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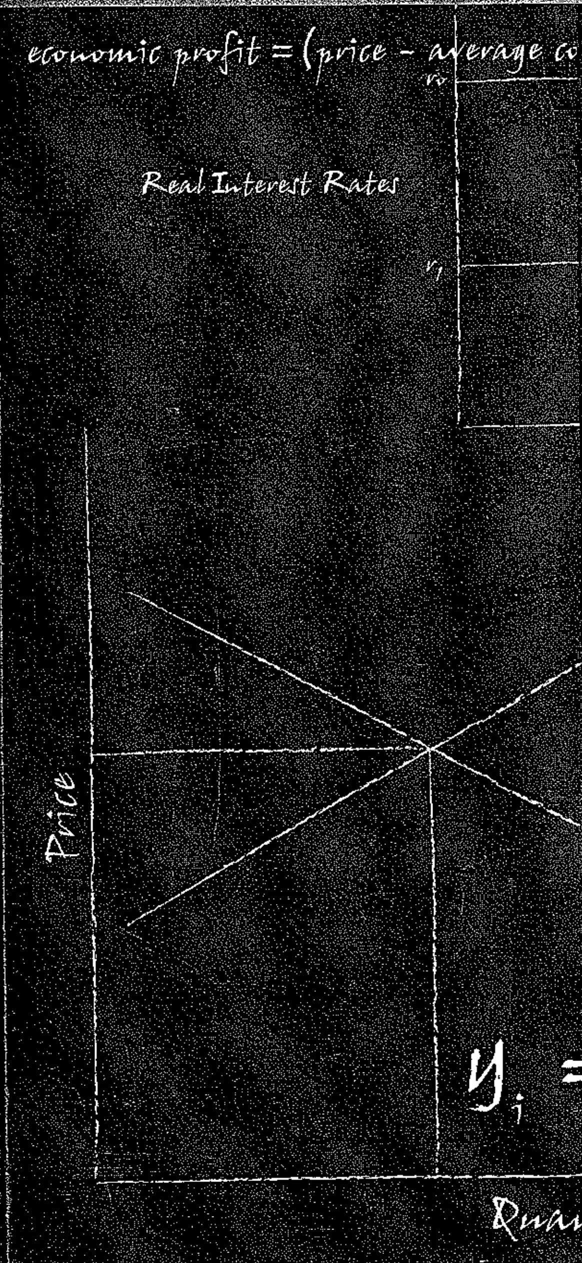

The Transition to Market-Based Economic Education: Evaluating Program Effectveness in Kazakhstan

Paul W. Grimes*, Meghan J. Millea, and Randall C. Campbell

Abstract: *This article presents an analysis of a program designed to enhance economic literacy through teacher training in the former Soviet Republic of Kazakhstan. The cognitive and affective outcomes for high school students who were taught by teachers trained through the National Council on Economic Education's (NCEE) International Economic Education Exchange Program (IEEEP) were examined and compared to those of students in courses taught by a sample of teachers who had not received training. Like most publicly supported programs, beneficiaries were not randomly chosen and assigned to treatment and control groups. To overcome the inherent sample selection issues we developed a two-stage regime switching model with selection which allowed for the interdependency of economic understanding and attitudes. The results indicate that students taught by trained teachers achieved higher post-course scores on standardized testing instruments, after controlling for differences in student attributes, teacher characteristics, and the non-random selection of teachers into the training program. However, both the cognitive and affective improvements would have been even greater if teachers had been randomly assigned to the program. The authors call for additional research to evaluate the criteria and methods used to recruit and select teachers for participation in training programs such as the IEEEP.*

Introduction

During the past fifteen years, the process of transition from command to market-based economies in the former Soviet Republics has been hindered by significant and widespread deficiencies in basic economic understanding by policymakers, business leaders, and average citizens alike. Built-up by generations of Communist rule, suspicions and misunderstandings about market functions have slowed the progress of transition throughout the former Soviet empire. The need

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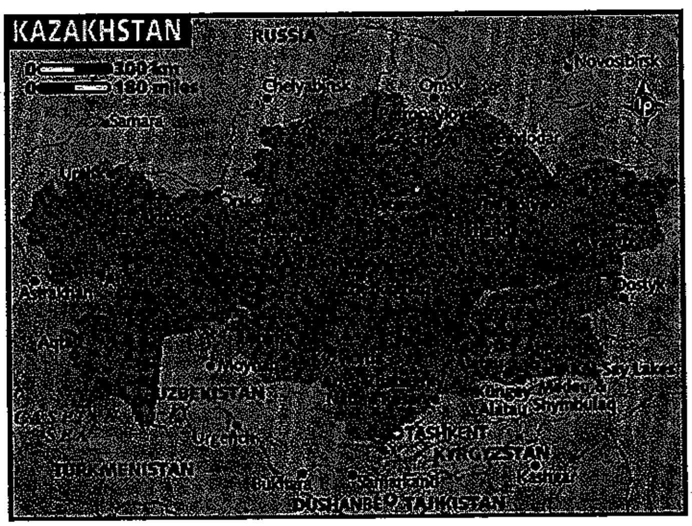
to develop economic human capital in the transition zone is widely recognized by those interested in fostering the development of stable economies and governments in the region. A review of the efforts to develop economic human capital in the transitional economies (Stuart, 2000) reveals that formal training and education programs are making progress in some areas, but many still face significant institutional and cultural hurdles.

Kazakhstan, in south central Asia (see Figure 1), is one republic that is receiving international aid to foster the teaching of basic economic principles throughout the nation's public schools. This oil rich republic's strategic location and potential for economic development have attracted the attention of the industrialized international community (Edwards, 2002). The United States Department of Education supports economic education programs in Kazakhstan through major grants awarded to the National Council on Economic Education (NCEE). In Kazakhstan the non-profit NCEE, which has promoted economic literacy through teacher training in the United States for more than fifty years, has focused its efforts on training professional educators how to teach and promote economic literacy within a transitional economy context.

