Student Effort as a Noncognitive Trait: The Impact of Teacher Judgment on Test Performance and School Decision[1]

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Abstract

Although the importance of noncognitive abilities on social or economic success has been acknowledged, there has been not much work on this issue, nor do we fully understand how to explain the impact of noncognitive traits.

This study examines a cultural resources/social interaction model of gatekeeping by school teachers using data for ninth-grade students. We test how teacher judgment of student effort contributes to educational achievement (test scores) as well as school decision (attending academic-based high school) when controlling for structural and cognitive factors. Using structural equation models to analyze data from the panel survey of Taiwan Youth Project (TYP), we construct student effort and class ranking as latent factors and allow them to mediate the effects of parental education and family income.

Two main findings are produced: First, the effect of teacher judgment on student effort is at least as contributive as the impact of class ranking. It implies that considering noncognitive traits in the stratification process is important. Second, for females, both effort and class ranking determine student's educational achievement. However, effort does not impact female's school decision. In contrast, for males the effect of class ranking disappears when considering student effort. Results indicate that the marginal effect of teachers' perception on boys' school habits is higher than that on girls'. In contrast, girls' later educational achievement as well as school decision is more sensitive to their past academic records.

Introduction

Prior studies have documented the importance of noncognitive abilities which determine student's social and economic success. This issue started from Bowles and Gintis' study (1976) which demonstrated that the kinds of characteristics employers want in their workers are the same characteristics that teachers want in their students. In the past decades, a lot of researchers have further dealt with the same issue and provided more evidence to corroborate the impact of noncognitive traits (e.g. Bowles & Ginties, 1976; 2002; Farkas, 2003; Heckman et al., 2006; Rosenbaum, 2001). Therefore, the pervasive view in the past literatures which accounted for cognitive ability, e.g. test scores, as the prevailing role in explaining the differences of personal achievements has been challenged (Heckman et al. 2006:477-478). It is thus surprising that prior academic discussions of skill and skill formation almost exclusively focused on measures of cognitive ability and ignored noncognitive traits. From a sociological perspective, to take both cognitive and noncognitive abilities into account might be an important case to reexamine in stratification process (Farkas, 2003).

The term 'noncognitive' has multiple meaning that covers various kinds of habits, behaviors and traits. Thus, it becomes important to understand what kinds of noncognitive traits are more contributive to determining personal success. We should also pursue theoretical implications to explain the mechanisms behind them. Previous research has found significant effects of student effort on their learning process (Sorensen & Hallinan, 1977; Marks, 2000; Johnson et al., 2001; Carborano, 2005; Kelly, 2008), which implies that academic rewards are associated with student's actions within specific structure positions at school (Carborano 2005). It is implied that while a wealth of studies has examined the effects of social structure on achievement (e.g., school tracking, family background), far less activity has centered on human agency- e.g. the engagement of a student in the learning process (Carbonaro, 2005).

Additionally, research on student effort as judged by teachers highlights the importance of considering teacher's perception on student's behaviors and attitudes (Farkas et al., 1990; Kelly, 2008; Lleras, 2008; Tach and Farkas, 2005). Using teacher's report to avoid overestimation of student's self report on their effort is just one of the important considerations for measuring student effort. Moreover, it is probable that teacher's perceptions of student's noncognitive traits are often influenced by student's background as well as teacher's subjectivity (Farkas, 1990; Lamont & Lareau, 1988). In this paper, we follow Farkas et al.'s (1990) cultural resource/ social interaction model by focusing on school reward outcomes based upon teacher's subjectivity of student's noncognitive traits as well as of their cognitive ability. The model suggests a subtle, longitudinal process of student/teacher interaction, and states that student's later educational performance would be influenced by teacher judgments (Lleras, 2008).

The goal of this study is to examine how student effort, evaluated by teachers, contributes to gaining a better understanding of achievement gap among students when controlling for other structural and cognitive factors. The second goal of this study is to examine how these factors influence students' school decision when they graduate from junior high school. We compare the effect of student effort versus the effect of class ranking which is related to cognitive performance. Figure 1 depicts the main features of conceptual framework. We hope this could help better understand why effort as a noncognitive trait is associated with educational outcome. By using structural equation model, we try to solve the problems of endogeneity and measurement error which may underestimate or overestimate the true effects.

