of large class is only marginally significant at 10% level and it becomes insignificant when we consider a simplified model. The impact of the enrollment is examined in detailed in Table 12.

When the mid-career salary is the dependent variable, all independent variables are significant at the 10% level except SAT/ACT score, high school rank, class size, and peer assessment variables. Since the mean mid-career salary is more than twice the mean starting salary, the estimated coefficients for most variables also doubled relative to the corresponding coefficients in the regression with the starting salary as the dependent variable. The calculation of the major index for the mid-career regression is based on the mid-career salary for majors. Its estimated coefficient remains close to one. The coefficient for the private school dummy is $4,030; at a zero rate of interest this will equal the excess costs of four years of private education over in-state public education in approximately 22 years, and in about 12 years if the comparison is with out-of-state tuition and fees (again at a zero interest rate).[15] The coefficient for peer

[15] Again the data for differences in costs come from Table 6. Adding interest to the calculations will extend the number of years required to equal the extra costs of a private education. However at an interest rate above 4.5 percent is no solution because the annual interests costs on the difference between four years of a private school education over an in-state education exceed the extra earnings ($4,030) of a private school education (at mid-career).

assessment is insignificant; however the coefficient for alumni giving rate changed from negative to positive and significant. These changes show that peer assessment may have only a short-term impact on returns, and the importance of peer assessment is replaced by alumni giving rate. This regression has one major data problem. The individual and institutional data for the mid-career salary regression should come from 15 years ago. We do not have access to complete data from 15 years ago; this may cause some problems.

For the salary increment regression, the variables with significant coefficients and the correctly hypothesized signs are the: major index, private school dummy, acceptance rate, faculty salary, student-faculty ratio, graduation rate, and alumni giving rate. Comparing the salary increment regression to the previous two regressions, the coefficients for the student-faculty ratio and graduation rate become important, while state income becomes unimportant. Small class size and expenditure per FTE are significant with signs that are contrary to expectations in this regression.

When the alumni giving rate is a dependent variable (since it may be an endogenous variable), the variables with significant coefficients and the correct hypothesized sign are: SAT/ACT score, two class size variables, enrollment, student-faculty ratio, percent full-time faculty, graduation rate, and mid-career salary. The coefficients for class size variables indicate that schools with a larger percentage of small classes have a greater alumni giving rate; conversely schools with a larger percentage of larger classes have a lower rate of alumni giving. School size is negatively related to alumni giving rate; smaller schools have higher alumni giving rates. Both student-faculty ratio and percent full-time faculty are important to alumni giving rate. These two variables may directly affect the perception of the students' assessment of their education. Faculty salaries directly impact faculty, not students, and it is not important for alumni giving. College selectivity measured by the SAT/ACT becomes important, but the acceptance rate is not. It seems that personal perception of their attributes is more important than the school's perception of students' attributes in determining the alumni giving rate. It is interesting that alumni giving rate is not significantly higher in private schools than in public schools after controlling for other variables such as class size, enrollment, student-faculty ratio, and percent full-time faculty. Both state income and major index variables are significant, but with wrong (hypothesized) signs. Mid-career salary is important in explaining alumni giving rate, and the two-stage least square estimations are estimated using both alumni giving rate and mid-career salary as endogenous variables.

After we remove the variables with insignificant coefficients and intuitively incorrect signs, the results of the simplified models are shown in Table 10. In the starting salary regression there is no major change between the "full" model and the simplified model. For mid-career salary, the peer assessment variable becomes positively significant in the simplified model. The results from starting salary and mid-career salary differ only in alumni giving rate. With the salary increment as the dependent variable, the explanatory variable for private schooling becomes marginally significant and the variables for the acceptance rate and student-faculty ratio are insignificant in the simplified model. The last two columns in Table 10 include the results from two-stage least square regressions with alumni giving rate as an endogenous variable. The instrumental variables for alumni giving rate are: SAT/ACT score, high school rank, two class size variables, student-faculty ratio, and percent full-time faculty. These variables are important for alumni giving rate, but not for mid-career salary and salary increment. The results from the two-stage least square estimations show that the alumni giving rate is not a significant variable affecting mid-career salaries.

Summarizing, our study shows that the three most important factors in determining the returns to education are: the choice of major, the college acceptance rate, and faculty salaries. State income (an environment variable) and peer assessment (a reputation variable) are also significant variables in predicting earnings.[16] The private school dummy has a positive impact, but its economic significance is relatively minor compared to the large difference between private and public tuition. The major index is the exceptional variable considered in this paper. Its significance in the regression implies that the students interested in ruminative careers should focus on of the choice of a major field instead of other factors (private school). This conclusion is similar to James *et al*. (1989).

We also considered other school characteristics: school size, enrollment profile, and the basic classifications by the Carnegie Foundation. School size is classified into five enrollment categories: under 1,000, 1,000 – 4,999, 5,000 – 9,999, 10,000 – 19,999, and 20,000 and more. The enrollment profile has five categories: exclusively undergraduate, very high undergraduate, high undergraduate, majority undergraduate, majority graduate. The Carnegie basic classifications include 33 categories from different associate degrees to special focus institutions. We include eight major groups: research universities (very high research activity), research universities (high research activity), doctoral/research universities, master's colleges and universities (larger programs), master's colleges and universities (medium programs), master's colleges and universities (smaller programs), baccalaureate colleges – arts and sciences, baccalaureate colleges – diverse fields. Using the data of school characteristics from IPEDS, the percentages for each category are shown in Table 11. We create dummy variables for these categories and include these variables in the simplified regression models. This procedure is

[16] In the appendix, we use our data and state classification as an example to estimate regressions with individual and grouped data.

similar to those of James *et al*. (1989) which investigated whether different categories of higher education have differential effects upon undergraduates. The regression results are shown in Table 12. For starting salary, we found that the schools with more than 10,000 students, majority graduate universities, high research universities, and doctoral/research universities have higher starting salaries. For mid-career salary, alumni giving rate is significant for ordinary least squares, but not significant for two-stage least squares. After removing the alumni giving rate, schools with more than 10,000 students, high research universities, and doctoral/research universities have higher mid-career salary; the enrollment variable is unimportant. With the salary increment as the dependent variable, acceptance rate and peer assessment become positive and significant compared to the previous simplified model; and schools with more than 5,000 students and doctoral/research universities have a higher salary increment in this specification.