Figure 1. Map of Kazakhstan



The International Economic Education Exchange Program (IEEEP) is the cornerstone of the NCEE's activities to train high school teachers in Kazakhstan, and the other nations of the transition zone, how to teach market-based economics using sound pedagogical materials and techniques (Elder and Sumilo, 1998). The inherent problems of transition from command-based economic systems to those which rely on the principles of the marketplace (e.g. inadequate property rights, irregular enforcement of contracts, limited access to capital markets, corruption in public services, etc.) create a tremendous need for economic literacy in this important and developing region of the world. IEEEP was conceived specifically to help meet this need and to further the progress of transition. In recent years, the NCEE has trained teachers from several nations through IEEEP, and evaluations of these efforts have been conducted for programs in Latvia, Lithuania, Ukraine, Poland, and Kyrgyzstan (Walstad, 1997; Spiro, 1998; Walstad and Rebeck, 2001). The primary conclusions of these assessments suggest that students of IEEEP-trained teachers demonstrated a larger increase in economic understanding relative to comparable students in courses taught by teachers who had not participated in IEEEP training.

The ultimate success of economic literacy programs in Kazakhstan will, of course, depend on the ability of citizens to establish the institutional and legal frameworks to foster and support the development of stable markets. To what extent programs like IEEEP assist in meeting this long-run goal is dependent upon the degree to which they successfully promote economic literacy. Assessing this first step is the focus of the analysis presented here.

Specifically, we examine the cognitive and affective outcomes[1] for high school students in Kazakhstan who were taught economics by IEEEP-trained teachers, and compare those outcomes to those of students in courses taught by teachers who did not receive IEEEP training. As with most public policy evaluations, it was impossible to randomly assign teachers and students to treatment and control groups. Thus, our methodology must account for the inherent selection issues that resulted in the formation of the sample under investigation.

Descriptions of the evaluation design and investigative sample are presented in the next section followed by the development of a two-stage switching regression model, corrected for sample selection, designed to capture the determinants of student economic understanding and market attitudes. The results from the empirical estimation of this model are then presented and discussed. The major conclusions drawn from these empirical results are outlined in the final section.

Evaluation Design and Investigative Sample

A quasi-experimental design similar to those employed by previous researchers of IEEEP programs in other nations was used to examine the effects of teacher training on high school students in Kazakhstan. Essentially, the analysis consisted of a comparison of outcome measures for students taught by IEEEP-trained teachers (a treatment group) to outcome measures for students taught by teachers who had not participated in the IEEEP training (a control group). As seen below, neither group was formed through a random assignment process. Thus, our evaluation methodology had to take into account the forces that determined the selection of teachers into the treatment and control groups. Furthermore, given the historical and institutional context of a transition economy such as Kazakhstan's, any successful program designed to enhance economic literacy must achieve positive changes in *both* knowledge and beliefs. Therefore, two primary student outcomes were investigated: the degree of cognitive understanding of basic economic principles, and the formation of positive attitudes toward market-based economic principles and policies (e.g., personal beliefs about individual and societal welfare outcomes of free markets).

NCEE-affiliated personnel trained teachers in Kazakhstan during 1999 through a series of seminars that closely paralleled the format of IEEEP programs conducted previously in other countries. Individual teachers voluntarily applied for these seminars after the distribution of announcements through their local school administrations and education ministries. The training seminars covered both economics content and teaching pedagogies. During the seminars, the trainers introduced the teachers to NCEE-produced classroom materials and lesson plans designed to foster an appreciation and understanding of the benefits which derive from a market-based economy. The trainers gave participating teachers copies of these materials and strongly encouraged them to integrate the lessons into their own courses. Subsequently, all treatment teachers reported using these materials. Classes taught by teachers from this group who had completed the IEEEP training, and who were also teaching high school economics courses during the 2000-2001 academic year, were chosen to serve as the treatment group for our analysis.

In order to isolate the effect of the IEEEP training, a control group of comparable economics teachers and students was required. Therefore, teachers in the treatment group were asked to identify colleagues who had *not* participated in the IEEEP training seminars but who were also teaching high school economics during the 2000-2001 academic year. From the pool of recommendations, classes taught by teachers meeting these criteria were chosen to serve as the control group.

During the spring of 2001, personnel from the Educational Development Center, Incorporated (EDC) administered a battery of surveys and tests to Kazak students in the economics courses taught by both the treatment and control group teachers, to determine their degree of understanding of basic economic concepts and their attitude concerning market-based principles and policies.

The EDC also trained the participating teachers how to conduct the surveys and tests in their classrooms and how to maintain the integrity of the resulting data throughout the evaluation period. (Limited amounts of additional data beyond what are reported here were collected from participating teachers and students. For an overview and analysis of the collected data, see EDC (2001) and Grimes and Millea (2001), respectively.) The student data were collected using the classic pre-course/post-course design. Thus, two observations of the students were made, one immediately before formal classroom instruction began, and one immediately following the conclusion of the course.

Students in all participating classrooms were asked to complete a Student Economics Survey (SES) comprised of 33 multiple choice questions. The first 23 questions consisted of an abbreviated version of the *Test of Economic Literacy* (Walstad and Rebeck, 1999), which measured economic understanding, while the remaining 10 questions consisted of an abbreviated version of the *Market Economy Attitude Survey* (*MEAS*), which measured attitudes toward market-based economic principles and policies. The *MEAS* was originally constructed from three independent survey instruments used in previous empirical studies: Alston, Kearl, and Vaughn (1992); Shiller, Boycko, and Korobov (1991); and Boeva and Shironin (1992).[2] Thus, the SES was designed to provide quantitative measures of the students' cognitive and affective outcomes resulting from instruction in economics.[3]

The total investigative sample consisted of 1,110 students drawn from 39 different classrooms.[4] Out of the 39 teachers, 21 had completed the IEEEP training seminars and, thus, they and their students comprised the treatment group. The remaining 18 untrained teachers and their students made up the control group. The abbreviated *TEL* and *MEAS* instruments were completed by a total of 591 students in the treatment group and 519 students in the control group. Additional data were also collected from individual students and teachers in both groups using a variety of survey instruments administered under controlled conditions.[5]

Table 1 reports the mean pre-course and post-course *TEL* and *MEAS* scores for both the treatment and control groups. The t-statistic reported in the table tests the hypothesis that the post-course mean score exceeded the pre-course mean score for the relevant evaluation instrument and student group. It is apparent from Table 1 that formal instruction in economics, whether by IEEEP-trained teachers or not, resulted in improved student economic understanding and attitudes toward market principles. The post-course means for both the *TEL* and *MEAS* instruments are significantly greater than the pre-course means in all cases. Although the treatment group demonstrated higher post-course means on both evaluation instruments relative to the control group, simple t-tests revealed no significant difference in the size of the learning and attitude *gain* between the two groups. However, it is important to note that if all else is the same between two groups, we should expect the group with the lower pre-course scores to narrow the gaps more significantly as both groups proceed through the semester for two reasons. First, since there are a given number of questions, those starting from a lower position have more room to improve while those starting from a higher position have less room for improvement. Second, students with more knowledge going into the course will be taught some things which they already know while students with less knowledge will learn these things for the first time.[6] Thus, the insignificant difference in the gain observed for the lower pre-course scoring control group and the higher pre-course scoring treatment group provides an indication that the training did have a positive effect on student learning.