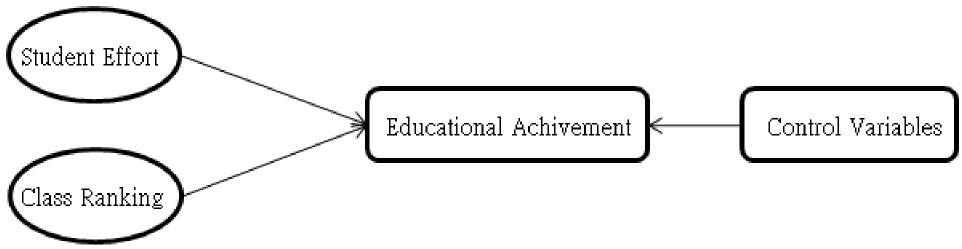

Figure 1. The Conceptual Framework for the Effects of Student Effort and Class Ranking on Educational Achievement

Student Effort as a Noncognitive Trait which Influences Educational Achievement

Effort refers to the level students engage in school matters, including working hard, participating in discussions, being attentive in class, finishing homework, attending class, avoiding distracting behavior, taking part in extracurricular activities, and so on (see Johnson et al., 2001). As students feel a strong sense of attachment to school assignments and have higher will to accomplish requests (e.g. homework, discipline) asked by teachers, they will have better academic achievement (Stewart, 2007). According to Gamoran and Nystrand (1992), engagement can be divided into two forms: procedural engagement and substantive engagement. The former includes effort which is followed by teacher's instruction and often seems routine so that students do not have to think critically. In contrast, the latter deals with critical thinking and genuine personal interest in searching for some extraordinary achievement in class.

It is important to measure student effort as one of the factors which contribute to educational attainment. It has often been found that effort and participation in class are significant predictors of student performance (Carbonaro, 2005; Lleras, 2008; Johnson et al., 2001). Carbonaro (2005) found that differences in effort largely explain track differences for middle school students. On average, students placed in an academic track often put more effort into learning than those from a less-academic based track. Moreover, this study implied that the marginal effect of effort is nearly the same even if students are placed in a different track. Kelly (2008) also focused on the effect of student engagement but demonstrated that only substantive engagement which relates to high-level thinking or authentic uptake has an impact on class grades.

In short, effort can be defined as the amount of time and energy students take in order to accomplish school requirements (Carbonaro, 2005). Effort can be seen as a noncognitive trait which reflects the degree of students' attitude or eagerness toward participating in school work as well as pursuing grade performance. This is especially true when considering how teachers assign grades evaluated by student's endeavor (Farkas et al., 1990; Kelly, 2008; Roscigno & Ainsworth-Darnell, 1999; Rosenbaum, 2001). There are two possible explanations. In the first place, teachers may use student's extra-curriculum performances or behaviors in class to adjust student's course grade. That is because rather than focusing on the amount of knowledge which students receive, developmental teachers tend to foster students engagement in order to encourage them to endeavor on school work (Kelly, 2008). Secondly, according to the correspondence principle (Bowles and Ginties, 2002), schools influence which cultural models children should be exposed to in order to assure they fit into the work world. In other words, schools assimilate student's behaviors at school to worker's performance in the workplace. The argument is that the noncognitive traits rewarded by employers are much the same ones that are rewarded by teachers.

Teacher Judgment of Student Effort

It is thus needless to emphasize the importance of student endeavor which accounts for the influence on school performance. Moreover, since the degree of effort is often evaluated by teachers (Farkas et al., 1990; Kelly, 2008; Lleras, 2008; Tach and Farkas, 2005), it is likely that teachers' subjectivity would influence their viewpoints about student engagement as well as influences students' school grades. Teachers evaluate each student effort, and reward students for being active participants in class in order to keep instruction moving along and to promote widespread growth in academic-related achievement (Kelly, 2008).

According to the cultural resource/ social interaction model, school rewards which students receive heavily rely on teacher judgment of both student cognitive and noncognitive performances (Farkas, 1990). This model emphasizes the influence of teacher bias. Teachers might play the role of gatekeepers to restrain or promote students' opportunity to get in high status positions (Lamont & Lareau, 1988). The model will also be strongly supported if teacher judgment of students' behaviors could explain the differential school success of gender, poverty, and ethnic group (Farkas, 1990; Roscigno & Ainsworth-Darnell, 1999). In short, the key influence of teachers' subjectivity on their students might be implemented through two possible paths: teacher's subjective perception toward students' behaviors as well as their "virtual" effect on student efforts.

If this is the case, then teacher's evaluation on student effort needs considering because teacher's opinion toward students may influence how students perceive themselves. From the self-fulfilling prophecy, students would lower their self image and effort if they receive limited expectation from their teachers (Farkas, 1990). The influence could be reciprocal, such that teachers further assign less demanding homework to those with lower self image who perform passively in class. Hence, cultural resource/ social interaction model which is operated by multiple feedbacks between teacher and student over a long time emphasizes the interaction between students and teachers. Lleras (2008) demonstrated that if students are judged to be more active by their teachers, they tend to have a higher probability for pursuing further education and getting higher earnings in later life. Moreover, it is likely to view teachers as a kind of resource wherein students with better impression perceived by teachers might get more assistance from teachers. For instance, Rosenbaum (2001:236-237) studies demonstrated that teachers often play an important role in helping high school students in the labor market by recommending them to employers.