Our empirical results are consistent with most other studies. We show that college selectivity is important to returns to college education. In our estimation, the significant measures of college selectivity are: the acceptance rate, faculty salary, private school dummy, and major index[17]. The data and variables used in our model are similar to those of Black and Smith (2006). But instead of using individual data, we use grouped data. In our econometric review section, we show that between-group estimators from grouped data are valid.[18] A possible problem in the Black and Smith (2006) study is that the number of observations in each group is too small to obtain robust results. Using individual data of 887 students they study the impact of group variables for 398 colleges and universities; given these data, there are on average less than three students for each college. Because the number of students in each group can be small, each

[17] Most studies use "college characteristics" and "college selectivity" interchangeable. Some studies use the college SAT as a measure of college selectivity (James *et al*. [1989] and Dale and Krueger [2002]).
[18] We do not have information on individuals such as parents' income and/or education level. This may create omitted variables problems.

group should have the same number of students and there should be no within-group varying characteristics if we are to have a valid econometric analysis (Donald and Lang [2007]). The conditions are difficult to obtain in most survey data.

Our empirical results are in general agreement with those of Dale and Krueger (2002, 2011). They found that unobserved students characteristics are important explanatory variables for the earnings of college graduates. Similarly, in our study we found that students' attributes such as SAT and high school standing are not important once acceptance rates are included in the regressions. The admission decisions of each school reflect both observed and unobserved students characteristics. We argue that although students' characteristics are not completely captured by the published data, the acceptance rate represents a valuable amalgam of both observed and unobserved characteristics.[19]

After controlling unobserved students' characteristics, Dale and Krueger (2002, 2011) conclude that college selectivity as measured by the college SAT had no impact on college graduates' earning students among those who were accepted and rejected by comparable schools (apart from non-minority students). To reach this conclusion they used an ingenious procedure: they formed 1,232 groups using the criteria of acceptance and rejection by comparable schools from a sample of 6,335 students and thirty schools. Their conclusion was based on the insignificant of the coefficient for the college SAT in their fixed-effect models estimating college graduates' earning. Their evidence shows that a student's decision on which school attended within a *given group* of comparable schools had no impact on future earnings. However their conclusion on the importance of college selectivity has to be approached cautiously. First, the

[19] Some examples of unpublished data are extracurricular activities, letters of recommendation, parental attributes, and essays in application packages.

insignificant coefficient of the college SAT in their fixed-effect model means that it is only insignificant for within-group effects. The conclusion into that “the college SAT or college selectivity is unimportant for college graduates’ earnings” does NOT come out of their study; the college SAT is unimportant only within a group of comparable schools. Their grouping method formed five or fewer schools in each group since each student in the group has only five or fewer applications and the comparable schools are matched in each application. To compare the impact of college selectivity among the restricted five schools is not the same as a comparison with any five schools, or between any two schools, or alternative groups of schools.[20] Second, the insignificant estimate for the college SAT within a group may not be caused by the similarity of college graduates’ earnings for all graduates in the group, but from the similarity of the schools in each group. Because of the large number of groups and the small number of schools in each group, it is quite possible that the schools in each formed group are very similar. If the schools within the group are homogenous, then we cannot compare college selectivity within a given group.[21] Even if one of the five schools in the group is less selective than the others, the estimated coefficient for the college SAT would be still insignificant if the student went to the most selective school. Third, in spite of insignificant within-group effects for the college SAT, we should also examine between-group effects; we want to know if the college SAT can explain groupings, and if the groupings can explain earnings. Like most studies with fixed-effect models, Dale and Krueger do not estimate the between-group effect of the college SAT. Their results

[20] Referring to Dale and Krueger’s results, Kotlikoff (2011) comments that “It’s good to know that Harvard applicants can safely attend Boston University ...”. This is not a legitimate comparison because comparisons of two schools are only meaningful if both schools are in the same group of five (at most) schools allowed in the Dale and Krueger sampling design; and, as a matter of fact, Boston University is not among the thirty schools from which their sample was drawn and from which groups were made.

[21] An example: if one group consists of students accepted at Yale, Harvard, and MIT, then which of those schools attended is unimportant in determining salary; another group could consist of Dennison, the University of North Carolina, and the University of Michigan; again the Dale and Krueger (2002) study shows which school they attend from that group does not matter. But, and very importantly, we cannot (using Dale and Krueger’s [2002] results) generalize and conclude that it makes no difference whether one attends Dennison or Harvard.

only show that there is no difference in salaries for students within specific groups. Their study does NOT show that there is no difference between groups.[22] It is quite possible that the college SAT has a strong between-group effect.[23] This implies that the college SAT may be important in explaining not only the grouping, but also college graduates' earning. Therefore, an alternative conclusion from their study is that college selectivity may yet be important in determining college graduates' earning. Still the results that we present in our paper generally support the intuition of Dale and Krueger; that in determining future income where you study is much less important than what you study.

V. Summary and Final comments

There are two issues that this paper addresses. One is econometric; we argue that there are two sets of parameters in the estimation with a cluster sample: the parameters to estimate within-group effects and the parameters to estimate between-group effects. Traditionally, most studies only report within-group estimates from fixed-effects models. We emphasize that it is important to consider between-group effects. If we ignore between-group effects, we may lead to incorrect conclusions on the impact of explanatory variables. There are three methods to estimate between-group effects. The first is to use the traditional between-group estimators; the second is to use regressions with group variables; the third is to use the two-step procedure of Donald and Lang (2007). The estimation of traditional between-group estimators is still valid. The interpretation of the estimated coefficients for the group mean variables should be cautious. If the coefficient for the between-group estimator is significant, it does not mean the grouping is

[22] Their study has been misused to make generalized comparisons for schools in different groups.
[23] Their "self-revelation model" is the same as the regression with group mean variables using the schools applied to as the criterion of grouping. Their results show the group mean variable of college SAT is significant.

important. It may simply mean that the explanatory variable is significant. The estimates for the group mean variables in the regressions with group variables show the net effects from the between-group and within-group effects. When the estimate is positive and significant, it means the between-group effect is greater than the within-group effect and the explanatory variable is important to explain both the dependent variable and the grouping.