However, simple t-tests cannot control for the inherent heterogeneity that naturally exists across students, teachers and classrooms. To isolate and determine the specific effect of IEEEP teacher training on student understanding and attitudes requires a more sophisticated form of analysis.

Table 1. Mean Pre-Course and Post-Course Scores by Group

Group	PRE *TEL*	POST *TEL*	Difference	t-Value*	N
Treatment	12.910 (3.546)	14.897 (4.154)	1.987	8.844***	591
Control	11.750 (3.337)	13.844 (3.886)	2.094	9.313***	519
Group	**PRE *MEAS***	**POST *MEAS***	**Difference**	**t-Value***	**N**
Treatment	6.510 (1.640)	6.883 (1.582)	0.374	3.990***	591
Control	5.910 (1.540)	6.324 (1.736)	0.418	4.104***	519

( ) - Standard Deviation

*** - Statistically significant at the .01 level, one-tailed test.

* - Tests the hypothesis that post-course mean is greater than pre-course mean.

The Empirical Models

A relatively rich empirical literature reveals that a number of student and teacher attributes can influence the cognitive and affective outcomes resulting from a high school course in economics for students in the United States (Becker, Greene and Rosen, 1990). Walstad (1997) and Walstad and Rebeck (2001) extended this literature by estimating traditional single equation educational production functions for samples of high school students in former Soviet Republics and Eastern European nations where the NCEE had delivered IEEEP teacher training. These latter studies are open to criticism for their failure to control for the sample selection issues inherent to most public policy programs where the evaluator does not have the ability to assign subjects to treatment and control groups. Our model developed below is designed to capture and control the effect of non-random sampling on the program's measured outcomes. The model employs a switching regression technique that was originally designed for policy evaluations where beneficiaries were not randomly assigned.

Furthermore, previous evaluations of IEEEP did not explicitly account for the interaction between the cognitive and affective domains that naturally occurs within the classroom environment. That is, previous evaluations of IEEEP have not accounted for the effect of students' economic understanding on attitude formation or the effect of students' attitude formation on economic understanding. The relationship between understanding and attitudes is of specific concern given the historical and institutional context of the Kazakhstan economy. All of the participants within the investigative sample live within an economy that is moving from a command-based system to a market-based system. Personal attitudes toward the old and familiar command economy may create a barrier to understanding and appreciating the relative benefits of transition. Also, unforeseen consequences of transition may erect attitudinal barriers to the acceptance of market-based principles. For these reasons, it is important to explicitly recognize that understanding and attitudes are naturally linked. To allow for the interaction between student understanding and attitudes, we postulated a student outcomes model of the following functional form:

$$\text{Economic Understanding} = f\ (\text{Treatment, Economic Attitude, Student Attributes, Teacher Attributes}) \quad [1]$$

$$\text{Economic Attitude} = f\ (\text{Treatment, Economic Understanding, Student Attributes, Teacher Attributes}) \quad [2]$$

Note that attitude appears on the right hand side of function [1] and that understanding appears on the right hand side of function [2]. This specification allows for the assumed simultaneous interaction of economic understanding and attitude formation to be estimated across the two equations. Educational production functions of similar form have been used in previous economic education program evaluations at the elementary (Grimes, 1995) and college levels (Grimes, Krehbiel, Nielsen, and Niss, 1989) for American students. Such specifications implicitly hypothesize a bi-directional association between attitude formation and economic understanding similar to that put forth by Hodgin (1984). Applying information theory to the process of learning, Hodgin argued that as students experience a course of study, their relative performances on assignments and examinations are received as messages and that these messages are then used as a basis in the formation of attitudes. In turn, attitudes are assumed to affect current study behavior and, therefore, the resulting degree of cognitive understanding.

Data collected from each participating teacher and student in the investigative sample were used to empirically estimate functions [1] and [2] using a regime switching regression technique that explicitly accounts for the selection process that determined which teachers received training and, thus, the assignment of student observations into the treatment and control groups.

Given a myriad of institutional constraints, teachers and their students could not be randomly assigned to either the treatment group or the control group. In fact, a selection process created both the treatment and control group subsamples. Subjects from the underlying population of secondary school economics teachers were selected into the treatment and control groups through the recruitment and admission processes overseen by local administrators of the training programs. Treatment teachers voluntarily applied for the training program and passed through an implicit admissions screen prior to training.[7] The selection process continued in the post-training period when the trained teachers then recruited untrained colleagues to participate in the evaluation as the control group. An appropriate technique that accounts for the selection phenomena must be used to control for this non-random assignment of subjects within a quasi-experimental framework.

Switching Regression with Selection

To analyze the effect of teacher training on student understanding and attitudes, we began with a standard educational outcomes regression model:

$$y_n = x'_n\beta + I\delta + \varepsilon_n, \; n = 1,\ldots,N$$

where x'_n represents the vector of student and teacher characteristics hypothesized to determine student understanding and attitudes, y_n. I is a categorical variable indicating whether a student's teacher had received the IEEEP training or not. However, I is not exogenous but reflective of the selection process discussed above. Thus, unless the selection process is explicitly accounted for, ordinary least squares estimation of the model would yield biased and inconsistent results. An instrumental variable technique could be used to remedy this selection bias problem; however, this would not account for the additional problem that the receipt of teacher training may lead to interactions with the vector of student characteristics and attributes. For example, a student with a relatively high *MEAS* score may respond differently to a *trained* teacher than would a student with a relatively low *MEAS* score. Therefore, as proposed by Maddala (1983, pp. 260-262), we constructed a switching regression model where each student and teacher attribute in the outcomes equations was allowed to obtain a different coefficient depending on whether the teacher was trained or not trained.

