ANALYSIS OF GRADUATION RATES FOR FOUR-YEAR COLLEGES: A MODEL OF INSTITUTIONAL PERFORMANCE USING IPEDS

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Under the George W. Bush U.S. presidential administration, the federal government pushed for greater accountability among institutions of higher education for educational outcomes. Graduation rate is a key performance indicator of institutional accountability. Previous researchers of student attrition focused primarily on the effects of student level factors on student persistence/withdrawal behavior. Recently, researchers put more focus on the effects of institutional characteristics on graduation rates, but most of these studies were exploratory and based on multiple regression models. No institutional model has existed to synthesize their results within a theoretical framework. Such an institutional model is needed to explain the process of student persistence at the institutional level. The purpose of this study was to develop a model of institutional performance in graduation rate for four-year, public and private not-for-profit, Title IV institutions in the United States. This study validated the institutional model based on the IPEDS dataset using the structural equation modeling (SEM) technique. Further group comparison analyses are conducted by fitting the same SEM model to several subgroup datasets based on grouping variables such as control, geographical region and state. Benchmarking analyses were conducted to demonstrate how administrators and policy-makers can use the institutional model to compare the performance of an institution with its peers and what policy changes can they pursue to improve graduation rates.

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INTRODUCTION

Under the George W. Bush U.S. presidential administration, the federal government pushed for greater accountability in higher education, similar to the No Child Left Behind (NCLB) legislation. Institutions are held accountable for education outcomes such as retention rates, graduation rates and preparation of employment after graduation (Goenner & Snaith, 2004b). Furthermore, the Federal Student Right-to-Know and Campus Security Act of 1991 (SRK) was passed by Congress on November 9, 1990, requiring institutions eligible for Title IV funding to disclose to all students and prospective students the completion or graduation rates of certificate- or degree-seeking, full-time students entering their institutions. This law requires each institution that participates in any Title IV program and is attended by students receiving athletically related student aid to annually submit a report to the Secretary of Education. This report not only contains the graduation/completion rates of all students by race/ethnicity, gender and sport, but also contains the average completion or graduation rates for the four most recent years. The graduation rates survey (GRS) component of Integrated Postsecondary Educational Data System (IPEDS) was developed specifically to help institutions respond to these requirements (Knapp, Kelly-Reid, Ginder, & Miller, 2008). Graduation rate is the most widely used performance measure for colleges and universities because it indicates how successfully an institution produce graduates who will enter the workforce as productive members of the society. Studies show that the average household income of bachelor's degree holders is about twice that of high-school graduates (Cohen & Ibrahim, 2008). In recent years, many states have introduced various types of accountability measures based on student outcomes and tied at least some funding to performance on outcome measures (Bailey, Jenkins, & Leinbach, 2005b).

To meet the accountability measure, institutions are expected to produce more graduates as evidenced by higher graduation rates. One way to achieve this is putting more resources to improve the educational process. An alternative is to increase the preparation of the students admitted to the institution (Goenner & Snaith, 2004b). Some people have criticized that graduation rates do not represent the real performance of an institution. For example, graduation rate cohort of first-time, full-time students does not account for a significant portion of community college students who are part-time and non-degree seeking. Others argue that the open admission policy of community colleges can experience lower graduation rates because many enrolled students are not prepared to complete their programs (T. Bailey, Jenkins, & Leinbach, 2005a). Graduation rates only account for first-time, full-time students who entered an institution in fall semesters and graduated from the same institution within 150% of the normal time to complete the degree. It does not account for students who transferred to other institutions. Studies show that nearly 60% of undergraduate students attended more than one institution. Institutions can raise their graduation rates by 10% simply by including the students transferred in through graduation (Cohen & Ibrahim, 2008). Astin (1997) also warned that the retention rate mandated by the SRK Act could be a misleading indicator of how well an institution retained its students because more than half of the variance in institutional retention rates were explained by the initial differences in students at enrollment rather than by any differential institutional effect. To solve these problems, Cohen and Ibrahim (2008) proposed graduation efficiency as opposed to the graduation rate to measure institutional performance in producing graduates. Graduation efficiency took transfer students into consideration and combined the average full-time-equivalent (FTE) freshmen and average FTE transfer students as the basis for the number of degrees awarded each year. Graduation rate, however, only took into account the first-time, full-time students as the basis of the cohort. In 2006, the Secretary of Education proposed a national "unit record system" to track every postsecondary student. It could be used to incorporate transfer students in graduation rate measure. This proposal died because of the high implementation cost and the potential violation of student privacy.

Recently, the National Center for Education Statistics (NCES) has greatly improved IPEDS data collection and distribution through online tools. IPEDS is a complex national database for collecting institutional data, such as institutional characteristics, financial data, graduation rates, enrollment data, financial aid data, etc. from most universities and colleges in the United States. Many researchers make use of the IPEDS dataset to conduct research on educational issues (Hahs-Vaughn, 2007; Thurgood et al., 2003). To calculate the 2008 graduation rate, four-year institutions should count the number of students who have graduated from the cohort started in the 2001-02 academic year. Likewise, two-year and less-than-two-year institutions should count the number of students who have graduated from the cohort started in the 2004-05 academic year (Knapp, Kelly-Reid, & Ginder, 2009).

Statement of the Problem

While many researchers have conducted research on graduation rate, most of their studies are exploratory rather than confirmatory. These exploratory studies focused on examining the relationship between the criterion variable (graduation rate) and its predictors (such as selectivity, financial aid, expenditures, student to faculty ratio, residential status, etc.) using multiple regression. Multiple regression, however, has its limitations. First, the predictors are assumed to be independent or uncorrelated. Violation of this assumption will lead to biased estimation due to multicollinearity. Second, the relationship between predictor variables cannot be expressed in the regression model. These limitations seriously hamper the ability to develop theories and test them using multiple regression method. However, advanced modeling techniques, such as path analytical modeling and structural equation modeling (SEM), are available to empirically validate a theory or a causal model based on a set of data. A theory is necessary to explain complex social phenomena, such as college persistence, because the theory can describe how various variables observed in a social phenomenon affect each other and the causal relationship between them. Several theories have been proposed to explain the individual student's dropout or persistence behavior, such as Tinto's (1975) theory of dropout from college (see Figure 1) and Astin's (1984) student involvement theory. Similar theories are yet to be developed to explain college persistence at the institutional level. Such institutional model can be developed based on the basic structure of Tinto's model and empirically validated by SEM using statistical software such as Analysis of Moment Structure (Amos) and Mplus (Muthen & Muthen, 1998-2007).

Purpose of the Study

The purpose of this study is to develop a model of institutional performance in graduate rate for four-year, public and private not-for-profit, Title IV institutions in the United States. This study validates the institutional model based on the IPEDS dataset using the structural equation modeling (SEM) technique. The model of institutional performance in graduation rate is based on the basic structure of Tinto's (1975) theory of college dropout. This model explains the process of college persistence in terms of graduation rate and other institutional characteristics derived from the IPEDS dataset.