Research Hypothesis and Measurement Errors Processing

Farkas (2003:544) mentioned that the noncognitive traits have both exogenous (innate) and endogenous (developed over time) aspects. It is possible that these skills and behaviors result from students' interaction with parents and teachers. This research uses student effort as judged by teachers to measure the noncognitive trait, and uses student's class ranking as a proxy to measure the cognitive trait. We compare the effect of student effort versus class ranking on academic achievement. We focus on ninth-grade students in junior high school. We hypothesize that student effort is positively associated with their educational outcome as well as school choice when taking cognitive traits as well as other structural based control variables into consideration. We use both Basic Ability Test Scores and attending high school (instead of other choices such as vocational school or not attending school anymore) as two dependent variables for measuring the issue.

It should be noted that ignoring the problems of endogeneity and measurement error would underestimate or overestimate the real impact of explanatory factors. These problems may be especially serious when running an OLS since it often leaves these problems behind. Heckman et al. (2006:476) mentioned that test scores often become imperfect proxies for latent cognitive and noncognitive abilities because they are affected by measured characteristics such as family background. Since these problems likely bias the estimates in different directions, it is hard to predict the real effect by using OLS estimates. Using a structural equation model could help accounting the effects of background variables as well as endogenous factor loadings by estimating a factor model.

Also, in Bielby et al's (1977) work, patterns of response error have been considered into the achievement model. For them, the assumption of random measurement error was of little importance and hardly be fully obtained here. Therefore, multiple indicators of background and achievement variables which specify the covariation among the indicators are generated by unobserved "true scores."

According to Bielby et al (1977:1244-1245), three types of response errors must be specified. First, response errors in the report of a variable may convey with the true scores on that variables. By capturing the slope coefficient, λ , in a factor model would prevent the correlation between the true scores and error terms. Second, the "within-occasion between-variable correlated errors" are often neglected that respondents tend to overstate the consistency between different variables ascertained on a single occasion. Third, the "within-variable between-occasion correlated errors" show correlations among response errors used to measure the same unobserved latent factors. The idea is that respondent's report of would be "contaminated" by the prior report of the same question. In this study, we consider the above three types of response errors. More detail will be depicted in the later section- Model Specification.

Research Data

The data are derived from Taiwan Youth Project (TYP), an ongoing panel study conducted at the Institute of Sociology, Academia Sinica, Taiwan. The project was started in the year 2000, and 9 waves of interviews have been conducted since then. The original respondents of this project include 2,696 7th graders (1st year of junior high) and 2,890 9th graders (3rd year of junior high) as well as one of their parents and their designated teacher of the class. These students were sampled from junior high schools located in the northern part of Taiwan in the year of 2000, including Taipei City, Taipei County, and Yi-Lan County. As Taipei is the largest metropolitan city in Taiwan, the economic activities in Yi-Lan are mostly agriculture-based, and Taipei County is in-between these two regions. The sample covers various levels of urbanization and economic structure. This panel study is designed to follow adolescent samples from early teenagers into young adulthood. In short, the goal of the research design is to cover various aspects of the interplay among family, school and community, which shape adolescents' future development.[2]

The study examines the Wave 3 and Wave 4 sample of adolescents who were 9th grade students at Wave 3. It also draws information from two supplemental TYP data sets: the Parent Data Set (for information from the parents of the Wave 3 adolescents), and the Designed teacher Data Set (for information from the designed teacher of the Wave 3 students). After we delete missing data listwise, the final sample size of this study contained 1197 male students and 1165 female students from 40 sample schools.

Methods and Variables

We use structural equation model for the analysis to examine the relationship among different factors. Maximum likelihood with robust standard errors is used for estimation. Figure 2 presents the essential features of a structural equation model with measurement errors.

For the first part, the dependent variable is student's Basic Competence Test (BC Test) for junior high school students. It is a continuous variable, which ranges from 0 to 300. The BC Test Scores is determinant to student's educational career when they graduate from junior high school. Students with higher BC Test Scores are more likely to enter academic-based, competitive senior high school instead of other choices, such as vocational school. Due to the Taiwanese educational policy, each BC Test taker has the chance to participate in this exam for second time if he/she is not satisfied with the grades earned the first time. The TYP data set collected the first time of student's BC Test Scores in wave 3 by asking the teachers to fill in each respondent's grades in their class. The second time of student's BC Test Scores was collected in wave 4 when most of the respondents had graduated from junior high school. Since a lot of respondents took this examination two times, we use the higher scores to represent their educational achievement.

For the second part of this study, we use attending academic-based high school in wave 4 as the dependent variable. This is a binary variable, in which 1 refers to "attending an academic-based high school" and 0 refers to "attending vocational school or not attending school anymore". It is often viewed as common sense that those with higher grades at school as well as those who pursue higher education tend to choose academic-based high school instead of entering into a vocational school. Linear probability model is used to combine into our structural equation framework.