Maddala proposes that the "regime switching regression framework" (his terminology) is an appropriate technique to evaluate the gross benefits of social program participation since it explicitly recognizes that the selection of participants into social programs is not an exogenous event. This parallels our case where the selection of teachers into the training program was not exogenously determined. To construct a regime switching regression model requires two primary steps; first, the estimation of a probit equation to account for the selection of observations into the treatment and control groups, and second, the estimation of separate outcomes regression equations (for the treatment and control groups), each of which includes a selectivity term derived from the first step.

In our case, the first step required the estimation of a probit equation to determine how teacher attributes affected the selection phenomenon of teachers into the IEEEP training program (which ultimately determined whether a given student was taught by a trained or untrained teacher). In this sense, the regime switching model is similar to Heckman's (1979) classic two-step estimation procedure to deal with selectivity. However, given our quasi-experimental project design, the dependent variables (student understanding and student attitudes) are observable for *both* the selected (treatment group) and unselected (control group) sub-samples. Thus, we observe the dependent variables for *all* observations in the full sample. Therefore, our model is similar to Peterson (1992) who also estimated a switching regression model to account for the sample selection among U.S. student test-takers who elected to enroll in a high school economics course.

For the second step, we estimated separate regression equations for students taught by IEEEP-trained and non-IEEEP-trained teachers. A selectivity term derived from the first step probit estimation (the inverse of Mill's Ratio) was included on the right hand side of these equations to account for the truncation caused by the teacher selection process. The effects of training on student outcomes were then calculated by evaluation of the estimated coefficients across the separate equations.

By estimating separate equations for the treatment and control groups, the model captures possible interactions that a simple training dummy variable in a single equation model could not capture. For example, students with relatively high pre-course test scores are likely to have relatively high post-course test scores, but the magnitude of the increase is likely to be greater if the students are taught by a trained teacher. Likewise, it is reasonable to expect that teachers with more positive attitudes and years of experience will likely implement the training in a better fashion resulting in greater student improvement. Thus, the switching regression framework is appropriate because the marginal effects of the student characteristics and teacher attributes in our model are expected to vary depending upon whether the teacher received training or not.

Note that in the first step the selection equation is estimated using teachers as the unit of observation, but in the second step, the unit of observation becomes the student. This is the case because the selection process occurred at the teachers' level, and students were not randomly assigned to teachers. The student outcomes equations contain the selectivity term that accounts for the selection of teachers into their relevant group. In this sense, our model parallels the regime switching regression model of Ransom (1987) who estimated wage equations for husbands after accounting for the selection of their wives into the labor force. The husbands' wage equations in Ransom's model contained a selectivity term derived from a probit equation that modeled the selection decision of wives to be either in or out of the labor force. In a parallel fashion, our student outcomes equations contain a selectivity term derived from probit equations that model the selection of teachers to receive or not receive the IEEEP training.

Econometric Procedures

For a more formal discussion of the econometric techniques employed, the following discussion outlines how we operationalized the steps necessary to construct and estimate our regime switching regression model that analyzes the effect of IEEEP training on student understanding and market attitudes. First, we used standard probit procedures to estimate the teachers' IEEEP participation equation, which is defined as:

$$I_i^* = z_i'\gamma + e_i, \quad i = 1,\ldots,T$$

where I_i^* is an unobservable latent variable that reflects whether a teacher is observed in the trained treatment group, z_i' is a 1xK vector of exogenous teacher characteristics hypothesized to determine if a teacher applies for, and is selected to receive, training, γ is a Kx1 vector of unknown parameters to be estimated, e_i is a random disturbance term, and T is the number of teachers in the full sample. We observe the variable

$$I_i = \begin{cases} 1 & I_i^* \geq 0 \quad \text{(Treatment group)} \\ 0 & I_i^* < 0 \quad \text{(Control group)} \end{cases}$$

In the second stage, the following two equations were defined for students in the *treatment group*,

$$y_{T1i} = \alpha_{T1} + y_{M1i}\,\delta_{T1} + x'_{T1i}\beta_{T1} + u_{T1i}$$

$$y_{M1i} = \alpha_{M1} + y_{T1i}\delta_{M1} + x'_{M1i}\beta_{M1} + u_{M1i}, \quad i = 1,\ldots,N_1$$

where is the POST TEL score, is the POST MEAS score, and are vectors of exogenous student and teacher attributes hypothesized to determine the post-course TEL and MEAS student scores, respectively, and are random disturbances, and is the number of students taught by IEEEP-trained teachers. Similarly, we defined the following two equations for the *control group*,

$$y_{T2i} = \alpha_{T2} + y_{M2i}\,\delta_{T2} + x'_{T2i}\beta_{T2} + u_{T2i}$$

$$y_{M2i} = \alpha_{M2} + y_{T2i}\,\delta_{M2} + x'_{M2i}\beta_{M2} + u_{M2i}, \quad i = 1,\ldots,N_1$$

(Note that subscripts T and M refer to *TEL* and *MEAS* respectively and subscripts 1 and 2 refer to treatment and control groups respectively.) We assumed that the random disturbances from the participation and two *TEL* equations have a trivariate normal distribution, with mean vector zero and covariance matrix

$$\Sigma_T = \mathrm{cov}(u_{T1i}, u_{T2i}, e_i) = \begin{bmatrix} \sigma_{T1}^2 & \sigma_{T12} & \sigma_{T1e} \\ \sigma_{T12} & \sigma_{T2}^2 & \sigma_{T2e} \\ \sigma_{T1e} & \sigma_{T2e} & 1 \end{bmatrix}$$

where is the disturbance term from the *TEL* equation for the treatment group, is the disturbance term from the *TEL* equation for the control group, and is the error term from the probit selection equation. We defined similarly for the MEAS and probit equations.[8]