Theoretical Framework

Tinto's (1975) model of dropout from college is the most frequently cited model in studies of retention and graduation rate (see Figure 1). Tinto (1975) found that institutions, in which students had better interaction with the academic environment and social environment, had better retention rates and graduation rates. The amount of resources and type of institutions (size, control, mission, religious affiliation, etc.) were factors influencing the environment and student outcomes. Both individual characteristics of students and institutional characteristics were essential to explaining retention and graduation rates (Goenner & Snaith, 2004b; Tinto, 1987). Tinto's theory is primarily based on student's individual attributes and behavior to explain retention. The basic structure of Tinto's model includes the precollege/background variables, initial and subsequent commitment variables, college integration variables and the persistence variable. Other researchers propose a set of institutional characteristics, which were contributing to higher retention rate, including control (public or private), residential status, institutional size, selectivity, tuition, financial aid and patterns of expenditure (Calcagno, Bailey, Jenkins, Kienzl, & Leinbach, 2008, p. 633; Ewell, Jones, & Kelly, 2003; Gansemer-Topf & Schuh, 2003; Goble, Rosenbaum, & Stephan, 2008, p. 65; Huffman & Schneiderman, 1997; Jacoby, 2006; Scott, Bailey, & Kienzl, 2006; Titus, 2004, 2006). The model of institutional performance in graduation rate proposed in this study is based on the basic structures of Tinto's (1975) model of college dropout and Astin's (1991) Input-Environment-Output theory to synthesize results from previous studies of effects of institutional characteristics on graduation rates. Figure 2 shows the proposed model of institutional performance in graduation rate.

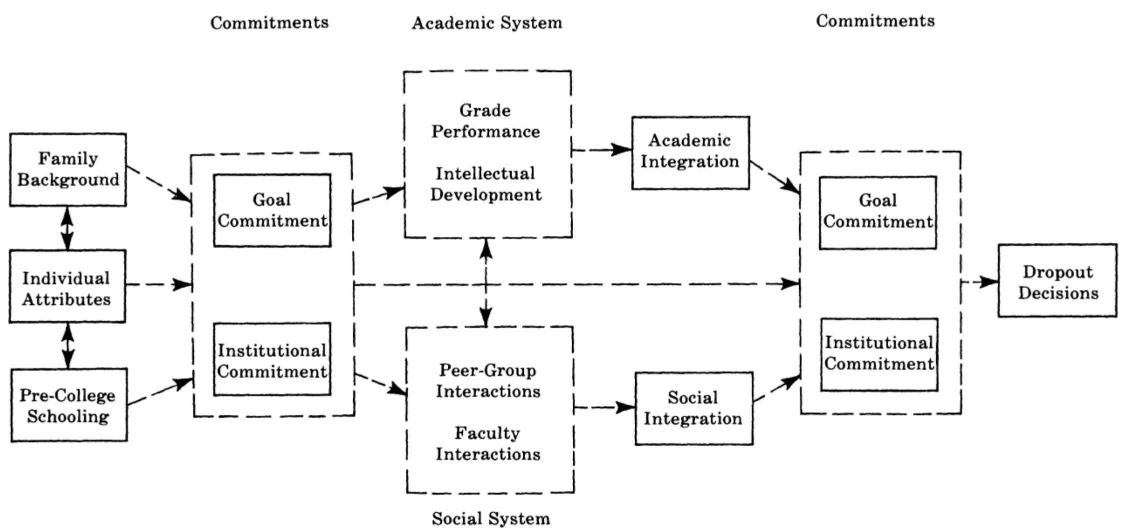

Figure 1. Tinto's model for dropout from college. (Tinto, 1975, p. 95)

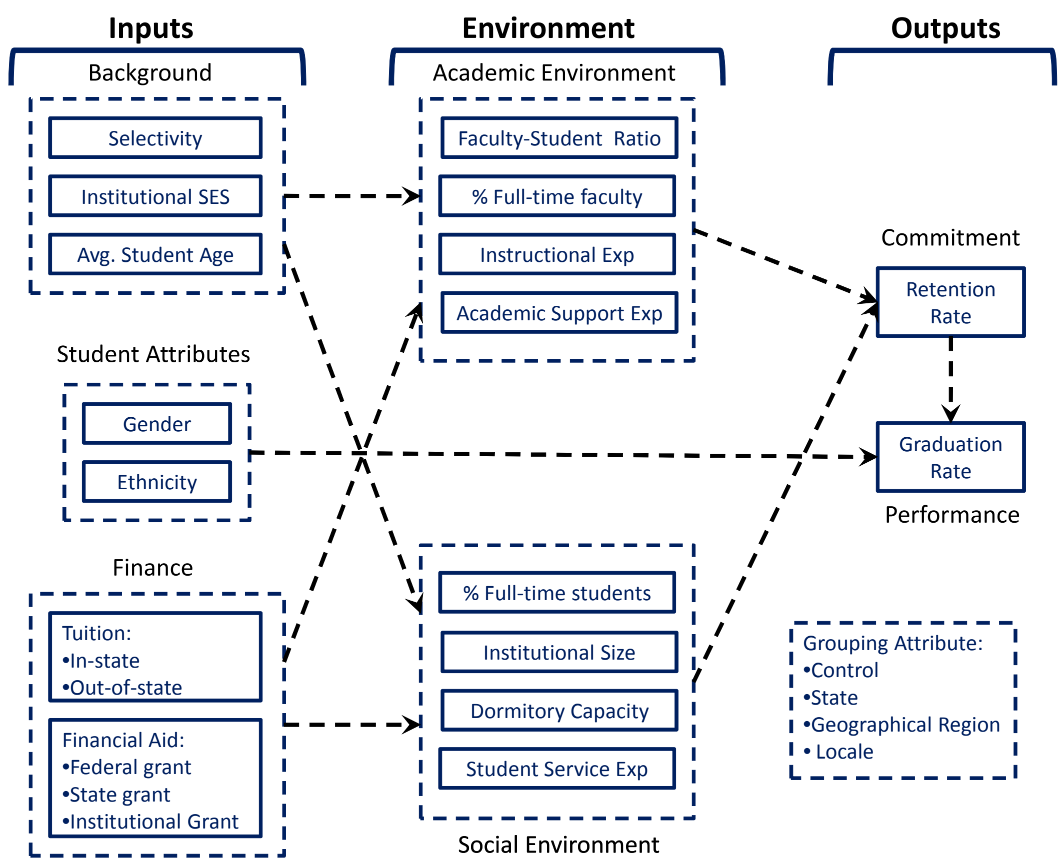

Figure 2. Conceptual model of institutional performance in graduation rate.