The second issue that this paper addresses is empirical; again the important findings are two-fold: The first is that the course of studies pursued in colleges and universities is an important determinant of post-graduation incomes; and the second is that where you study has a modest impact on incomes after graduation. In our study the variable constructed for measuring the dollar impact of the choice of major (the starting-salary major index) has both statistically and economically significant effects on salaries; after controlling for other variables an increase in the index translates almost one-to-one into an increase in the graduate's income. In contrast, at a zero rate of interest it takes approximately 59 years for the excess earnings in starting salaries attributable to a private education to equal the extra costs of four years of private schooling (relative to paying in-state tuition at a public college). This immediately raises the question: Why do parents and students pay so much more to be educated in private colleges and universities?

There are a number avenues that can be examined in investigating this question. Four that we have identified are: 1) the stated tuition that private institutions list is greater than the price actually charged. Price discrimination is rampant in higher education; consequently the differences between what private schools actually charge over public schools may be much less than list prices. In addition to the list price, one major cost for attending college is the opportunity cost, including the time spent and earning forgone in the college education. This opportunity cost is the same for attending the private and public schools. Since our analysis relies on list prices, we may have overstated the excess costs of private schools. 2) The amenities that private schools offer are valued for their immediate benefits rather than their effects upon future incomes. A collegial atmosphere, counseling, and other attributes have value; if they are valued for themselves, there is no reason for their costs to be captured in future incomes. Compare the differences between first class air travel and tourist class; passengers pay extra for the services provided in first class travel, yet we do not expect the first class passengers to arrive faster because they flew first class. Using this analogy it may be that the amenities of a private education are simply intrinsically valuable. 3) The retention rates and four year graduation rates of private schools are typically greater than those of publically funded institutions. Adjusting for these differences will affect the calculation of relative profitability; however making these adjustments is difficult because of the entanglement of self-selection, endogenerity, and identification problems. And 4) there are moral hazards; the people who actually pay the tuition are very frequently NOT the recipients of the education. The burdens on third party payers (whether they be relatives, governments, charities, trusts, or whatnot) are less likely to affect actual students because the tuition payments do not directly reduce the incomes of the student beneficiaries dollar per dollar.

There remain unaddressed issues that concern this subject; we have identified some, there are likely to be others which are unknown to us. We emphasize that this paper suggests that post-graduation salaries depend markedly more on what you study, rather than on where you study.

Appendix: An Empirical Example of Using Group Mean Variables

In regressions with cluster samples, we use four different regression models to include individual data and group means (Equations 17-20). This appendix provides an example to estimate these equations with our data. In most studies on the returns to college education, the individual data are students and the grouped data are colleges. Since we do not have data for individual students, we treat colleges as individual data and aggregate college data based on state locations to form grouped data. Our regression models had state income as an environmental variable. If our grouping method is based on states, the state income is a group variable since it has invariant values in each state. In this example, we show different regression models with individual and grouped data, where the variables for grouped data are group means of explanatory variables and state income.

Table 13 shows the regression results. The first two columns show the results from the OLS without state classification. With the state classification, the next two columns show the estimates from the standard fixed-effects model and between-group model, separately. The fixed-effects model uses 51 dummy variables for states and the between-group model use the sample means from each state for the regression. The regression specifications for these two effects are similar to Equations (17) and (18), where the subscript g represents the state. The next two columns show the regressions estimating both within-group effects and between-group effects. The "FE+BE" column shows the results for the regression specification similar to Equation (19). The independent variables include mean deviations $X_{gj} - \bar{X}_g$ and group means $\bar{X}_g$. The estimated coefficients are direct measures of within-group and between-group effects. Most estimates for the within-group effects are close to their corresponding estimates for the between-group effects, except for faculty salary. The within-group estimate for the impact of faculty salary is 0.105; the between-group effect is 0.214. To understand what this means, suppose the faculty salaries for two schools in a state have a difference of $10,000. The graduates' earnings from these two schools will have a difference of $1,050. However, for two different states where mean faculty salaries differ by $10,000, the effect of this state difference on the salaries of college graduates will be $2,140 in favor of students graduating in the high-faculty-salary state. State effects have a positive impact on the relationship between faculty salaries and the earnings of graduates; the between state effect is greater than within state effect, i.e. if the same dollar difference was for two institutions within the same state, then effect would be smaller than the effect on institutions located in different states.

The "FE+Group" column shows the results for the regression specification similar to Equation (20). The independent variables include X_{gj} and all group means $\bar{X}_g$. When all group mean variables are included in the regression, the estimated coefficients for X_{gj} are the within-group estimates; these are exactly the same as the coefficients from the fixed-effect model and those coefficients for $X_{gj} - \bar{X}_g$ under "FE+BE." The coefficients of the group variables in "FE+Group" column are NOT estimates for between-group effects. These effects can be calculated by adding the coefficient of the group mean variable to the corresponding within-group effect coefficient. A test can be applied to the coefficient of group mean variables in the "FE+Group" column: when the coefficient is positive and significant, the variable's between-group effect is greater than its within-group effect. The insignificant t-statistics of each coefficient of the group mean variables in this column show that the coefficient for within-group effect is similar to the coefficient for between-group effect. The only significant group mean variable in this specification is faculty salary; this coefficient is positive and significant at the 1%

level. We can conclude that the between-group effect for faculty salary (0.214) is significantly greater than its within-group effect (0.105) in column "FE+BE."

The last column shows the results of regression by adding state income group variable to the regression in the "FE+BE" column. The results of the estimated coefficients for this column are similar to those in the column of "FE+BE". All group mean variables are significant. This regression shows that all within-group effects, between-group effects and the effects from group variables can be included in one regression.