Since the test scores for the treatment group are observed given that the teacher received IEEEP training, and the test scores for the control group are observed given that the teacher did not receive IEEEP training, the distributions of test scores for each group are truncated. The conditional expectations, given the truncation, of the error terms for the *TEL* equations are

$$E(u_{T1i} \mid I_i^* \geq 0) = E(u_{T1i} \mid e_i \geq -z_i'\gamma) = \sigma_{T1e} \cdot \frac{\phi(z_i'\gamma)}{\Phi(z_i'\gamma)} = \sigma_{T1e} \cdot \lambda_{1i} = \beta_{T\lambda 1} \lambda_{1i}$$

$$E(u_{T2i} \mid I_i^* < 0) = E(u_{T2i} \mid e_i < -z_i'\gamma) = \sigma_{T2e} \cdot \frac{\phi(z_i'\gamma)}{1-\Phi(z_i'\gamma)} = -\sigma_{T2e} \cdot \lambda_{2i} = -\beta_{T\lambda 2} \lambda_{2i}$$

where and are the standard normal p.d.f. and c.d.f., respectively, evaluated at . The conditional expectations of the errors terms for the *MEAS* are likewise defined. The 's (which are the inverse of Mill's Ratio) reflect the probability of an individual student being observed in the relevant treatment or control group. By including this selectivity variable on the right hand side, the following can then be estimated for the *treatment group*,

$$Y_{T1i} = \alpha_{T1} + Y_{M1i}\,\delta_{T1} + X_{T1i}'\,\beta_{T1} + \lambda_{1i}\beta_{T\lambda 1} + v_{T1i}$$

$$Y_{M1i} = \alpha_{M1} + Y_{T1i}\,\delta_{M1} + X_{M1i}'\,\beta_{M1} + \lambda_{1i}\,\beta_{M\lambda 1} + v_{M1i}$$

and the following can be estimated for the *control group*,

$$y_{T2i} = \alpha_{T2} + y_{M2i}\,\sigma_{T2} + x_{T2i}'\,\beta_{T2} - \lambda_{2i}\,\beta_{T\lambda 2} + v_{T2i}$$

$$y_{M2i} = \alpha_{M2} + y_{T2i}\,\sigma_{M2} + x_{M2i}'\,\beta_{M2} - \lambda_{2i}\,\beta_{M\lambda 2} + v_{M2i}$$

The random disturbances for the treatment group equations, given by

$$v_{T1i} = u_{T1i} - \lambda_{1i}\ \beta_{T\lambda 1} \text{ and } v_{M1i} = u_{M1i} - \lambda_{1i}\ \beta_{M\lambda 1}$$

have conditional means equal to zero. The same applies to the control group disturbances, which are given by

$$v_{T2i} = u_{T2i} - \lambda_{2i}\ \beta_{T\lambda 2} \text{ and } v_{M2i} = u_{M2i} - \lambda_{2i}\ \beta_{M\lambda 2}$$

These disturbances are heteroskedastic since the conditional variances depend on the λ_i's, which vary by individual. We estimated each system of equations using two-stage least squares, replacing the right hand side values for POST *TEL* and POST *MEAS* scores with their predicted values.[9] Following Hill, Adkins, and Bender (2003) we calculated asymptotic standard errors based on the Murphy and Topel (1985) general result, which accounts for both the heteroskedasticity and the fact that the error terms include the λ_i's, which are estimated.

Selection Equation Results

The first step in resolving the model required estimation of the selection equation [4] by probit, to reveal the determinants of the probability that any given teacher would receive the IEEEP training. Although the specific underlying personal and professional characteristics used by the local education administrators to screen successful applicants for participation in the training program were not explicitly stated, the application procedures naturally revealed a number of teacher attributes during the selection process. Several teacher characteristics that likely influenced the application and screening process were entered on the right hand side of the probit equation. Table 2 presents the definitions of these variables used to estimate the selection equation, and Table 3 reports the mean and standard deviation of each variable for both the treatment group and the control group, as well as for the sample as a whole.

Table 2. Definition of Variables Used to Estimate Selection Equation

Variable Labels	Definition
Dependent Variable:	
IEEEP	Teacher received IEEEP training = 1; otherwise = 0.
Independent Variables:	
TEACHER AGE	Teacher's age in years.
TEACHER GENDER	Teacher is male = 1; otherwise = 0.
TEACHER ATTITUDE	Teacher's score on the 10-item MEAS instrument taken prior to receiving training.
GRADE LEVEL	Teacher instructs grades 10 and 11 = 1; otherwise = 0.
JUNIOR ACHIEVEMENT	Teacher has participated in programs sponsored by Junior Achievement = 1; otherwise = 0
ECONOMICS EXPERIENCE	Number of years teacher has taught economics.

Table 3. Mean and Standard Deviation of Selection Equation Variables by Group

Variable	Treatment Group	Control Group	Total Sample
IEEEP	1.000 (0.000)	0.000 (0.000)	0.532 (0.499)
TEACHER AGE	37.333 (8.327)	34.278 (7.699)	35.923 (8.086)
TEACHER GENDER	0.333 (0.483)	0.167 (0.383)	0.256 (0.442)
TEACHER ATTITUDE	8.190 (1.470)	7.500 (1.618)	7.872 (1.559)
GRADE LEVEL	0.857 (0.359)	0.778 (0.428)	0.821 (0.389)
JUNIOR ACHIEVEMENT	0.571 (0.507)	0.333 (0.485)	0.462 (0.505)
ECONOMICS EXPERIENCE	3.905 (4.170)	2.833 (1.855)	3.410 (3.314)
N	21	18	39

( ) - Standard Deviation

Examination of Table 3 reveals a number of differences between the teachers in the trained treatment group and the teachers in the untrained control group. For example, treatment group teachers were about three years older and had about one additional year of experience teaching economics than the control group teachers. In addition, a larger percentage of the treatment group was male and demonstrated more positive attitudes toward market economics based on the 10-question *MEAS* instrument taken prior to training. Also, more than half of the treatment group teachers had experience with programs sponsored by Junior Achievement, another pro-market education program operating in Kazakhstan.

The probit results for the selection equation [4] are reported in Table 4. All of the estimated coefficients took the expected signs (see, EDC (2001) for a description of teacher characteristics for the NCEE-training population) and the equation correctly predicted almost 75 percent of the observations. However, only two of the independent variable coefficients were found to be statistically significant when evaluated with the appropriate one-tailed test (this is not surprising given the limited number of teacher observations). Although the sample size is small, these results suggest the primary preferences that formed the basis of the selection process that ultimately determined whether any individual student was observed in either the treatment group or the control group. Specifically, IEEEP-trained teachers were more likely to be male and have previous experience with other pro-market training programs, relative to the untrained control group teachers, *ceteris paribus*. The results seen in Table 4 were used to calculate the inverse of Mill's Ratio for each student observation, which was then entered into the student outcomes equations to estimate Heckman's selection coefficient, β_λ.