The most prominent features of Tinto's model are the social and academic integrations and the goal and institutional commitments. Because Tinto's model is longitudinal, the commitments are measured before the students enter into the institution and after they have started the process of integration into the social and academic systems in the college. The initial commitments are determined by the students' background, individual attributes and high school experiences. The subsequent commitments are determined by the results of the social and academic integrations. Finally, the subsequent commitments will influence the students' dropout decision. The proposed model of institutional performance in graduation rate basically follows the same structure, but the variables are institutional attributes (such as institutional SES, average age of students, tuition, faculty-student ratio, percentage of full-time faculty, instructional expenditures, academic support expenditures, percentage of full-time students, institutional size, dormitory capacity, locale and student service expenditures) and student attributes aggregated at the institutional level (such as selectivity, financial aid, gender and ethnicity). These variables are classified into seven categories: background, student attributes, finance, academic environment, social environment, commitment and performance. These seven categories of variables are organized in a structure similar to Astin's (1991) input-environment-output model. The inputs include background, student attributes and finance; the environment includes social environment and academic environment; and the outputs include the retention rate and graduation rate. In Tinto's model, the inputs include the background, student attributes, high school experiences and initial goal and institutional commitments because they are measured before the students enter into college education. Also, the social and academic systems, social and academic integrations and subsequent goal and institutional commitments in Tinto's model capture the environment component of Astin's model. Finally, the dropout decision in Tinto's model is equivalent the output component of Astin's model.

The proposed model of institutional performance in graduation rates is a longitudinal model because all variables are measured in the cohort year except for the graduation rate itself. For example, 2001 is the cohort year of 2007 graduation rate for baccalaureate degrees because the graduation rate is calculated from the total number of completers within 150% of normal time divided by the revised cohort minus any allowable exclusions (Knapp et al., 2008). The 150% of normal time to complete a baccalaureate degree is six years. The variables in the institutional model are measured in the cohort year because the first year of college is the most critical period for college persistence. Finally, the grouping variables (control, state and geographical region) are not expressed as part of the path structure of the institutional model because their influences permeate the whole path structure. These grouping attributes are used to divide the dataset into subgroup datasets for group comparison analyses of the whole model between different groups of institutions. This strategy helps keep the model parsimonious and also help analyze the structural differences between different groups of institutions. The structural differences are captured by the differences in the path coefficients, which describe the relationships between variables in different paths in the model.

Research Questions and Hypotheses

The model of institutional performance in graduation rate is tested by answering the following research questions and by testing the individual research hypotheses. Question 1 is related to finding the differences in graduation rates between groups of institutions based on control, gender, race/ethnicity, state and geographical region. Question 2 is related to testing the measurement models (their validity and reliability) of the unobserved variables (background, finance, academic environment and social environment) by the observed variables. For example, the unobserved variable, academic environment, is measured by four observed variables: faculty-student ratio, percentage of full-time faculty, instructional expenditures and academic support expenditures. Confirmatory factory analysis (CFA) is used to test these measurement models. Question 3 is related to testing the structural model represented by the path structure between exogenous and endogenous variables (background, finance, academic environment, social environment, commitment and graduation rate).

1. Which groups of institutions have significantly different graduation rates compared with other groups of institutions based on control, geographical region, state, Carnegie classification code, degree of urbanization, religious affiliation and regional accreditation agency of the institutions?
2. What are the validity and reliability of the factor models of student background, student finance, academic environment and social environment to measure the underlying constructs in the institutional model of graduation rates?

3. To what degree does the overall institutional model of graduation rates fit the dataset and its subsets based on the groups of institutions identified by answering the first research question?

Below are the research hypotheses to be tested in this study.

H1. There are significant differences in the graduation rates between groups of institutions based on control, geographical region, state, Carnegie classification code, degree of urbanization, religious affiliation and regional accreditation agency of the institutions.

H2. The validity and reliability of the factor models of student background, student finance, academic environment and social environment are established to measure the underlying constructs in the institutional model of graduation rates.

H3. The institutional model of graduation rates fits the dataset and its subsets based on the groups of institutions identified by answering the first research question.

Significance of the Study

This study is significant because it is the first one to synthesize the major institutional predictors of graduation rate from existing studies in a single conceptual framework based on Tinto's (1975) model of college dropout and Astin's (1991) input-environment-output model. The model of institutional performance in graduation rate not only can evaluate the predictive effects of different institutional characteristics on the graduation rate but also can evaluate the interrelationship between these institutional characteristics. Furthermore, this institutional model can be used to benchmark institutional performance not only based on their graduation rates but also based on the interrelationships between the institutional characteristics and how their interaction effects influence the graduation rates. Because a national dataset (IPEDS) is used to test the model of institutional performance, it has high generalizability to predict and evaluate performance of public and private not-for-profit institutions in producing baccalaureate graduates across the United States.

Definitions of Terms

Terms and variables that are used in the model of institutional performance in graduation rates are defined below in alphabetical order. The definitions of the IPEDS variables used to define these terms are summarized in the Appendix.

Academic environment is a concept derived from the academic system of Tinto's (1975) model of college dropouts. In Tinto's model, "colleges are made up of both social and academic systems" (p. 92) but he did not explicitly define what social and academic systems were because he was more concerned about the student-level academic integration to the academic system. Academic integration can be measured in terms of the student's grade performance and intellectual development. Academic environment in the proposed model of institutional performance in graduation rate is an institutional level concept and it can include anything related to the students' academic performance and intellectual development in college education. In this study, academic environment is a continuous latent variable measured by four observed variables from the IPEDS 2001 dataset: faculty-student ratio, percentage of full-time faculty, instructional expenditures and academic support expenditures. These observed variables are chosen based on previous studies about the relationship between these institutional characteristics and graduation rates.

Academic support expenditures per FTE student is the average amount of academic support expenditures per full-time equivalent student enrolled in an institution. It is a continuous observed variables derived from the IPEDS 2001 dataset based on the instructional expenditures (*b043*) variable divided by the full-time equivalent enrollment (*fte*) variable.

Average age of students (*efage*) is an observed continuous variable from the IPEDS 2001 dataset.

Commitment is a concept also derived from the concepts of goal commitment and institutional commitment in Tinto's (1975) model of college dropouts. Tinto distinguished pre-college commitment and commitment developed in college years. These two commitment concepts are motivational factors for persistence in college. In this study, commitment is defined and measured by the observed full-time student retention rate variable (*ret_pcf*) from the IPEDS 2003 dataset because more students retained in the school year after the cohort year may indicate a stronger commitment from the students to the institution. This variable is not available in the IPEDS 2002 dataset because it was first introduced in the IPEDS 2003 dataset.

Dormitory capacity is the maximum number of students that the institution can provide residential facilities for, whether on or off campus. This is the continuous observed variable (*roomcap*) from the IPEDS 2001 dataset.

Ethnicity is a categorical observed variable (1 = Nonresident Alien, 2 = Black non-Hispanic, 3 = American Indian or Alaska Native, 4 = Asian or Pacific Islander, 5 =

Hispanic, 6 = White non-Hispanic and 7 = Ethnicity Unknown) derived from the IPEDS 2007 dataset. It is a variable decoupled from the graduation rate variables.