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Figure 1

Figure 1.1

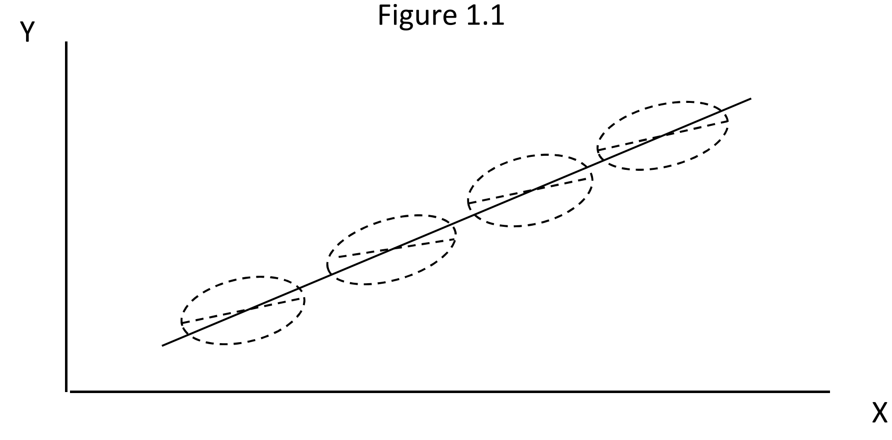

Figure 1.2

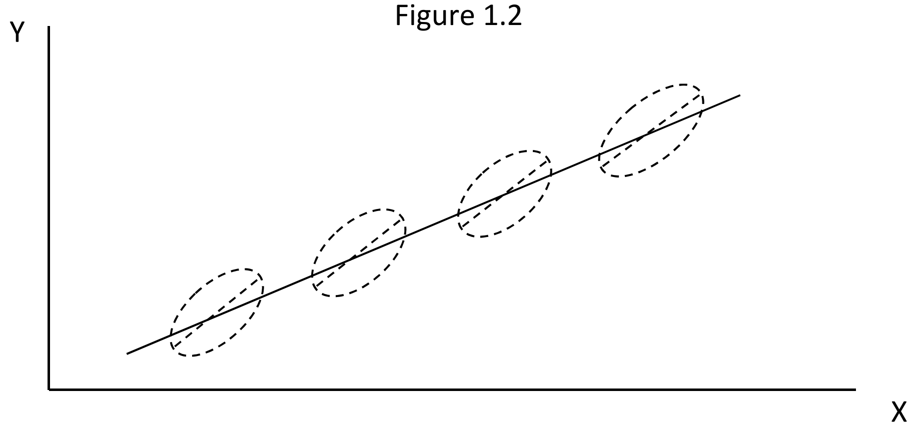

Figure 1.3

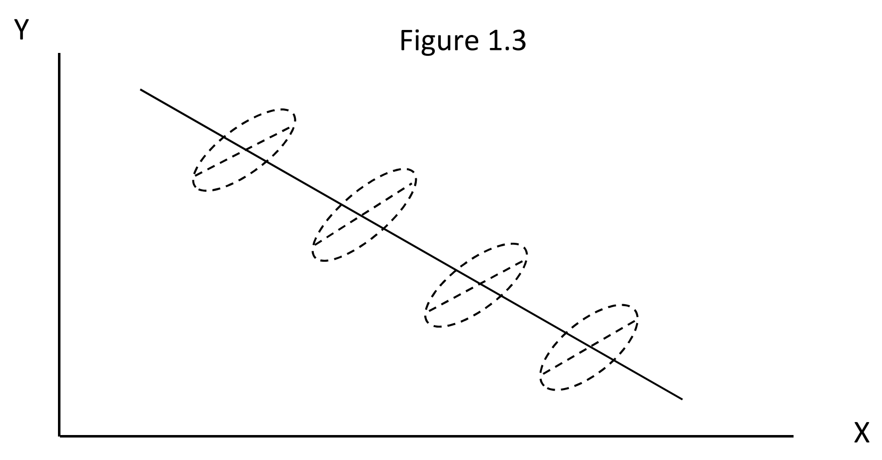

Table 1
A Sample of Six Individuals in Three Groups

i	SAT_{gj}	Group 1 $\overline{SAT_1}$	Group 2 $\overline{SAT_2}$	Group 3 $\overline{SAT_3}$	$SAT_{gj} - \overline{SAT_g}$
A	550	500			50
B	550		550		0
C	550			600	-50
D	600	500			100
E	600		550		50
F	600			600	0

Table 2
All Possible Changes with an Increment of 50 Points in SAT

		Within-group Change or Mean-deviation Change	Between-group change
i	A→D	(600 – 500) – (550 – 500) = 50	
ii	B→E	(600 – 550) – (550 – 550) = 50	
iii	C→F	(600 – 600) – (550 – 600) = 50	
iv	A→E	(600 – 550) – (550 – 500) = 0	(550 – 500) = 50
v	A→F	(600 – 600) – (550 – 500) = –50	(600 – 500) = 100
vi	B→D	(600 – 500) – (550 – 550) = 100	(500 – 550) = –50
vii	B→F	(600 – 600) – (550 – 550) = 0	(600 – 550) = 50
viii	C→D	(600 – 500) – (550 – 600) = 150	(500 – 600) = –100
xi	C→E	(600 – 550) – (550 – 600) = 100	(550 – 600) = –50

Table 3
Sampling Distribution to Measure a Change in SAT

Pooled Sample		Within-Group Sample (Mean Deviation Change)		Between-Group Sample		Group Variable Sample	
SAT_i	Frequency	$SAT_{gj} - \overline{SAT_g}$	Frequency	$\overline{SAT_g}$	Frequency	$\overline{SAT_g}$	Frequency
550	3	-50	1	500	1	500	2
600	3	0	2	550	1	550	2
		50	2	600	1	600	2
		100	1				

Table 4 Measures of School Quality Used by the *U.S. News and World Report*

A. Peer assessment (25%)
B. Graduation and freshman retention (20% or 25%)
    1. Six-year graduation rate (80%)
    2. Freshman retention rate (20%)
C. Faculty Resources (20%)
    1. Class size, 1 – 19 students (30%)
    2. Class size, 50+ students (10%)
    3. faculty salary (35%)
    4. faculty's highest degree (15%)
    5. Student-faculty Ratio (5%)
    6. % full-time faculty (5%)
D. Student Selectivity (15%)
    1. SAT/ACT (50%)
    2. High school standing in top 10% or 25% (40%)
    3. Acceptance rate (10%)
E. Financial Resources (10%)
    1. Financial resources per student
F. Alumni giving rate (5%)
G. Graduation rate performance (5%)
H. Other Variables not used by the *U.S. News and World Report*:
    1. State median income
    2. Major index
    3. Private school dummy
    4. School size
    5. Enrollment profile classification by Carnegie Foundation
    6. College and university classification by Carnegie Foundation