[2] For more information, please visit **TYP's official website**: http://www.typ.sinica.edu.tw/E/

(Figure 2 is about here)

This study takes both student effort and class ranking as two latent explanatory factors. The noncognitive factor- student effort- is measured using teacher judgments on three dimensions: 'How is his/her effort of academic learning?', 'How is his/her overall behavioral performance in school?', and 'How is his/her learning ability?' Student's class ranking, which is also measured by teacher judgments, is obtained both from the wave 2 questionnaire (8th grade in March, 2001) and the wave 3 questionnaire (9th grade in March, 2002). These two time points of student's class ranking are used as a proxy for measuring adolescent cognitive performance during the 2nd and 3rd year of junior's stage. Class ranking is recoded as a continuous variable in order to simplify the model and results. We employ confirmatory factor analysis to construct these two latent variables. The reliability for both these two factors is high (the cronbach's alpha is more than 0.85 for each latent variable).

The following variables are controlled in the model: parental education (in years), family income (log), student's gender, educational expectation (in years) and geographic location (Taipei city, Taipei county, and Yi-lan county). Since father's education and mother's education may be not the same, we use the higher one to represent parental education. Moreover, if the information of parental education and family income is missing from the parental data set but replaced by children's response instead, we create dummy variables "who answers the question" to control the measurement error (1=children, 0=parent). MPLUS is used to estimate the structural equation models and measurement errors.

Table 1 presents the means and standard deviations for the key variables used in our analysis. The items used for measuring the latent factors are also included in this table. For items which are related to student effort, the higher the score, the more the teacher thought that student fits the description. If the effect of student effort on academic performance is significant, we expect the correlations are in a positive direction. The association between class ranking and school performance is expected to be negative, in which students who get the highest grades on average in class will be ranked 1st.

(Table 1 is about here)

Model Specification

The strategy of this study is to estimate and specify measurement models separately for the 1197 male students and 1165 female students. We estimate substantive parameters in the full samples that have been corrected for response error. The structural model is presented in the path diagram of Figure 2. The variables enclosed in ellipses are unobserved factors. The substantive portion of Figure 2 is a fully recursive model among true effects, represented by the following two structural equations:

$$BCTestScores = \alpha_1 + \beta_1(StudentEffort) + \beta_2(ClassRanking) + \sum_i^n \beta_{3i}(ControlVars) + u_1 \quad (1.1)$$

$$SchoolDecision = \alpha_2 + \beta_4(StudentEffort) + \beta_5(ClassRanking) + \sum_i^n \beta_{6i}(ControlVars) + u_2 \quad (1.2)$$

where the disturbances u_i are independent of each other and of the explanatory variables in their respective equations. These substantive equations are identified in terms of the true variances and covariances. Hence, the fully recursive structure does not constrain estimates of parameters of the measurement model.

The measurement component of Figure 2 is:

$$x_{11} = \lambda_{11}(StudentEffort) + e_{11} \ , \quad (2.1a)$$

$$x_{12} = \lambda_{12}(StudentEffort) + e_{12} \ , \quad (2.1b)$$

$$x_{13} = \lambda_{13}(StudentEffort) + e_{13} \ , \quad (2.1c)$$

$$x_{21} = \lambda_{21}(ClassRanking) + e_{21} \ , \quad (2.2a)$$

$$x_{22} = \lambda_{22}(ClassRanking) + e_{22} \ , \quad (2.2b)$$

The models allow both between-factor correlated (correlations of ε between latent factors) and within-factor correlated (correlations of ε within latent factors) response error. We establish a metric for the true scores by fixing λ_{11}= λ_{21}=1.0. In other words, we fix the metric of the true scores to be the same as that of the observed reports which are used in models for the sample. It is necessary to normalize in this kind because the metric of an unobserved variable is arbitrary, and consequently the slope coefficients with respect to indicators are identifiable only relative to each other. A coefficient λ_{i2} or λ_{i3} which is grater (smaller) than unity indicates a conditional expectation slope on the true coefficient which is steeper (flatter) than the slope of the on the true coefficient.

The measurement models are all based on equations (2) and differ only in the specification of the covariances among the e_{ij}. In order to test models of fit, Goodness-of-fit test, the Comparative Fit Index (CFI) and the value of Root Mean Square Error of Approximation (RMSEA) for the various measurement models are reported in Table 2. The baseline model, Model A, does not take the noncognitive factor-student effort- into consideration. The full models, from Model B to Model E, consider the whole mechanisms which include the effects of student effort. Both Model A and Model B permit only random measurement errors. In this way, the e_{ij} are assumed to be mutually uncorrelated.