Faculty-student ratio is defined as the ratio of full-time instructional faculty to full-time equivalent students enrolled in an institution. It is a continuous observed variable derived from the IPEDS 2001 dataset by dividing the number of full-time instructional faculty (*empcount*) variable by the full-time equivalent enrollment (*fte*) variable. This ratio should be between 0 and 1.

Federal grant is the average amount of federal grant aid received by the students attending an institution. It is a continuous observed variable (*fgrnt_a*) from the IPEDS 2001 dataset.

Gender is a dichotomous observed variable (1 = Male and 2 = Female) derived from the IPEDS 2007 dataset. It is a variable decoupled from the graduation rate variables.

Graduation rate is a continuous observed variable derived from the IPEDS 2007 dataset with range from 0 to 100%. It is calculated as the total number of completers, who entered an institution as full-time, first-time degree/certificate-seeking undergraduate students in the fall semester of the cohort year, within 150% of normal completion time divided by the revised cohort minus any allowable exclusions (Knapp et al., 2008). For example, the cohort year of 2007 graduation rate for baccalaureate degrees is 2001. This is the criterion variable in this study.

In-state tuition is a continuous observed variable (*tuition2*) from the IPEDS 2001 dataset.

Institutional grant is the average amount of institutional grant aid received by the students attending an institution. It is a continuous observed variable (*igrnt_a*) from the IPEDS 2001 dataset.

Institutional selectivity represents the degree of competitiveness to which an institution can attract qualified students (Alon & Tienda, 2005). It is a continuous observed variable measured by the 25th percentile of the combined verbal and math ACT scores (*acten25* and *actmt25*) derived from the IPEDS 2001 dataset with a range from 2 to 72.

Institutional size is defined as the total full-time undergraduate students enrolled in an institution. This is a continuous variable with range from 0 to 100% and is derived from the following variables in the IPEDS 2001 dataset: grand total enrollment for men (*efrace15*), grand total enrollment for women (*efrace16*), attendance status (*section*) and level of study (*lstudy*).

Institutional socioeconomic status (SES) is defined as one minus the percentage of federal grant aid recipients (*fgrnt_p*) in an institution based on Pike's (2006) definition of institutional SES. The percentage of federal grant aid recipients (*fgrnt_p*) is a continuous observed variable from the IPEDS 2001 dataset with a range from 0 to 100%. The larger the Institutional SES, the higher the SES of undergraduate students attending the institution and vice versa. This percentage indicates the average socioeconomic status of the student body in an institution because the federal grants, such as Pell grants, are need based financial aid.

Instructional expenditure per FTE student is the average amount of instructional expenditures per full-time equivalent student enrolled in an institution. It is a continuous observed variables derived from the IPEDS 2001 dataset based on the instructional expenditures (*b013*) variable divided by the full-time equivalent enrollment (*fte*) variable.

Locale is the degree of urbanization variable from the IPEDS 2001 dataset. It is a categorical variable with a eight-level scale: 1 = Large city, 2 = Mid-size city, 3 = Urban fringe of large city, 4 = Urban fringe of mid-size city, 5 = Large town, 6 = Small town, 7 = Rural, 9 = Not assigned. This variable represents the amount of amount of external opportunities available in the community where the institution is located. The more urbanized the community is, the more external opportunities are available in the community.

Out-of-state tuition is a continuous observed variable (*tuition3*) from the IPEDS 2001 dataset.

Percentage of full-time faculty is defined as the ratio of all full-time staff with faculty status to all faculty members (both full-time and part-time) in an institution. It is a continuous observed variable based on the following variables in the IPEDS 2001 dataset: tenured faculty (*fstat1*), non-tenured on tenure track faculty (*fstat2*), not on tenure track faculty (*fstat3*) and employee type (*typecd*). The employee type variable is a categorical variable (1 = Full-time non-medical, 2 = Full-time medical only, 3 = Part-time non-medical and 4 = Part-time medical only) and is used to distinguish full-time and part-time faculty members.

Percentage of full-time student is ratio of full-time undergraduate students enrolled in an institution to all undergraduate students (both full-time and part-time) enrolled in that institution. This is a continuous variable with range from 0 to 100% and is derived from the following variables in the IPEDS 2001 dataset: grand total enrollment for men (*efrace15*), grand total enrollment for women (*efrace16*), attendance status (*section*) and level of study (*lstudy*).

Social environment, like academic environment, is derived from the social system of Tinto's (1975) model of college dropouts. The social system is not explicitly defined in Tinto's model but the related concept, social integration, is defined by "both levels of integration and degrees of congruency between the individual and his social environment… primarily through informal peer group associations, semi-formal extracurricular activities, and interaction with faculty and administrative personnel within the college" (p. 107). Social environment is an institutional level concept and it can include anything that can affect the socialization and association that a student will develop in college education. In this study, social environment is a continuous latent variable measured by five observed variables from the IPEDS 2001 dataset: percentage of full-time students, institutional size, dormitory capacity and student service expenditures. These observed variables are chosen based on previous studies about the relationship between these institutional characteristics and graduation rates.

State grant is the average amount of state grant aid received by the students attending an institution. It is a continuous observed variable (*sgrnt_a*) from the IPEDS 2001 dataset.

Student attributes includes gender and ethnicity which are student attributes aggregated at the institutional level and are used as grouping variables in this study for group comparison analyses. They are included in the model of institutional performance in graduation rates primarily for illustrative purpose because they correspond to the individual characteristics in Tinto's model (see Figure 1). Because gender and ethnicity in IPEDS datasets are embedded in graduation rates as type identifiers, the gender and ethnicity variables are created by restructuring the graduation rate variables from multivariate format to univariate format.

Student background is a continuous latent variable measured by three observed variables: selectivity, institutional socioeconomic status (SES) and average age of students. It represents the academic and socioeconomic background of the student body in an institution because selectivity and average age of students affect the academic preparedness of the students entering an institution.

Student finance represents the overall financial costs and resources of the students attending an institution. It is a continuous latent variable measured by five observed variables from the IPEDS 2001 dataset: in-state tuition, out-of-state tuition, average amount of federal grant received per FTE student, average amount of state grant received per FTE student and average amount of institutional grant received per FTE student.

Student service expenditures per FTE student is the average amount of expenditures per full-time equivalent student enrolled in an institution expended for admissions, registrar activities, and activities whose primary purpose is to contribute to students' emotional and physical well-being and to their intellectual, cultural, and social development outside the context of the formal instructional program. It is a continuous observed variables derived from the IPEDS 2001 dataset based on the student service expenditures (*b063*) variable divided by the full-time equivalent enrollment (*fte*) variable.