Table 5 Salaries for Undergraduate Degrees

	Starting Salary	Mid-Career Salary		Starting Salary	Mid-Career Salary
Accounting	46500	77600	Health Sciences	37800	69600
Advertising	36900	71800	History	38800	70000
Aerospace Engineering	59600	109000	Horticulture	37200	53400
Agriculture	40900	66700	Hospitality and Tourism	37000	54300
Anthropology	37600	63200	Hotel Business Management	37400	66400
Architecture	42900	78300	Human Resources	37800	59600
Art History	36300	62400	Industrial Engineering	57100	95000
Biochemistry	41700	94200	Industrial Technology	49500	79600
Biology	39500	71800	Information Technology	49400	75200
Business Administration	42900	73000	Interior Design	35700	59900
Business Management	43300	72100	International Business	41900	77800
Chemical Engineering	65700	107000	International Relations	41400	80500
Chemistry	42900	82300	Journalism	36300	65300
Civil Engineering	55100	93000	Landscape Architecture	43100	70800
Communications	38700	68400	Management Information Systems	51900	87200
Computer Engineering	61700	105000	Marketing	41500	81500
Computer Science	56400	97400	Mathematics	47000	93600
Computing and Information Systems	50900	86700	Mechanical Engineering	58900	98300
Construction Management	53400	89600	Medical Technology	46600	58400
Criminal Justice	35900	59300	Microbiology	39800	73200
Drama	35600	56600	Music	34000	52000
Economics	50200	101000	Nursing	54900	69000
Education	36200	54100	Occupational Therapy	61300	73400
Electrical Engineering	60200	102000	Philosophy	40000	76700
Elementary Education	33000	42400	Physics	51100	98800
English	37800	66900	Political Science	41300	77300
Environmental Engineering	53400	94500	Psychology	36000	61000
Environmental Science	43300	78700	Public Relations	36700	62600
Fashion Design	36700	62800	Radio and Television	34000	67000
Film Production	38200	71800	Religious Studies	35300	57500
Finance	48500	89400	Social Work	33400	41600
Fine Arts	35800	56300	Sociology	36500	57900
Foods and Nutrition	41700	58200	Spanish	35600	52600
Forestry	39700	64200	Statistics	48600	94500
Geography	40400	69300	Theology	34800	51500
Geology	45100	84200	Urban Planning	43300	77000
Graphic Design	36000	59400	Zoology	37000	74400
Health Care Administration	37900	61000			

Source: *PayScale 2009 College Salary Report.*

Table 6 Descriptive Statistics

Table 6A. All Schools

	Mean	Median	Std. Dev.	Minimum	Maximum	Sum	N
Salary, Starting	44,487	43,450	6,082	31,900	71,100	25,090,800	564
Salary, Mid-career	79,239	77,000	14,487	42,200	129,000	44,690,800	564
Salary Increment	34,752	33,800	9,929	7,900	70,800	19,600,000	564
State Income	50,759	49,267	6,627	36,499	65,652	28,627,883	564
Major Index, Starting	42,024	41,507	2,901	36,215	58,214	23,701,257	564
Major Index, Mid-career	70,491	69,324	5,799	58,537	98,711	39,757,113	564
Major Index, Increment	28,467	27,754	3691	18,950	43,047	16,055,856	564
SAT/ACT*	60.27	58	11.60	27.5	93	33,389	554
Top 10 % High School (%)	34.63	26	25.02	1	100	17,039	492
Acceptance Rate (%)	62.27	65	20.31	8	100	34,806	559
Class Size, 1–19 (%)	48.72	46	15.55	14	100	26,991	554
Class Size, 50+ (%)	6.75	5	6.26	0	30	3,741	554
Enrollment	8,228	5,786	7,218	340	43,026	4,640,332	564
Faculty Salary	75,178	72,610	16,255	40,633	146,331	42,400,656	564
Student-Faculty Ratio (%)	16.24	16	5.34	5	60	9,162	564
Full-time faculty (%)	83.02	86	12.22	28	100	46,327	558
Expenditure per FTE	9,620	7,037	8,543	1,805	71,859	5,262,060	547
Graduation Rate (%)	60.80	60	18.52	16	98	34,289	564
Freshman Retention (%)	80.67	81	10.04	53	99	45,339	562
Peer Assessment	2.98	3	0.63	1.80	5	1,662	558
Alumni Giving Rate (%)	15.86	12	12.22	1	67	8,643	545
Tuition & Fee–Public (in-state)	6,516	6,200	2,219	2,832	13,706	1,954,776	300
Tuition & Fee–Public (out-state)	16,263	15,217	4,821	5,526	33,069	4,878,827	300
Tuition & Fee– Private	28,871	29,070	7,687	4,080	40,422	7,448,596	258
Starting Salary, Major	43,179	40,900	8,130	33,000	65,700	3,238,400	75
Mid-career Salary, Major	73,547	71,800	15,908	41,600	109,000	5,516,000	75
Salary Increment, Major	30,368	30,100	10,145	8,200	52,500	2,277,600	75

Note: *SAT/ACT are the median test scores and are converted into the UC score based on University of California Test Score Translation.

Data Sources: *PayScale 2009 College Salary Report*, *2010 edition of America's Best Colleges* by U.S. News and World Report, and IPEDS.