Table 4. Determinants of Teacher Selection for Training: Probit Results

Variable	**Probit Coefficient For Equation [4]**
CONSTANT	-3.117* (1.970)
TEACHER AGE	0.023 (0.801)
TEACHER GENDER	0.836# (1.569)
TEACHER ATTITUDE	0.145 (0.990)
GRADE LEVEL	0.574 (0.982)
JUNIOR ACHIEVEMENT	0.746# (1.615)
ECONOMICS EXPERIENCE	0.075 (1.025)
Log-likelihood	-22.426
Percent of Correct Predictions	74.359

( ) - Absolute value of t-statistic.
* - Statistically significant at the .10 level, two-tailed test.
# - Statistically significant at the .10 level, one-tailed test.

Student Outcomes Equations Results

Table 5 presents the specification for each variable, according to category, used to estimate the student outcomes equations ([13] through [16]). The dependent variables, POST *TEL* and POST *MEAS*, measure the stock of economic understanding and the degree of positive attitudes toward the marketplace achieved by students as they exit their course of study.[10] Table 5 also reports the expected sign, based on the existing empirical literature, for each variable that appears on the right hand side of one or both equations. The vector of student attributes included pre-course scores for the *TEL* and *MEAS* instruments (to control for initial stocks of knowledge and attitude formation), as well as the students' genders and ages. Teacher attributes included the teachers' attitudes as reflected by the short-form *MEAS* and a measure of teaching experience.

Table 5. Definition of Variables Used to Estimate Student Outcomes Equations

Variable Labels	Definition
Dependent Variables:	
POST TEL [+]	Student's score on the post-course administration of 23-item TEL examination.
POST MEAS [+]	Student's score on the post-course administration of 10-item MEAS instrument.
Student Attributes:	
PRE TEL [+]	Student's score on the pre-course administration of 23-item TEL examination.
PRE MEAS [+]	Student's score on the pre-course administration of 10-item MEAS instrument.
GENDER [-]	Student is male = 1; otherwise = 0.
AGE [+]	Student's age in years.
Teacher Attributes:	
TEACHER ATTITUDE [+]	Teacher's score on the 10-item MEAS instrument.
EXPERIENCE [+]	Years of service in current teaching position.
Selection Coefficient:	
LAMBDA (+/-)	Selection equation parameter; the inverse of Mill's Ratio.

[ ] - Expected value when entered as a right hand side variable

Table 6. Mean and Standard Deviation of Student Outcomes Equations Variables by Group

Variable	Treatment Group	Control Group	Total Sample
POST *TEL*	14.897 (4.154)	13.844 (3.886)	14.405 (4.063)
POST *MEAS*	6.883 (1.582)	6.324 (1.736)	6.622 (1.679)
PRE *TEL*	12.910 (3.546)	11.750 (3.337)	12.368 (3.497)
PRE *MEAS*	6.510 (1.640)	5.910 (1.540)	6.230 (1.620)
GENDER	0.394 (0.489)	0.422 (0.494)	0.407 (0.492)
AGE	15.257 (1.147)	15.435 (1.362)	15.340 (1.255)
TEACHER ATTITUDE	8.403 (1.429)	7.524 (1.581)	7.992 (1.564)
EXPERIENCE	10.504 (6.067)	10.389 (7.935)	10.451 (6.999)
N	591	519	1110

( ) - Standard Deviation

Table 6 presents the mean and standard deviation for each of the variables included in the empirical specification of the student outcomes equations by evaluation group and in total for the full sample. Very few substantial differences between the treatment and control student groups are apparent in Table 6. However, the control group included a larger proportion of male students while the treatment group reported more positive market attitudes. In fact, the mean *MEAS* score for the treatment group teachers, as reflected in the TEACHER ATTITUDE variable, was about twelve percent greater than the mean *MEAS* score for the control group teachers.

The two-stage regime switching regression results revealed how these and other factors influenced the degree of economic understanding and attitude formation measured for students in the investigative sample. The two-stage least squares regression results for the student outcomes equations ([13] through [16]) are reported in Table 7.[11] To insure proper identification of the system, one exogenous variable was omitted from each equation (Greene, 2003). Thus, PRE *MEAS* was excluded from the economic understanding equations and PRE *TEL* was excluded from the economic attitude equations.[12] Both sets of estimated equations yielded a significant F-statistic and an acceptable adjusted R^2 for cross-sectional data.

Table 7. Determinants of Student Outcomes: Two-Stage Least Squares Regression Results

Variable	POST *TEL* Treatment Equation [13]	POST *TEL* Control Equation [15]	POST *MEAS* Treatment Equation [14]	POST *MEAS* Control Equation [16]
CONSTANT	-5.994*	10.214*	5.228***	3.238***
	(1.678)	(1.703)	(5.033)	(3.981)
PRE TEL	0.534***	0.095	—	—
	(9.921)	(1.020)		
POST MEAS	0.326	-2.608	—	—
	(0.952)	(1.604)		
PRE MEAS	—	—	0.266***	0.060
			(6.742)	(0.996)
POST TEL	—	—	0.067**	-0.161
			(2.127)	(0.987)
GENDER	-0.547**	-0.909	-0.025	-0.361**
	(1.986)	(1.104)	(0.204)	(2.260)
AGE	0.119	0.645***	-0.027	0.116
	(0.962)	(2.845)	(0.535)	(0.872)
TEACHER ATTITUDE	0.858***	0.834	-0.029	0.379***
	(3.824)	(1.115)	(0.382)	(3.390)
EXPERIENCE	0.107***	0.021	-0.022*	0.001
	(3.427)	(0.338)	(1.838)	(0.065)
LAMBDA	3.217***	-4.195***	-0.307	-0.642
	(3.887)	(2.205)	(1.269)	(0.823)
F-Statistic	55.539	6.763	11.191	12.017
Adjusted R2	0.393	0.072	0.108	0.130

( ) - Absolute value of t-statistic.
* - Statistically significant at the .10 level, two-tailed test.
** - Statistically significant at the .05 level, two-tailed test.
*** - Statistically significant at the .01 level, two-tailed test.

As seen in Table 7, many of the estimated coefficients in both sets of student outcomes equations obtained their expected sign and were found to be statistically significant.[13] The explicit assumption that student understanding and attitude formation are interdependent is partially supported by the positive and statistically significant POST *TEL* coefficient in the economic attitude equation for the treatment group. Thus, end-of-course economic understanding positively affected student attitudes toward market-based principles and policies within the treatment group, *ceteris paribus*. However, this result was not found for the control group. Although economic attitudes, as measured by POST *MEAS* scores, were also not found to be significant in the economic understanding equations, the POST *TEL* coefficient in the attitude equation for the treatment group suggests that we should not completely ignore the inter-connections between student understanding and attitudes in the transitional economy context.