We estimate other full models (from Model C to Model E in table 2) which are variations of model B. By using the measurement error variances and error correlations to correct the observed variance-covariance matrices, more stable estimates of the substantive parameters may be obtained. Model C corresponds to the model which was specified by Bowles (1972). This model differs from the model B only in that within-factor error correlations are fixed to be 0.5 instead of 0. Model D allow within-factor error correlations without fixing them to be any specific number. Model E, the final measurement model for full model, allows both within-factor and between-factor correlations.[3] In model E, the final full model, the value of RMSEA is 0.02 for male and 0.03 for female. The value of RMSEA ranged lower than 0.05 indicates the overall fit of the model is not bad. The CFI is 0.998 for male and 0.996 for female. Also, CFI coefficient which values is greater than 0.9 implies the best fit. Table 3 presents measurement model parameter estimates derived from Model E.

(Table 2 is about here)

(Table 3 is about here)

Results

Table 4 and Table 5 present the parameter estimates of the structural equation model of BC Test Scores and attending high school, separating by gender. The baseline model, Model A, indicates the effects of class ranking and other control variables. Thus, the effect of student effort is totally ignored in this model. This analysis is analogous to conventional OLS regression except that it takes measurement errors into consideration. In contrast, the full model, Model E, add student effort into the analysis. The full model also contains response error correlations within and between unobserved factors (see Table 2).

(Table 4 is about here)

(Table 5 is about here)

In the first place, we consider the effect of exogenous variables on student's BC Test Scores. According to the baseline model, parental education has a significant positive effect on BC Test Scores for both male and female. The effect of family income on the dependent

[3] A few of error term correlations are fixed at 0.5 or ignored in order to making convergence.

variable is not significant. Besides, the effects of living outside of metropolitan area in contrast to Taipei city as well as the effect of educational expectations are significant. Results also demonstrate the negative, significant association between class ranking and BC Test Scores.

The full models in Table 4 and Table 5 include the noncognitive factor- student effort. In contrast to baseline model, results demonstrate that most of the coefficients of the exogenous variables decrease significantly in the full model in contrast to baseline model, with the exception that the negative impacts of those living outside of Taipei City increase. Comparing the effects of student effort and class ranking in the full model, the most interesting finding is that the effect of class ranking disappears for male respondents when taking student effort into consideration. In contrast, both student effort and class ranking have significant effects on BC Test Scores for female respondents. Looking up the absolute value of standardized coefficients for female respondents (Table 5), the results suggest that even though the effects of student effort and class are both significant, the magnitude of student effort is higher than the magnitude of class ranking (0.38 versus 0.31).

Secondly, we consider the effect of exogenous variables on entering academic-based high school. The unstandardized coefficients can be viewed as the marginal probability of attending high school in contrast to those who does not. Most of the findings are similar to the former results when considering the variance of BC Test. However, there are some notable exceptions. Looking at the baseline model, the effect of family income is significant for female respondents. If family income is higher, daughters would have higher chance to choose attending high school when they graduate from junior high school. Besides, the magnitude of the effects of living outside of metropolitan area in contrast to Taipei city is slightly weaker. These findings may be resort to the educational expansion policy that students who live outside of metropolitan area have much equal chance to attend a high school in contrast to those living in city.

Looking at the full models in Table 4 and Table 5, results also demonstrate that for male respondents, the effect of class ranking disappears when taking student effort into consideration. But for female respondents, the impact of class ranking on attending high school still remains, whereas there is no significant impact of student effort. This finding is not only contradicted to our hypothesis, but also shows gender differences in the schooling process.

Discussion

The main finding from this research is that student effort, as reported by teachers, determines educational achievement. It implicates that cultural resources model as well as social interaction model of educational achievement are strongly supported in this research. Early work by Farkas et al (1990) presented evidence which suggesting that student effort judged by teachers is important in studying educational achievement. However, they used OLS models which may underestimate the real effect of explanatory factors. Since this study deals much effort on solving the problems of endogeneity and measurement error by using structural equation models, our findings might provide stronger evidence to show how teacher judgment of student effort influences student's educational outcome.

Our paper argues for the necessity to explicitly include measures of student effort and the perception of this behavior perceived by gatekeepers in the stratification process. Further attempts to examine the micro-processes of teacher-student interaction underlying stratification outcomes are needed.

Results also imply that noncognitive traits exert as an important role as cognitive traits in the stratification process. In this study, we use student effort for measuring the effect of noncognitive traits, and use two time points of class ranking as a proxy for measuring student cognitive performance. Although class ranking cannot fully represents student's cognitive ability, for cognitive ability often refers the IQ related test scores (see Heckman et al., 2006), findings from this research at least shows that student engagement, as measured by student effort, should be one of the significant traits in promoting success in educational achievement.

Gender difference is found dealing with the effect of student effort and class ranking. For male respondents, effort is the main determinant of both test performance and school decision (attending an academic-based high school or not) in contrast to class ranking. For female respondents, both effort and class ranking significantly determine test performance. However, teacher's perception on girl's engagement at school does not significantly influence female student's decision on types of school. Instead, their choice is much influenced by past academic record at school and family background.