Table 6B. Public Schools

	Mean	Median	Std. Dev.	Minimum	Maximum	Sum	N
Salary, Starting	43,188	42,700	4,545	34,000	58,900	12,956,400	300
Salary, Mid-career	75,291	74,700	10,588	42,200	112,000	22,587,400	300
Salary Increment	32,103	32,050	7,238	7,900	54,900	9,631,000	300
State Income	49,996	49,267	6,985	36,499	65,652	14,998,926	300
Major Index, Starting	41,858	41,588	2,331	37,939	56,620	12,557,274	300
Major Index, Mid-career	69,369	68,474	4,655	60,694	96,431	20,810,755	300
Major Index, Increment	27,512	27,058	2,888	20,983	39,811	8,253,481	300
SAT/ACT	55.80	54	8.46	33	78	16,460	295
Top 10 % High School (%)	25.20	20	20.58	4	100	6,149	244
Acceptance Rate (%)	68.61	69	16.26	22	100	20,377	297
Class Size, 1–19 (%)	38.55	39	9.80	14	69	11,335	294
Class Size, 50+ (%)	10.22	10	6.16	0	30	3,004	294
Enrollment	12,163	10,310	7,421	1,120	43,026	3,648,972	300
Faculty Salary	73,231	71,704	12,693	50,891	116,003	21,969,360	300
Student-Faculty Ratio (%)	18.85	19	3.22	10	35	5,655	300
Full-time faculty (%)	85.81	87	8.66	50	100	25,400	296
Expenditure per FTE	6,596	5,650	2,885	2,806	22,876	1,912,748	290
Graduation Rate (%)	52.48	51	15.52	17	93	15,743	300
Freshman Retention (%)	77.54	77	8.97	53	97	23,108	298
Peer Assessment	2.82	2.7	0.48	1.9	4.7	844	299
Alumni Giving Rate (%)	9.97	9	6.60	1	67	2,882	289
Tuition & Fee–in-state	6,516	6,200	2,219	2,832	13,706	1,954,776	300
Tuition & Fee–out-state	16,263	15,217	4,821	5,526	33,069	4,878,827	300

Table 6C. Private Schools

	Mean	Median	Std. Dev.	Minimum	Maximum	Sum	N
Salary, Starting	45,964	44,600	7,181	31,900	71,100	12,134,400	264
Salary, Mid-career	83,725	82,650	16,849	47,500	129,000	22,103,400	264
Salary Increment	37,761	37,150	11,592	8,600	70,800	9,969,000	264
State Income	51,625	49,267	6,092	39,418	65,652	13,628,957	264
Major Index, Starting	42,212	41,290	3,430	36,215	58,214	11,143,983	264
Major Index, Mid-career	71,767	70,590	6,655	58,537	98,711	18,946,358	264
Major Index, Increment	29,554	29,148	4,177	18,950	43,047	7,802,375	264
SAT/ACT	65	65	13	27.5	92.5	16,929	259
Top 10 % High School (%)	44	38	26	1	99	10,890	248
Acceptance Rate (%)	55	59.8	22	8	100	14,430	262
Class Size, 1–19 (%)	60	62	13	27	100	15,656	260
Class Size, 50+ (%)	3	1	3	0	17	738	260
Enrollment	3,755	2,589	3,345	340	27,986	991,360	264
Faculty Salary	77,391	73,934	19,318	40,633	146,331	20,431,296	264
Student-Faculty Ratio (%)	13	13	6	5	60	3,507	264
Full-time faculty (%)	80	83.5	15	28	99	20,927	262
Expenditure per FTE	13,032	9,777	11,144	1,805	71,859	3,349,312	257
Graduation Rate (%)	70	72	17	16	98	18,546	264
Freshman Retention (%)	84	86	10	54	99	22,232	264
Peer Assessment	3	3	1	1.8	4.9	818	259
Alumni Giving Rate (%)	23	20	14	1	63	5,761	256
Tuition & Fee– Private	28,871	29,070	7,687	4,080	40,422	7,448,596	258

Table 7 Correlation between Salary and Independent Variables

	Starting Salary	Mid-Career Salary	Salary Increment
Salary, Mid-Career	84%	100%	
Salary Increment	62%	94%	100%
State Income	29%	30%	27%
Major Index, Starting	62%	40%	21%
Major Index, Mid-career	77%	69%	54%
Major Index, Increment	72%	77%	68%
SAT/ACT	59%	71%	68%
Top 10 % High School	60%	70%	66%
Acceptance Rate	-48%	-57%	-54%
Class Size, 1–19	16%	20%	19%
Class Size, 50+	19%	17%	12%
Enrollment	10%	10%	8%
Faculty Salary	70%	78%	71%
Student-Faculty Ratio	-26%	-38%	-39%
% Full-time faculty	15%	24%	26%
Expenditure per FTE	58%	61%	54%
Graduation Rate	51%	66%	65%
Freshman Retention	55%	69%	67%
Peer Assessment	55%	65%	61%
Alumni Giving Rate	35%	51%	54%

Table 8 Correlation for Independent Variables

	State Income	Major Index Starting	Major Index Mid-Career	Major Index Increment	SAT/ACT	Top 10% High School	Acceptance Rate
Major Index, Starting	-2%	100%					
Major Index, Mid-career	10%	84%	100%				
Major Index, Increment	18%	54%	91%	100%			
SAT/ACT	11%	23%	57%	72%	100%		
Top 10% of High School	16%	21%	54%	68%	87%	100%	
Acceptance Rate	-21%	-4%	-33%	-49%	-67%	-71%	100%
Class Size, 1–19	6%	1%	15%	22%	39%	43%	-34%
Class Size, 50+	-9%	15%	17%	15%	6%	12%	5%
Enrollment	-5%	-2%	0%	2%	-1%	3%	7%
Faculty Salary	31%	26%	55%	65%	69%	71%	-60%
Student-Faculty Ratio	-14%	-7%	-26%	-36%	-50%	-47%	43%
% Full-time faculty	-17%	15%	26%	30%	37%	36%	-13%
Expenditure per FTE	15%	22%	45%	54%	70%	70%	-59%
Graduation Rate	23%	9%	43%	60%	87%	80%	-59%
Freshman Retention	26%	12%	46%	62%	85%	78%	-63%
Peer Assessment	19%	12%	43%	57%	79%	81%	-60%
Alumni Giving Rate	6%	6%	35%	51%	76%	71%	-57%

Table 8 Correlation for Independent Variables (Cont.)