With respect to the estimated coefficients for the student attributes variables, Table 7 reveals that the students' stock of economic knowledge and the degree of positive attitudes toward market principles positively affected the relevant corresponding student outcome for the treatment group.[14] This is seen in the positive and significant PRE *TEL* coefficient in the treatment group's economic understanding equation and the positive and significant PRE *MEAS* coefficient in the treatment group's economic attitude equation. As expected, and consistent with other studies, the GENDER coefficient obtained a negative sign in both sets of equations but was only statistically significant in the economic understanding equation for the treatment group and in the economic attitude equation for the control group. Thus, male students in the treatment group left their economics course with lower levels of economic understanding than their female cohorts, all else being equal. Likewise, male students in the control group left the course with less positive attitudes toward market economics than their female classmates, *ceteris paribus*. However, the estimated differences are relatively small when the magnitudes of the gender coefficients are compared to the *TEL* and *MEAS* scales. The positive and significant AGE coefficient in the economic understanding equation for the control group indicates that older students in this group left their economics course with a relatively larger degree of understanding than their younger classmates, *ceteris paribus*. Again, this is consistent with the empirical literature.

Teacher attributes were also found to affect student understanding and attitude formation. Most importantly, Table 7 reveals that TEACHER ATTITUDES had a positive impact on students' post-course *TEL* scores for the treatment group. Apparently, positive teacher attitudes toward market-based economic principles and policies improve the learning environment and/or enhance the delivery of course materials for trained *teachers* in a way that augments student learning. Thus, trained teachers through their relatively superior instruction did a better job reinforcing the pre-existing positive attitudes of their students. The relatively less effective instruction of the untrained control teachers did not bolster pro-market attitudes in their students.

In a similar fashion, the positive and statistically significant EXPERIENCE coefficient in both treatment group equations indicates that the number of years trained teachers have held their current instructional position enhanced their students' end-of-course economic understanding and attitudes while the EXPERIENCE coefficient was insignificant in both control group equations.

Following Maddala (1983), we used the estimated equations reported in Table 7 to calculate the expected gross differences in economic understanding and economic attitudes between the treatment and control groups of students. The expected gross benefit of being taught by an IEEEP-trained teacher for any given individual is equal to

$$E(y_{1i} \mid I_i = 1) - E(y_{2i} \mid I_i = 1) = x_i'\beta_1 + \sigma_{1e}\lambda_{1i} - (x_i'\beta_2 - \sigma_{2e}\lambda_{1i}) = x_i'(\beta_1 - \beta_2) + (\sigma_{1e} + \sigma_{2e})\lambda_{1i}$$

Calculation of this value at the sample means of both the *TEL* and *MEAS* data reveals the expected benefit of IEEEP training on students, *given the selection process* that occurred. However, since the last term in equation [19] reflects the expected benefit due to sample selection, the expected value of the learning and attitudinal benefits *without sample selection* can also be estimated by calculating $x_i'(\beta_1 - \beta_2)$.

This technique reveals that the average student in courses taught by IEEEP-trained teachers was expected to score 2.34 points higher on the *TEL* than if the same student had been taught by an untrained teacher, given the selection of teachers into the training program.[15] Calculation of the learning benefit without accounting for the selection process results in an expected gain of 2.89 test points, a 23 percent improvement over the expected score with selection. This same pattern is found when examining the expected attitudinal benefits. The average student in courses taught by IEEEP-trained teachers was expected to score 0.46 points higher on the 10-point *MEAS* scale when the selection term is included and 0.99 points higher when the selection term is omitted. Thus, our results indicate that IEEEP training in Kazakhstan was effective in significantly improving student understanding and attitudes; however, it also appears that *both the cognitive and affective gains would have been even greater if teachers had been randomly assigned to the program.* A sample of teachers more representative of the entire distribution would have resulted in relatively greater changes in student outcomes.

How did the selection process result in lowering expected student outcomes? The most probable explanation is that teachers who applied and were ultimately accepted into the training program were relatively better teachers than those not selected, and therefore, the realized marginal benefits of training on their productivity was small. (Recall from Table 3 that the treatment group teachers had more teaching experience, overall and with respect to economics, and a more positive attitude toward market-based economics.) The reverse would also hold true; teachers who demonstrated a relative lack of economic knowledge, skills and positive attitude, and who therefore, may not have applied to, or been chosen for the training program, would have had the most to potentially gain from the training. Our results suggest that program designers should pay close attention to how teachers are solicited and chosen for training programs such as IEEEP. The teachers with the best credentials and who exhibit the most enthusiasm and interest in a training program may not have the most to gain from the program's efforts. Thus, expansion of the training program to include teachers closer to the mean would generate significantly greater benefits. Clearly, future research is needed to determine optimal selection procedures for relatively expensive training programs such as IEEEP. Please note that no attempt has been made here, or in previous studies, to evaluate the cost-effectiveness of such programs.

Conclusions

Several important conclusions can be drawn from our evaluation of the IEEEP outreach efforts in Kazakhstan. First and foremost, the results from the two-stage switching regression model with selection indicate that high school students in courses taught by IEEEP-trained teachers left their courses with a significantly greater level of economic understanding and a more positive attitude toward market-based principles and policies than did students in courses taught by teachers who had not been trained. This is true even after controlling for differences in student attributes, teacher attributes, and the selection process that resulted in the assignment of student observations to the treatment and control groups. Second, the empirical results suggest that learning and attitude formation may not be independent for our sample of students. This is particularly important within the context of a transition economy where attitudes toward market-based concepts are influenced by the historical and institutional environment of a command-based system. Additional research is needed to clarify the relationship between learning market-based economics and personal attitudes toward the marketplace in the transition zone. Also, our results suggest that the ultimate student learning and attitudinal benefits of IEEEP training in Kazakhstan were significantly influenced by the selection process that determined which teachers participated in the program. Specifically, our model indicates that larger improvements in *TEL* and *MEAS* scores would have been observed if economics teachers had been randomly assigned to the training program. This suggests that the program administrators may have "skimmed the cream" from the top of the distribution of teachers who, due to their productivity advantage, had relatively less to gain from the training. Thus, the current result may actually *underestimate* the potential benefits of the IEEEP program if it were available to a more representative sample of the teacher population. By extending the program to more teachers farther down the distribution, student benefits are expected to rise. Additional research is needed to determine if optimal selection criteria can be developed to maximize the returns to programs such as IEEEP.