Limitations

There are several limitations in the model of institutional performance in graduation rate. First, all variables are at the institutional level and they cannot accurately indicate individual behavior such as individual persistent/dropout decision. The purpose of this study, however, is to evaluate institutional performance in graduation rate. The unit of analysis is the institution, not the individual students. Second, the choice of variables is limited by the IPEDS dataset. Although IPEDS is the most comprehensive national dataset for institutional data of higher education, it is a multi-purpose dataset and may not contain the best information related to graduation rate and institutional performance. This limitation is not a crucial one because IPEDS contains plenty of detailed information measured at the institutional level. Other sources of data can also be used in the model if needed. Third, the model of institutional performance in graduation rate is the first model of this kind ever developed. There is no reference model to judge this model in terms of predictive power on the criterion variable, choice of predictor variables and strengths of relationships between variables. Therefore, this study is best viewed as an exploratory study and its results are tentative. More research and replication studies are needed to refine the institutional model.

Delimitations

To fully understand the effects on graduation rate from individual students as well as from institutional characteristics, we need to use multi-level modeling technique such as hierarchical linear modeling (HLM). However, that is outside the scope of this study but can be a good area for future research. Also, it may be a good approach to develop the institutional model as a first step into the more comprehensive multi-level model because the institutional model itself is a new invention by this study. Also, this study is focused on graduation rate for baccalaureate degrees rather than two-year associate's degrees in community colleges. Therefore, only public and private not-for-profit four-year institutions are discussed because they are the majority of Title IV institutions. The private for-profit four-year institutions are also excluded from this study to make the scope of this study more manageable.

Advanced Statistical Methods

To fully understand the statistical analyses used in this study, readers should have at least basic understanding of the following statistical methods: multiple regression method, factor analysis (exploratory and confirmatory), structured equation modeling. Besides, it will be helpful to have some understanding of test of statistical significance, effect size and student *t*-test.

Multiple regression method is a statistical method to analyze the collective and separate effects of two or more independent variables on a dependent variables (Pedhazur, 1997). Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) are techniques to measure the underlying constructs of some observed variables. EFA is exploratory and does not require a theory before conducting it to examine the underlying factor structure of a set of observed variables. However, the resulted factors may or may not be interpretable. Unlike EFA, CFA requires a theory to define the factor structure before testing the fit of the factor structure to the data (Thompson, 2004). Both types of factor analyses are widely used in psychometric researches and other researches. Structural equation modeling (SEM) is an advanced technique which combines CFA and path analytical modeling. A path model is a network of variables (observed or unobserved) specified in an exogenous-endogenous relationship which can be interpreted as causal relationship when certain conditions are met. SEM is a powerful technique to test a theory against a set of data because the factor structure and the path structure are evaluated simultaneously to test the fit of a theory to a set of data (Kline, 1998; Schumacker & Lomax, 2004). Readers, who are not familiar with these advanced statistical methods, are encouraged to consult the above references. Hinkle, Wiersma and Jurs (2003) gave a good general introduction to common statistical methods.

CHAPTER 2

REVIEW OF THE LITERATURE

Under the George W. Bush U.S. presidential administration, the federal government pushed for greater accountability for colleges, similar to the No Child Left Behind (NCLB) legislation. Institutions were held accountable for educational outcomes such as retention rates, graduation rates and preparation of employment after graduation (Goenner & Snaith, 2004b). Furthermore, the Federal Student Right-to-Know and Campus Security Act of 1991 (SRK) was passed by Congress on November 9, 1990, requiring institutions eligible for Title IV funding to disclose completion or graduation rates of certificate- or degree-seeking, full-time students entering an institution to all students and prospective students. Accountability measures of institutions are closely related to student outcomes because helping students succeed should be the primary mission of all colleges and universities. Major works on college student attrition began four decades ago (Rootman, 1972; Spady, 1970, 1971; Tinto, 1975), after the mass higher education resulted by the G.I. bill. Because of its manifold expansion and because of its important social function, higher education had attracted a lot of resources and public attention. It is important to understand the causes of the high dropout rates in colleges and universities.

According to Ryan (2004), traditional studies of persistence, attrition and retention were based on student-behavior and were built from the following works:

Tinto's (1975) concepts of academic and social integration, Pascarella and Terenzini's (1991) student interactions, Astin's (1993) student involvement, Bean's (1979) student satisfaction and attrition and Kuh's (2001) student engagement. While these theories are focused on important factors such as student pre-college characteristics and student integration in the college, they often mischaracterize the roles of institutional characteristics and state characteristics in explaining the phenomenon of student attrition.

Although student level factors are important to explain college persistence, administrators and policy-makers often want to look at performance measures at the institutional level, such as graduation rate and retention rate. These performance measures are more comparable across institutions and are readily connected to institutional characteristics. An important advantage of the institutional performance approach is that similar institutions can have their performance measures benchmarked against their peers, which share similar institutional characteristics such as selectivity, preparedness of entering students, instructional expenditures, etc. In the last two decades, serious works have been done in this area (Astin, 1997; Bailey, Calcagno, Jenkins, Leinbach, & Kienzl, 2006; Blose, 1999; Caison, 2007; Gansemer-Topf & Schuh, 2006; Goenner & Snaith, 2003; Pascarella & Terenzini, 1991; Ryan, 2005; Scott et al., 2006).

Neither student-level nor institutional-level analysis is sufficient to explain the whole process of college attrition. A more robust approach is to look at both levels of information simultaneously. The multi-level method is designed to analyze data which have nested or hierarchical structure, such as students nested in schools and schools nested in states, etc. A few researchers employed the multi-level method to study the college attrition problem (Kim & Conrad, 2006; Strauss & Volkwein, 2002).

Student Level Research on College Attrition

Tinto's Student Integration Theory

Most researchers of college retention traced back to Tinto's (1975) seminal work on college dropout. Based on the previous works by Spady (1970, 1971) and Rootman (1972), Tinto developed a full blown model for dropout from college. Figure 1 shows the schematic diagram of Tinto's model. The model was built upon Durkheim's theory of suicide and the cost-benefit analysis of economics of education. According to Durkheim, suicidal behavior was related to the individual's insufficient integration into the society. Tinto held that Durkheim's theory of suicide was applicable to explain college dropout because a college was viewed as a social system in which individual students integrated with the academic and social domains. Tinto used the concept of congruency to describe this integration. The degree of congruency between student's intellectual development and the prevailing intellectual climate of the institution determined the degree of academic integration. Likewise, social integration was also determined by the congruency between a student and his or her social environment in college. When a student failed to integrate into the academic and social subsystems in the college, he or she would drop out, either voluntary or by academic dismissal.