Therefore, findings implicate that the influence of teacher judgment on boys is different from girls. The marginal effect of teacher's perception on boy's school habits is higher than that on girl's school habits. Results also imply that girls' later educational achievement as well as school decision is more sensitive to their past academic records in contrast to boys'. Future research is needed to address how to further explain the gender difference between the correlation of student effort and their educational achievement.

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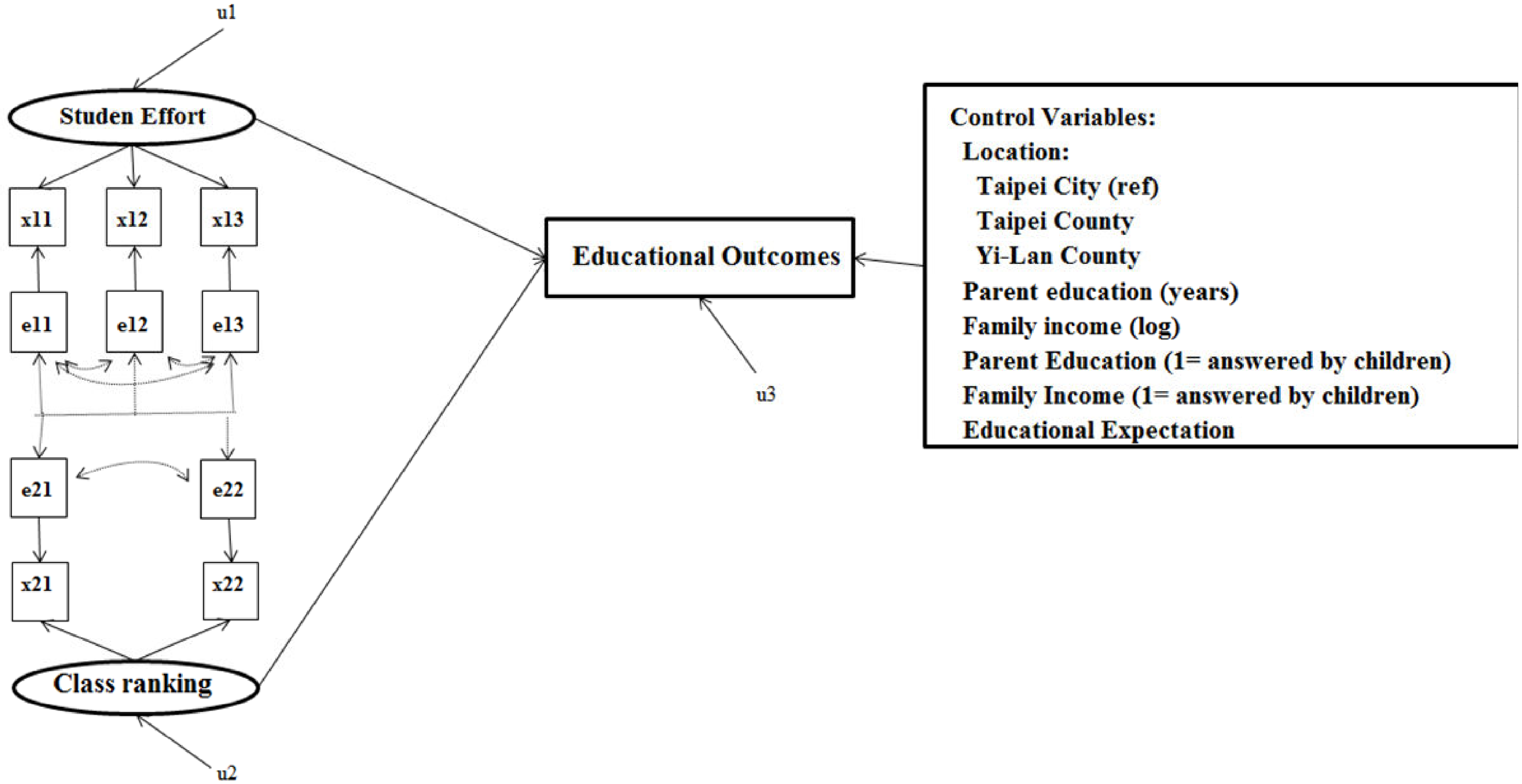

Figure 2. Essential Features of a Structural Equation Model with Measurement Errors

Table 1. Descriptive Results for the Key Variables

	Male (N=1197)				Female (N=1165)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
BC Test Scores	153.40	62.13	0	300	160.85	56.78	0	290
Attending Academic-based High School	0.39		0	1	0.43		0	1
Parental Education	11.52	3.20	0	20	11.48	3.09	0	20
Family Income (% answered by children)	0.27		0	1	0.26		0	1
Taipei County	0.37		0	1	0.39		0	1
Yi-lan County	0.23		0	1	0.23		0	1
Parental Education (% answered by children)	0.24		0	1	0.23		0	1
Family Income (log)	10.72	1.28	0	13.59	10.70	1.13	0	13.71
Educational Expectation	14.66	2.58	9	20	15.09	2.17	9	20
Class Ranking:								
Wave 2	18.23	10.39	3	35	15.79	9.46	3	35
Wave 3	18.44	10.58	3	35	16.73	9.77	3	35
Student Effort: Compare with students of the same age,								
How is his/her effort of academic learning?	3.81	1.75	1	7	4.54	1.60	1	7
How is his/her overall behavioral performanc	4.72	1.47	1	7	5.26	1.31	1	7
How is his/her learning ability?	4.42	1.65	1	7	4.67	1.44	1	7