What this research cannot address is how the spread of economic literacy will ultimately affect the transition process over the long-run. Pleskovic, Aslund, Bader, and Campbell (2000) have noted, "To successfully complete the transition, countries need to build indigenous capacity to formulate and analyze economic policies; they need to train a corps of policymakers, researchers, and teachers who have a full understanding of how a market economy functions" (p. 87). Economic literacy programs such as IEEEP are only a first step in the development of this indigenous capacity. How the growth and dissemination of economic human capital influences the development of newly independent nations such as Kazakhstan is the true test of such programs and can only be answered as the future unfolds.

Endnotes

[1]*Cognitive* outcomes include measures of knowledge and understanding. *Affective* outcomes include measures of attitude and belief. In this study, all measures are derived from individual responses to test questions and survey items.

[2]See Walstad (1997) for a brief overview of the external sources used to construct the abbreviated *MEAS* instrument. The complete *MEAS* is reproduced in EDC (2001).

[3]A variety of tests were conducted to confirm the reliability and validity of the abbreviated *TEL* and *MEAS* evaluation instruments for the Kazakhstan sample of students. See Grimes and Millea (2001) for the detailed results from these tests.

[4]A slightly larger number of teachers and classes were originally recruited for the project but a few were removed from the final sample by the EDC due to incomplete and problematic responses. For example, some individual students failed to comply with instructions or damaged their computerized score sheets in a way that prevented them from being included in the final sample. EDC did not supply the authors with any indication that such cases were not random in nature.

[5]A detailed analysis of all the collected data can be found in Grimes and Millea (2001).

[6]As one referee pointed out, it is also possible that a "cumulative effect" of learning may occur – those who already know some basic concepts have the ability to build upon a stronger foundation and learn even more over time. In this case, however, we do not observe this outcome.

[7]The selection of participants was not an open "contest" whereby application forms were widely distributed and interested teachers freely applied and a committee or director accepted some and rejected others. Rather, because of the perceived "perks" (travel, free materials, meals, etc.) of the program, school administrators, who had been informed of the training opportunity, "encouraged" those teachers who would best represent their schools to apply. These teachers then made the voluntary decision to complete the application process or not. Thus, a selection process that was dependent upon aspects of the teachers' potential to use and apply the training was at work in determining which teachers received the training. Because the control group consisted of teachers from the same schools where the trained teachers worked, they were available as potential candidates for the training program, but they either were not encouraged to apply or they did apply and were passed over. Unfortunately, we do not know which is the case for any given subject, however, it is reasonable to expect that these teachers share common characteristics with members of the treatment group since they are drawn from the same relevant population of economics teachers. This is sufficient to construct and estimate our selection equation.

[8]The term σ_{T12} is the covariance between the estimated *TEL* equations for the treatment group and the control group (equations [13] and [15]). It may be reasonable to assume that this term equals zero since these are two different groups of students. However, Maddala (1983) assumes a trivariate normal distribution for the selection, treatment, and control equations in his general regime switching regression model. Furthermore, he notes that this covariance term is unestimable and that it does not affect the other parameter estimates. We include σ_{T12} in our covariance matrix for completeness only. (Note that the parallel case for the *MEAS* equations also holds true.)

[9]The error terms v_{T1i} and v_{M1i} (and similarly v_{T2i} and v_{M2i}) are likely correlated, which suggests we should estimate the model using three-stage least squares. However, since both equations in our system are exactly identified, 2SLS and 3SLS results are equivalent as noted by Judge et al. (1988, p. 651). The first-stage estimates to obtain the predicted values for POST *TEL* and POST *MEAS* scores are available from the authors on request.

[10]Some researchers argue that the dependent variables in evaluation studies such as this should be specified as the difference between pre-course and post-course scores in order to capture the "value-added" of the treatment being investigated. However, Walstad (1987a) demonstrates that difference scores compound the inherent measurement errors of the evaluation instruments, which can lead to unreliable results. Thus, we chose to use post-course scores as the dependent variables within the model presented here. However, as part of our specification tests, we also estimated the student outcomes equations using variations of the difference scores approach. These estimations yielded results similar to and consistent with those presented here. This suggests that our reported results are stable and robust. Copies of the specification tests are available upon written request of the authors.

[11]Although other estimation techniques have been proposed to estimate multiple output educational production functions (Chizmar and Zak, 1983), the two-stage regression technique is most appropriate given our assumed functional form. See Walstad (1987b) for a discussion of two-stage least squares regression within the context of estimating educational production functions.

[12]Given the exogenous variables that were candidates for exclusion, the PRE *MEAS* and PRE *TEL* variables were chosen due to their relatively high degree of correlation with their post-course counterparts, which were included in the relevant equation.

[13]As a specification and sensitivity test, we also estimated an OLS model for the full sample with a dummy variable for IEEEP training and the Heckman selection term. The parameter estimates generally fell between the ones presented in Table 7, as expected. The resulting coefficients for the IEEEP dummies were positive and significant in both the *TEL* and *MEAS* equations. Using these results and following Greene (p. 788), we estimated the difference in scores between students with trained and untrained teachers. This approach yielded an estimated improvement of 5.08 points on the *TEL* and 0.85 points on the *MEAS* due to training. Both of these are greater than the training effects estimates drawn from the regime switching model. We concluded that the positive effects of training are robust results and that the regime switching estimates are of reasonable magnitude. Copies of this test and others are available upon request.

[14]The inclusion of pre-course scores as regressors inherently introduces a degree of measurement error given the use of post-course scores as dependent variables. An obvious solution to this problem is to utilize an instrumental variables technique. Unfortunately, an adequate set of instruments was not available in the current data to properly specify instruments for pre-course economic understanding and attitudes.

[15]OLS estimation of the individual equations and 2SLS estimation of the system of equations both yield positive and significant gains related to IEEEP training, which is consistent with the switching regression estimates. However, the magnitude of the estimated gains is smaller – about 0.5 points for the *TEL* and 0.25 points for the *MEAS*. Nevertheless, the finding of positive student gains due to teachers' IEEEP training was robust across all estimation techniques.

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