Brunsden, Davies, Shevlin and Bracken (2000) criticized Tinto, that he was misguided by Durkheim's theory of suicide because dropout from college was not necessarily as negative as suicide was. Students dropping out from college may have positive reasons such as pursuing a better life. Not distinguishing these differences would result in confusing results. However, Tinto (1982) had clarified that his theory was primarily concerned with differences, within academic institutions, between dropouts as academic failure and as voluntary withdrawal. Tinto focused on the characteristics which institutions themselves were at least partially responsible for and could change their policy to reduce such attrition. His model was purposed to explain the process of particular forms of dropout behavior rather than to maximize its explanation of variance in dropout behavior. It appeared that Brunsden's criticism against Tinto's model came from a theoretical and conceptual perspective but Tinto held a much more pragmatic view toward his model. To Tinto, what was important was how the integration process helped explain the dropout process and what kinds of intervention administrators could take to facilitate social and academic integration in their institutions to result in lower dropout rates. The integration concept applied to Durkheim's theory of suicide could also be applied to Tinto's theory of college dropout even though the two outcomes were different.

In Tinto's model, students brought along their individual characteristics to the college and integrated into its social and academic subsystems. Individual characteristics relevant to persistence included background characteristics (such as social status, high school experiences, community of residence, individual attributes like gender and race/ethnicity) and motivational attributes (such as career and educational goals). Individual's educational goal commitment and institutional commitment were the two main factors determining dropout decision. Goal and institutional commitment were in turn determined by the individual’s academic and social integration in the college. Academic integration was measured in terms of grade performance and intellectual development. The former related more directly to external values and rewards whereas the latter related more to internal rewards. Social integration occurred primarily through informal peer group associations, extracurricular activities and interaction with faculty and administrative personnel in the college. Supportive groups and subcultures were formed through social integration. Excessive social integration through friendship could, however, work against academic integration by limiting the student's time and energy invested in the latter and vice versa. Extracurricular activities linked to the academic system provided both social and academic rewards. Student interaction with faculty was more important in the student's major field than in other areas. While both social and academic integration affected dropout from college, academic integration was the more important factor because it related more closely to direct and tangible rewards in the educational system.

Over the years, many researchers had pointed out different problems in Tinto’s model. Pascarella, Duby and Iverson (1983) noted several discrepancies from what Tinto’s theory would predict when it was applied to commuter institutions as opposed to residential institutions. Pascarella and Terenzini (1983) pointed out the gender effect on persistence/withdrawal behavior and the compensatory effect on academic and social integration as well as on goal and institutional commitment. Bean (1985) emphasized the important effect of dropout intention (he called it dropout syndrome) on college persistence. Brunsden et al. (2000) argued that the main weakness of Tinto's theory was inadequate conceptualization. The concepts of social and academic integration were not clearly defined and they were not defined in terms of individual student's perception. Several researchers pointed out the impact of financial aid on college persistence and graduation (Alon, 2005; Alon & Tienda, 2005; Cabrera, Nora, & Castaneda, 1992; Chen & DesJardins, 2008; DesJardins, 2001).

All of the above criticisms were no surprise to Tinto. In fact, Tinto (1975) recognized the limitations of his theory in two areas but he chose not to explicitly include them in his model. First, external impacts from outside the college, such as the changing supply and demand in the job market, could also affect the individual’s decision to stay in college. Second, institutional characteristics, which affected college dropout at the aggregate level, included the institution’s type, resources, facilities, structural arrangements and composition of its members. Public institutions tended to have higher dropout rates than private institutions. Two-year colleges also tended to have higher dropout rates than the four-year colleges. Furthermore, Tinto (1982) recognized the following shortcomings in his theory: (1) insufficient emphasis on finances in student decisions concerning higher education persistence, (2) failure to highlight the important effects of gender, race and social status backgrounds on college persistence, and (3) not dealing with the specific issues peculiar to two-year college sector. First, the role of finances in student disengagement may vary in different stages of the student's experience in college education. For example, financial needs in early college years had greater and long-term impact on the student. Financial needs occurred closer to degree completion were viewed as short-term and easier to overcome. Second, comparisons of dropout rates among different group of students were important to discover specific social and institutional disadvantages which disproportionally diminished retention rate among particular minority groups. It was not sufficient to include gender and race variables into the regression equation, but specific models needed to be developed for specific groups to capture the factors relevant to the groups. The results should reveal how policy could be changed to correct the group disadvantages.

Bean's Student Attrition Theory

Unlike Tinto, whose theory was based on Durkheim's theory of suicide, Bean (1979) built his student attrition theory based upon the turnover theory in work organizations. That is, student attrition is analogous to employee turnover in work organizations. In his model, Bean formulated four categories of variables: student background, organizational determinants, intervening variables and dependent variable having their causal relationships in that order and direction. Organizational determinants consisted of 18 variables, including routinization, institutional quality and communication rules. The two intervening variables were satisfaction and institutional commitment. Routinization was defined as "the degree to which the role of being a student is viewed as repetitive" (p. 37). Bean tested his model on a sample of 907 freshman students (366 females and 541 males) from a major mid-western university. For the female group, institutional commitment, institutional quality and routinization were the most significant predictors of dropout (21% explained variance in dropout). For the male group, institutional commitment, routinization, satisfaction and communication rules were the most significant predictors of dropout (12% explained variance in dropout).

The major findings of Bean's study were: (1) males and females left the university for different reasons but both shared institutional commitment as the most important intervening variable; and (2) opportunity variables such as opportunity to transfer were important in determining institutional commitment. In another study, Bean (1985) developed a causal model using path analysis to predict a latent construct called dropout syndrome, which was measured by intent to leave, discussing leaving and actual attrition. Bean used four categories of exogenous variables: academic factors, social-psychological factors, environmental factors and socialization/selection factors. Bean tested his model on four groups of college students divided by year levels and the explained variances in dropout syndrome for the four groups were: 47% for freshmen, 35% for sophomores, 27% for juniors and 35% overall. The model had more explanatory power on the dropout intention among the freshmen group compared with the other three groups. As a student stayed longer in an institution, more factors may influence his or her dropout decision. The variance explained in persistence by this study was higher than the variance explained by previous studies. This result was probably attributed to the psychological factor included in Bean's model.

Although Tinto and Bean developed their models based upon different theoretical frameworks, they shared many similar constructs, such as academic factors, social-psychological factors and student background characteristics. Cabrera and Castaneda (1992) examined the convergent and discriminant validity between these two major theories of college persistence—Tinto's (1975, 1982, 1987, 1988) student integration theory and Bean's (1979, 1985) student attrition theory. They used confirmatory factor analysis (CFA) and structural equation modeling (SEM) techniques in LISREL software to analyze the data collected from a sample of 2,453 freshmen entering a large southwestern urban institution in fall 1988. Both models (representing the two theories) fitted the data well as indicated by the model fit indices (GFI = .981 and .987, AGFI = .963 and .971 and RMR = .056 and .063 respectively). The indicators of two factors (academic integration and institutional commitment) of the Tinto’s student integration model were found to have high correlation with the indicators of two factors (courses and institutional quality and fit) of the Bean’s student attrition model. Further analysis using CFA showed that the two factors from the two models were largely representing the same constructs. This result proved that these two theories converged in two areas—academic integration and institutional commitment. Furthermore, Tinto's student integration model was more robust compared with Bean's student attrition model when judged in terms of the number of hypotheses validated. About 70% of the hypotheses from Tinto's model were confirmed, but only 40% of the hypotheses from Bean's model were confirmed. However, Bean's model had higher predictive power than Tinto's model, explaining 60% (versus 36%) of the variance in “intent to persist” and 44% (versus 38%) in “persistence.” These differences were attributed to the significant effects of external factors in Bean's model, such as parental encouragement and support from friends and finances. This result showed that the Tinto's and Bean's theories could be combined to improve the understanding of the student attrition process.