Table 2. Chi-square Goodness-OF-Fit, CFI, and RMSEA Test for Measurement Models

	Male (N=1197)					Female (N=1165)				
	Chi-square	df	P	CFI	RMSEA	Chi-square	df	P	CFI	RMSEA
-Dependent Variable: BCTestScore-										
Baseline Model:										
A random measurement error	7.222	7	0.406	1.00	0.005	3.218	7	0.8641	1.00	0.000
Full Model:										
B random measurement error	342.025	28	0.000	0.955	0.097	313.972	28	0.000	0.952	0.094
C within-factor correlated error fixed at .5	228.68	28	0.000	0.971	0.077	284.242	28	0.000	0.957	0.089
D within-factor correlated error	53.516	26	0.0012	0.996	0.030	65.491	26	0.000	0.993	0.036
E Within-factor and between-factor correlated error	32.965	22	0.0624	0.998	0.020	43.652	22	0.0039	0.996	0.029
-Dependent Variable: Attending High School-										
Baseline Model:										
A random measurement error	5.719	7	0.5728	1.000	0.000	5.613	7	0.5855	1.000	0.000
Full Model:										
B random measurement error	318.786	28	0.000	0.95	0.093	283.996	28	0.000	0.95	0.088
C within-factor correlated error fixed at .5	215.342	28	0.000	0.968	0.075	275.325	28	0.000	0.951	0.087
D within-factor correlated error	58.621	26	0.0003	0.994	0.032	57.949	26	0.0003	0.994	0.032
E Within-factor and between-factor correlated error	32.575	22	0.0681	0.998	0.020	47.611	22	0.0012	0.995	0.032

Table 3. Measurement Model Parameter Estimates

	Male (N=1197)					Female (N=1165)				
-Dependent Variable: BCTestScore-										
True Ti		EFFORT		CLASSRANKING			EFFORT		CLASSRANKING	
Observed xi	eff1	eff2	eff3	cr2	cr3	eff1	eff2	eff3	cr2	cr3
SD of Error	0.90	1.47	0.70	19.32	12.61	0.93	1.21	0.46	12.77	17.89
	(17.74)	(22.32)	(16.52)	(15.27)	(10.35)	(18.51)	(21.08)	(12.27)	(10.76)	(14.15)
SD of True Score		2.16		88.68			1.63		76.65	
		(17.94)		(20.67)			(16.12)		(20.62)	
Relative Slope	1.00	0.56	0.97	1.00	1.06	1.00	0.56	1.00	1.00	1.01
	(0.00)	(24.84)	(36.36)	(0.00)	(51.31)	(0.00)	(21.54)	(32.18)	(0.00)	(45.53)
-Dependent Variable: Attending High School-										
True Ti	eff1	eff2	eff3	cr2	cr3	eff1	eff2	eff3	cr2	cr3
Observed xi	0.89	1.51	0.70	17.42	14.58	0.94	1.21	0.45	12.49	18.20
SD of Error	(15.12)	(19.31)	(13.92)	(10.30)	(8.37)	(16.61)	(17.57)	(9.58)	(7.60)	(10.77)
SD of True Score		2.17		90.32			1.62		76.95	
		(17.53)		(20.34)			(15.55)		(19.78)	
Relative Slope	1.00	0.54	0.96	1.00	1.04	1.00	0.56	1.00	1.00	1.00
	(0.00)	(19.28)	(32.71)	(0.00)	(43.15)	(0.00)	(16.72)	(28.53)	(0.00)	(37.86)

Est./S.E. scores are in bracket

Table 4. Parameter Estimates of the Structural Equation Model: Male (N=1197)