	Class Size 1–19	Class Size 50+	Enroll-ment	Faculty Salary	Student/ Faculty Ratio	Full-time Faculty	Expe. per FTE	Grad. Rate	Fresh-man Rete. Rate	Peer Assess-ment
Class Size, 50+	-56%	100%								
Enrollment	-54%	77%	100%							
Faculty Salary	11%	30%	26%	100%						
Student/Faculty Ratio	-58%	40%	42%	-32%	100%					
% Full-time Faculty	-18%	38%	27%	24%	-10%	100%				
Expenditure Per FTE	42%	0%	-9%	69%	-52%	26%	100%			
Graduation Rate	36%	-1%	-1%	62%	-49%	34%	59%	100%		
Freshman Retention	20%	12%	13%	69%	-42%	36%	57%	92%	100%	
Peer Assessment	26%	8%	9%	66%	-42%	36%	66%	76%	76%	100%
Alumni Giving Rate	53%	-22%	-26%	42%	-61%	36%	56%	72%	63%	63%

Table 9 Preliminary Estimations

	Starting Salary	Mid-Career Salary	Salary Increment	Alumni Giving Rate
State Income	0.129[a] (0.027)	0.206[a] (0.061)	0.084[c] (0.049)	-0.092[b] (0.051)
Major Index	1.111[a] (0.072)	0.983[a] (0.094)	0.856[a] (0.119)	-0.180[b] (0.092)
Private School	1516[a] (570)	4030[a] (1332)	2545[a] (1074)	0.615 (1.151)
SAT/ACT	41.94 (44.03)	-9.52 (94.24)	-39.81 (68.47)	0.247[a] (0.077)
Top 10% High School	-11.87 (12.32)	-22.41 (28.49)	-10.07 (23.70)	0.039[c] (0.025)
Acceptance Rate	-36.44[a] (14.75)	-75.46[a] (29.03)	-42.60[b] (20.86)	-0.027 (0.027)
Class Size, 1–19	-5.73 (21.12)	-45.89 (39.06)	-40.80[b] (27.98)	0.118[a] (0.035)
Class Size, 50+	73.34[c] (44.60)	102.66 (86.42)	24.70 (62.25)	-0.164[b] (0.081)
Enrollment	0.063[b] (0.031)	0.127[b] (0.073)	0.069 (0.058)	-0.207[a] (0.069)
Faculty Salary	0.105[a] (0.019)	0.347[a] (0.040)	0.244[a] (0.030)	-0.050 (0.0046)
Student-Faculty Ratio	-4.45 (55.56)	23.30[c] (47.17)	-166.78[b] (96.59)	-0.357[a] (0.103)
% Full-time Faculty	-16.19 (20.32)	-174[c] (115)	41.39 (37.79)	0.268[a] (0.042)
Expenditure per FTE	0.039 (0.031)	-0.087[c] (0.062)	-0.132[a] (0.048)	-0.077 (0.061)
Graduation Rate	35.36 (31.13)	101.59[c] (64.09)	69.67[b] (51.30)	0.176[a] (0.047)
Freshman Retention	-50.29 (54.90)	-143.30[c] (110.59)	-96.39 (90.22)	-0.038 (0.087)
Peer Assessment	1176[a] (489)	1401 (1171)	226.86 (958.23)	1.39 (1.20)
Alumni Giving Rate (Mid-Career Salary)	-10.48 (24.21)	110.73[b] (57.94)	126.61[a] (50.98)	0.087[b] (0.047)
C	-18555[a] (5358)	-20949[b] (10808)	-5344 (8338)	-15.61[b] (9.03)
$\bar{R}^2$	0.787	0.783	0.651	0.749
N	460	460	460	460

Note: The numbers in the parentheses are the Newey-West HAC standard errors. The superscript "a" indicates the significance at 1% level for one-tailed test; "b" indicates 5% of significance level; "c" indicates 10% of significance level. The coefficients for Alumni Giving Rate (Mid-Career Salary) are for alumni giving rate for the first three columns; and for mid-career salary for the last column.

Table 10 Simplified Models

	Starting Salary	Mid-Career Salary	Salary Increment	Mid-Career Salary (TSLS)	Salary Increment (TSLS)
State Income	0.126[a]	0.232[a]	0.112[a]	0.162[a]	0.071[c]
	(0.021)	(0.051)	(0.043)	(0.060)	(0.048)
Major Index	1.126[a]	0.965[a]	0.712[a]	0.987[a]	0.7776[a]
	(0.066)	(0.078)	(0.110)	(0.092)	(0.112)
Private School	1487[a]	3302[a]	1412[c]	2862[a]	1369[c]
	(367)	(966)	(871)	(1136)	(862)
Acceptance Rate	-36.13[a]	-38.58[b]		-50.57[b]	
	(9.20)	(20.94)		(27.50)	
Enrollment	0.088[a]	0.188[a]	0.088[a]	0.082	0.035
	(0.021)	(0.055)	(0.050)	(0.068)	(0.054)
Faculty Salary	0.120[a]	0.326[a]	0.213[a]	0.317[a]	0.217[a]
	(0.016)	(0.034)	(0.025)	(0.037)	(0.026)
Graduation Rate			67.90[a]	104.53[b]	73.05[b]
			(27.92)	(48.30)	(38.71)
Peer Assessment	1348[a]	2054[b]		1382[c]	
	(300)	(894)		(1041)	
Alumni Giving Rate		124.02[a]	113.43[a]	-12.61	77.11
		(45.57)	(36.77)	(108)	(69.51)
C	-21435[a]	-33748[a]	-14489[a]	-31595[a]	-13771[a]
	(2878)	(5415)	(2914)	(6001)	(3065)
$\bar{R}^2$	0.764	0.769	0.631	0.773	0.644
N	553	534	545	474	478

Note: See Table 9.

Table 11 School Sizes and Carnegie Classifications of Schools

	All Schools		Public Schools		Private Schools	
	Percent	Count	Percent	Count	Percent	Count
	100%	564	53.19%	300	46.81%	264
School Size						
Under 1000	0.71%	4	0.00%	0	1.52%	4
1000 – 4,999	27.31%	154	2.67%	8	55.30%	146
5,000 – 9,999	22.34%	126	22.33%	67	22.35%	59
10,000 – 19,999	26.95%	152	37.00%	111	15.53%	41
20,000 +	22.70%	128	38.00%	114	5.30%	14
Enrollment Profile Classification						
Excursively Undergraduate	10.99%	62	2.00%	6	21.21%	56
Very High Undergraduate	27.84%	157	31.67%	95	23.48%	62
High Undergraduate	40.07%	226	55.00%	165	23.11%	61
Majority Undergraduate	18.26%	103	11.33%	34	26.14%	69
Majority Graduate	2.84%	16	0.00%	0	6.06%	16
Carnegie Basic Classification						
Research (Very High)	16.49%	93	21.00%	63	11.36%	30
Research (High)	16.31%	92	23.00%	69	8.71%	23
Doctoral/Research	7.45%	42	7.33%	22	7.58%	20
Master (Larger Programs)	29.26%	165	35.67%	107	21.97%	58
Master (Medium Programs)	8.33%	47	7.33%	22	9.47%	25
Master (Smaller Programs)	2.84%	16	1.67%	5	4.17%	11
BA – Arts and Sciences	14.54%	82	1.67%	5	29.17%	77
BA – Diverse Fields	3.19%	18	1.00%	3	5.68%	15
Others	1.60%	9	1.33%	4	1.89%	5

Data Source: IPEDS.