Cabrera’s Elaborations on Tinto’s Theory

Building upon Tinto's and Bean's works, Cabrera, Nora and Castaneda (1992) examined the role of finances on college persistence using a causal model to analyze the data collected from a sample of 466 freshmen at a large public urban commuter institution. The results showed that the model accounted for 47% of the variance in persistence and 25.5% of the variance in intent to persist. The model fit indices (GFI = .996, AGFI = .985, RMR = .035) showed that the model fit the data well. Finances were thought to have an objective dimension, which was related to a student’s availability of resources such as financial aid received and a subjective dimension, which was related to the student's satisfaction with financial support. The total effects on persistence by financial aid was 27%, only second to the largest contributing factor, 60% by intent to persist. This result showed the importance of financial aid in influencing student persistence. One implication of financial aid was its impact on institutional commitment. Financial aid as form of recognition of academic performance may increase commitment to the institution. Another practical implication of financial aid was concerning the effectiveness of different aid types in fostering persistence. Work-study program was an efficient form of financial aid to promote social and academic integration and to increase persistence because it encouraged students to interact with staff and faculty and peers in the institution as well as provided the financial resources.

Besides the financial effects on persistence, Cabrera and Nora (1993) also found the effect of encouragement from significant others upon social integration and goal commitment. Significant others’ influence, such as encouragement from families and friends to pursue college education, affected the student's academic and social integration because such encouragement developed educational aspirations among high school students and on subsequent postsecondary social integration. They also found that pre-college academic performance exerted direct effects on academic integration because it embraced abilities and motivations to participate in the academic component of the institution. This result contradicted Tinto’s theory in which pre-college characteristics only had indirect effect on persistence via the student’s social and academic integration and goal and institutional commitment. At last, they found that compensatory (non-causal) relationships existed between social and academic integration as well as goal and institutional commitment. Cabrera and associates enhanced Tinto’s theory by clarifying the roles of financial aid and significant others’ influences on persistence.

Pascarella and Terenzini’s Student Interaction Theory

In a partial test of Tinto’s (1975) theory, Pascarella and Terenzini (1977) used regression analysis to investigate the pattern of student-faculty informal interaction beyond the classroom between the college persisters and voluntary leavers in a 1975 fall sample of 355 freshman students at Syracuse University, New York. The findings showed that college persisters had significantly higher informal interaction with faculty in six categories, particularly in matters related to intellectual and academic interest, than the voluntary leavers after student sex, academic aptitude and personality attributes were controlled. The results supported the informal student-faculty interaction part of Tinto's theory of college withdrawal although the relationship between informal student-faculty interaction and persistence was not directly tested. Other untested components of Tinto's theory were social and academic integration and goal and institutional commitment.

Based on a 1976 fall sample of 773 freshmen from Syracuse University, Pascarella and Terenzini (1980) used principle component factor analysis to build a measurement model for the major components of Tinto's (1975) theory—peer-group interactions, interaction with faculty, faculty concern for student, academic and intellectual development, and institutional and goal commitments. The five-factor measurement model accounted for 44% of the variances in the observed correlation matrix generated from 30 scale items. Then, they used the five-factor measurement model to conduct discriminant analysis to predict persisters and voluntary dropouts. These five-factors explained 21.46% of the variation in group membership of persisters and voluntary dropouts whereas the student background characteristics only explained 4.45% of the variation, mostly due to gender difference. The most significant factors were institutional and goal commitments followed by interactions with faculty, faculty concern for student development and teaching. This study did not test Tinto’s theory but it generated the five factor scales to measure the major components of Tinto’s theory.

After conducting two partial tests on Tinto’s theory, Pascarella and Terenzini (1983) used path analysis to test the validity of Tinto's (1975) model as a whole, based on a sample of 763 freshmen (402 males and 361 females) from a residential university. They fit the model on the overall sample, then on the male and female groups separately. The results generally supported Tinto's theory with two interesting findings: gender effect on persistence/withdrawal behavior and compensatory effects between academic and social integration and between institutional and goal commitment. For female students, social integration appeared to be a stronger factor than academic integration whereas the opposite was true for male students. Students who scored lower in social integration tended to score higher in academic integration and vice versa. The same compensatory effect was on goal and institutional commitment. This was one of the first confirmatory studies to test the entirety of Tinto's theory using path analytical technique. The variance explained in persistence was about 18% and the residual variances of all endogenous variables were about 20%, indicating a low model fit and a medium effect size. But no model fit statistics was reported to confirm this model fit problem.

In another path analytical study to validate Tinto's model, Pascarella and Chapman (1983) used a multi-institutional sample of 2,326 freshmen from 11 postsecondary institutions. The results generally confirmed the validity of Tinto's theory. Further group comparison analysis by segregating the data based on institution type yielded meaningful insights of how institutional characteristics influenced the effects of social and academic integration on voluntary withdrawal behavior. Social integration exerted stronger influence on persistence at four-year primarily residential institutions, while academic integration was a more important factor at two- and four-year primarily commuter institutions. The explained variance in persistence for these three groups (four-year residential institutions, two-year commuter institutions, and four-year commuter institutions) and the overall group were 15.4%, 10.8%, 15.0% and 12.0% respectively. The Student Involvement Questionnaire (SIQ) was developed to collect data from freshman students in four areas: (1) student background characteristics such as sex, age, high school grade point average, student socioeconomic status, affiliation needs scale and achievement need scale; (2) institutional characteristics such as two-year versus four-year, institutional size and percent of undergraduate students living on campus; (3) constructs for academic integration and social integration; and (4) two scales for institutional commitment and goal commitment. The dichotomous dependent variable, persistence, was provided by the institutions in the following semester based on the students' continuous enrollment. They did not analyze the inter-institutional effect although the sampling had a hierarchical nature. To do that would require the use of hierarchical linear modeling (HLM) technique to distinguish the effect at institutional level and the effect at individual level. Like the previous study, this study was also short of model fit statistics and also had model fit problem due to high residual variances.