			Baseline Model (Model A)			Full Model (Model E)			Baseline Model VS Full Model Comparison
Independent Variables	→	Dependent Variables	Unstandardized Coefficient	Coef./S.E.	StdYX	Unstandardized Coefficient	Coef./S.E.	StdYX	
-Dependent Variable: BCTestScore-									
Student Effort	→	**BC Test Scores**				**28.061**	**7.86**	**0.66**	
Class Ranking	→	**BC Test Scores**	**-4.598**	**-32.581**	**-0.698**	**-0.784**	**-1.51**	**-0.12**	***
Parental Education	→	BC Test Scores	2.753	7.877	0.142	1.74	4.82	0.09	***
Family Income (ln)	→	BC Test Scores	0.476	0.614	0.01	0.27	0.36	0.01	***
Taipei County (ref: Taipei City)	→	BC Test Scores	-5.414	-2.397	-0.042	-9.409	-4.18	-0.07	***
Yi-Lan County (ref: Taipei City)	→	BC Test Scores	-13.765	-5.214	-0.094	-15.035	-5.86	-0.10	***
Parental Education (1=Children Responded)	→	BC Test Scores	-3.938	-0.742	-0.027	1.366	0.26	0.01	***
Family Income (1=Children Responded)	→	BC Test Scores	6.076	1.19	0.043	1.692	0.34	0.01	***
Educational Expectation	→	BC Test Scores	4.093	8.63	0.17	3.169	6.82	0.13	***
-Dependent Variable: Attending High School-									
Student Effort	→	**BC Test Scores**				**0.182**	**4.69**	**0.55**	
Class Ranking	→	**BC Test Scores**	**-0.024**	**-15.884**	**-0.479**	**0.000**	**0.03**	**0.00**	***
Parental Education	→	BC Test Scores	0.02	4.93	0.133	0.014	3.20	0.09	***
Family Income (ln)	→	**BC Test Scores**	0.004	0.424	0.01	0.003	0.30	0.01	
Taipei County (ref: Taipei City)	→	BC Test Scores	-0.011	-0.403	-0.011	-0.036	-1.33	-0.04	***
Yi-Lan County (ref: Taipei City)	→	BC Test Scores	-0.075	-2.425	-0.065	-0.081	-2.61	-0.07	***
Parental Education (1=Children Responded)	→	BC Test Scores	-0.1	-1.609	-0.088	-0.067	-1.07	-0.06	***
Family Income (1=Children Responded)	→	**BC Test Scores**	0.037	0.616	0.034	0.009	0.16	0.01	***
Educational Expectation	→	BC Test Scores	0.024	4.358	0.127	0.019	3.39	0.10	***

Note: $p < 0.05$ if \|Coef/S.E.\| > 1.96

Table 5. Parameter Estimates of the Structural Equation Model: Female (N=1165)

Independent Variables	→	Dependent Variables	Baseline Model (Model A) Unstandardized Coefficient	Coef./S.E.	StdYX	Full Model (Model E) Unstandardized Coefficient	Coef./S.E.	StdYX	Baseline Model VS Full Model Comparison
-Dependent Variable: BCTestScore-									
Student Effort	→	**BC Test Scores**				**16.965**	**4.82**	**0.38**	
Class Ranking	→	**BC Test Scores**	**-4.169**	**-28.566**	**-0.645**	**-2.024**	**-4.11**	**-0.31**	***
Parental Education	→	BC Test Scores	3.709	10.663	0.202	3.107	8.96	0.17	***
Family Income (ln)	→	BC Test Scores	1.431	1.613	0.028	1.335	1.59	0.03	***
Taipei County (ref: Taipei City)	→	BC Test Scores	-7.845	-3.463	-0.067	-10.824	-4.83	-0.09	***
Yi-Lan County (ref: Taipei City)	→	BC Test Scores	-14.465	-5.438	-0.108	-16.345	-6.41	-0.12	***
Parental Education (1=Children Responded)	→	BC Test Scores	0.88	0.164	0.007	0.645	0.13	0.01	***
Family Income (1=Children Responded)	→	BC Test Scores	-4.003	-0.779	-0.031	-3.367	-0.69	-0.03	***
Educational Expectation	→	BC Test Scores	4.257	7.696	0.162	3.807	7.25	0.15	***
-Dependent Variable: Attending High School-									
Student Effort	→	**BC Test Scores**				**0.025**	**0.59**	**0.06**	
Class Ranking	→	**BC Test Scores**	**-0.025**	**-14.755**	**-0.448**	**-0.022**	**-3.73**	**-0.39**	***
Parental Education	→	BC Test Scores	0.024	5.514	0.147	0.022	5.02	0.14	***
Family Income (ln)	→	**BC Test Scores**	0.026	2.372	0.059	0.026	2.40	0.06	
Taipei County (ref: Taipei City)	→	BC Test Scores	-0.062	-2.218	-0.061	-0.064	-2.23	-0.06	***
Yi-Lan County (ref: Taipei City)	→	BC Test Scores	-0.06	-1.823	-0.051	-0.061	-1.86	-0.05	
Parental Education (1=Children Responded)	→	BC Test Scores	0.042	0.637	0.036	0.041	0.63	0.04	
Family Income (1=Children Responded)	→	BC Test Scores	-0.032	-0.507	-0.028	-0.031	-0.49	-0.03	
Educational Expectation	→	BC Test Scores	0.029	4.329	0.128	0.029	4.23	0.13	

Note: $p < 0.05$ if |Coef/S.E.| > 1.96