Table 12 Estimations with Different School Sizes and Carnegie Classifications

	Starting Salary	Mid-career Salary	Mid-career Salary (TSLS)	Mid-career Salary	Salary Increment	Salary Increment (TSLS)
State Income	0.139[a] (0.022)	0.273[a] (0.051)	0.241[a] (0.055)	0.211[a] (0.055)	0.117[a] (0.042)	0.105[a] (0.042)
Major Index	1.102[a] (0.066)	0.950[a] (0.080)	0.944[a] (0.080)	0.936[a] (0.076)	0.751[a] (0.112)	0.754[a] (0.115)
Private School	1611[a] (382)	3662[a] (1011)	3158[a] (1110)	2674[a] (1000)	1578[b] (898)	1473[c] (912)
Acceptance Rate	-35.02[a] (8.83)	-37.52[b] (20.15)	-37.98[b] (21.67)	-39.37[b] (20.83)	82.55[a] (27.59)	76.96[b] (29.86)
Enrollment	0.056[b] (0.032)	0.228[a] (0.068)				
Faculty Salary	0.096[a] (0.017)	0.265[a] (0.034)	0.256[a] (0.035)	0.279[a] (0.034)	0.182[a] (0.031)	0.182[a] (0.031)
Graduation Rate			64.66[b] (37.07)	67.76[b] (29.98)		
Peer Assessment	1910[a] (342)	3869[a] (1043)	3769[a] (1106)	4262[a] (977)		
Alumni Giving Rate		143.10[a] (46.52)	66.98 (110.49)		136.14[a] (39.57)	145.02[b] (78.51)
School Size (5,000–9,999)		1411[c] (863)	1919[c] (1355)		1885[b] (975)	1886[b] (1030)
School Size (10,000–19,999)	951[a] (372)	1507[b] (835)	2874[b] (1582)	1165[c] (892)	2144[b] (1106)	2219[b] (1144)
School Size (20,000+)	918[c] (586)		3792[b] (1703)	1826[b] (931)	2893[a] (1215)	2881[b] (1269)
Majority Graduate School	1872[a] (719)					
Research University (High)	745[b] (342)	2640[a] (870)	2249[a] (871)	2497[a] (837)		
Doctor/Research University	1181[b] (574)	5124[a] (1159)	4756[a] (1219)	4095[a] (1124)	2016[a] (790)	2357[a] (903)
C	-21643[a] (2809)	-38001[a] (5326)	-36803[a] (5193)	-35481[a] (5132)	-15916[a] (2987)	-15122[a] (2962)
$\bar{R}^2$	0.772	0.778	0.777	0.769	0.635	0.637
N	553	534	531	553	545	537

Note: See Table 9.

Table 13 Starting Salary, Simplified Models with State Cluster

	OLS	OLS	Fixed Effect (FE)	Between Effect (BE)	FE+BE*	FE+Group	FE+BE +Group*
State Income	0.126[a] (0.021)						0.100[a] (0.025)
Major Index*	1.126[a] (0.066)	1.086[a] (0.060)	1.129[a] (0.063)		1.129[a] (0.061)	1.129[a] (0.061)	1.129[a] (0.063)
Private School*	1487[a] (367)	1477[a] (345)	1459[a] (366)		1459[a] (353)	1459[a] (352)	1459[a] (344)
Acceptance Rate*	-36.13[a] (9.20)	-36.64[a] (9.68)	-30.77[a] (10.34)		-30.77[a] (11.16)	-30.77[a] (11.16)	-30.77[a] (11.05)
Enrollment*	0.088[a] (0.021)	0.068[a] (0.021)	0.089[a] (0.017)		0.089[a] (0.023)	0.089[a] (0.023)	0.089[a] (0.023)
Faculty Salary*	0.120[a] (0.016)	0.143[a] (0.015)	0.105[a] (0.019)		0.105[a] (0.017)	0.105[a] (0.017)	0.105[a] (0.017)
Peer Assessment*	1348[a] (303)	1261[a] (303)	1661[a] (448)		1661[a] (354)	1661[a] (354)	1161[a] (350)
$\overline{Major\ Index}_g$				1.098[a] (0.385)	1.263[a] (0.247)	0.133 (0.252)	1.306[a] (0.246)
$\overline{Private\ School}_g$				162.03 (1991)	1259 (987)	-199 (1025)	1523[b] (951)
$\overline{Acceptance\ Rate}_g$				-28.23 (30.69)	-21.04 (20.95)	9.732 (24.72)	-39.72[b] (20.86)
$\overline{Enrollment}_g$				0.022 (0.102)	0.074[c] (0.057)	-0.015 (0.063)	0.120[b] (0.058)
$\overline{Faculty\ Salary}_g$				0.196[a] (0.033)	0.214[a] (0.023)	0.110[a] (0.026)	0.158[a] (0.027)
$\overline{Peer\ Assessment}_g$				1357 (1391)	1768[a] (754)	108 (852)	1109[c] (788)
C	-21435[a] (2878)	-14830[a] (2565)	-15321[a] (2814)	-19035 (19078)	-29894[a] (11641)	-29894[a] (11641)	-29939[a] (11949)
$\bar{R}^2$	0.764	0.750	0.754	0.660	0.764	0.767	0.771
N	553	553	553	51	553	553	553

Note: Each variable X_{gj}^* is either X_{gj} or the mean deviation, $X_{gj} - \bar{X}_g$. For the two columns with "*", each independent variable with "*" is the mean deviation such as $X_{gj}^* = X_{gj} - \bar{X}_g$. For other columns, $X_{gj}^* = X_{gj}$. The group mean variable $\bar{X}_g$ is the mean for each state. See Table 9.