In another study, Pascarella, Duby and Iverson (1983) tested Tinto's theory in a non-residential postsecondary institution. They used a sample of 579 freshman students at a large, urban, commuter university in the mid-west. The results showed several contradictions to Tinto's theory. First, academic integration rather than social integration was the primary mediating factor between initial and subsequent institutional commitments. Second, student background characteristics had significant direct effects on persistence/withdrawal behavior without mediating through the integration and commitment process. Third, neither goal commitment nor institutional commitment had a direct effect on persistence but institutional commitment had an indirect effect through student intention to persist. Student intention alone increased the explained variance in persistence from 19% to 28%. This unexpected result indicated that the person-environment fit concept of Tinto's theory might need to be re-conceptualized in commuter institutions. Tinto's theory was originally developed in the residential setting where students developed their goal and institution commitments through academic and social integrations. Social integration, however, was not viewed as an important factor in commuter setting because little opportunity was provided to build social integration at commuter institutions. In fact, social integration showed negative effect on persistence because social integration may reflect affiliation needs more than social association in the institution. Like the previous two path analytical studies, Pascarella and associates did not report any model fit statistics in this study, but the high residual variances in the endogenous variables indicated that the model did not fit the data well. The role of intention to persist is probably important in persistence/withdrawal behavior, but the problem is how intention caused the action. The effect of intention on persistence may change over time. So, it is important to characterize intention by the time factor.

Pascarella, Terenzini and Wolfle (1986) investigated the impact of pre-college orientation program on the persistence of freshman students within the Tinto's framework based on a sample of 773 freshmen of a medium-sized residential university (about 10,000 undergraduate students). The results generally supported the theoretical expectations of Tinto's theory. The pre-college orientation program did not have a significant direct effect on persistence/withdrawal decision but it had a significant indirect effect mainly mediated through college social integration and subsequent institutional commitment, particularly from involvement in extracurricular activities and informal interaction with faculty.

Astin's Student Involvement Theory

The theory of student involvement traced back to Astin's (1975) longitudinal study of college dropouts to identify factors that significantly affected the student's persistence in the college environment. According to Astin (1999), "student involvement refers to the amount of physical and psychological energy that the student devotes to the academic experience" (p. 518). "The persister-dropout phenomenon provides an ideal paradigm for studying student involvement" (p. 524). For example, living in a campus residence was positively related to retention because the student living on campus had more time and opportunity to get involved in all aspects of campus life. Participation in social fraternities and extracurricular activities was also positively related to retention because these activities allowed students to develop friendship with peers and get more involved in campus life. Likewise, holding a part-time job on campus, such as work-study programs, would increase retention because this kind of work activities enhanced the student's involvement within the campus. On the other hand, out-of-campus full-time job would diminish retention because they were competing objects that drained away the student time. Furthermore, student's ability to identify with the institution had positive impact on retention. This was why commuter colleges had higher dropout rate because their students spent less time on the campus and were less involved in campus activities. The most precious institutional resource was student time. The level of learning and development that a student could achieve was directly proportional to the amount of time and effort he or she put in the process. Student time was also a finite resource and its allocation was a zero-sum game. When a student committed his or her time on certain activities, that student would have less time to spend on other activities. So, administrators and faculty members must recognize that all institutional policy and practice could affect the way students spent their time and the amount of effort they invested in academic activities. Kuh's student engagement theory was built upon the basic principles of Astin's student involvement theory.

Kuh's Student Engagement Theory

Kuh, Gruce, Shoup, Kinzie and Gonyea (2008) used multiple regression analyses to examine the effects of engagement in purposeful educational activities during the first year of college on first-year GPA and second-year persistence. Between 2000 and 2003, they used the National Survey of Student Engagement (NSSE) and campus institutional research records to collect the data from a sample of 6,193 students who enrolled in 18 baccalaureate-granting colleges and universities with differing institutional characteristics. They also examine the interaction effect between first-year engagement and race/ethnicity. The results showed that student engagement was positively related to academic outcomes and persistence. Student engagement also had a compensatory effect on academic outcomes and persistence. For example, the time spent on educational activities was more than compensating the pre-college SAT/ACT disadvantage. Compared with White students, Hispanic students were benefited more in GPA by the same amount of increase in engagement. African American students were more likely to return in the second year than the White students after both invested above average amount of engagement. Kuh et al. (2008) concluded, "Student engagement in educationally purposeful activities during the first year of college had a positive, statistically significant effect on persistence, even after controlling for background characteristics, other college experiences during the first college year, academic achievement, and financial aid" (p. 551). Kuh's study produced meaningful results about the differential engagement effects on student outcomes and persistence between the disadvantaged groups (such as students from low-income family and minorities) and the majority White students. Intervening programs aimed at improving engagement among disadvantaged students were worth the effort because these programs could help them jump over their hurdles and achieve a higher improvement rate than the non-disadvantaged students. This was a valued-added concept in education.

Stage's Motivational Orientation

Stage (1989) used the motivational orientation construct as a blocking factor to analyze college withdrawal within the Tinto framework. She suggested that "typologies such as motivations of students for enrolling in college (motivation orientation) can be used in a Tinto-based study to identify subgroups of students for analysis" (p. 385). Stage (1989) had the following researched questions:

1. What were the motivational orientations of first-year university students?
2. Did students within differing motivational orientation typologies exhibit different patterns of experiences which led to attrition early in the first year of college?
3. To what extent was it possible to identify, for students within particular motivational orientation categories, specific patterns of social and academic involvement that affected attrition? (p. 387)

In Stage's study, student's responses to the 40-item Educational Participation Scales (EPS) were factor analyzed for principle component factors with oblique rotation. Seven factors were identified using factor loading of .4 or higher. Most students fell into three categories: (1) certification—motivated by practical reasons such as earning a degree or finding a job; (2) cognitive—motivated by academic reasons such as seeking knowledge; and (3) community service—motivated by gaining skills to help others. Based on the motivational orientation score, Stage divided a sample of 260 students at a major public university in the Southwest into three groups: certification (150 students), cognitive (72 students) and community service (38 students). Stage used LISREL software to fit three SEM models (based on Tinto's framework) to the three subgroup datasets. Different "persistence patterns" were observed among the three subgroups. For the certification and the cognitive subgroups, academic integration and later institutional commitment were the most significant predictors of persistence. For the community service subgroup, later goal commitment and institutional commitment had significant influences on persistence. Stage (1989) concluded, "Psychosocial differences among college students are a useful alternative to traditional demographic characteristics for identifying subsets of college students who might react similarly to college experiences" (p. 396). Compensatory relationships among variables within the Tinto's framework might represent different persistence patterns among different groups of students. For example, academic integration had its strongest positive influence on persistence at relatively low levels of social integration. When social integration decreased, the influence of academic integration on persistence became more important. An important contribution from

Stage's study is that she uses psychological factors rather than traditional student demographic or socioeconomic characteristics to classify students for group comparison analyses. This kind of classification scheme is useful to discover behavioral patterns of different groups within the same theoretical framework because it offers a flexible way to classify subjects into meaningful groups.

Other Elaborations on Tinto's Model

Besides the above key researchers who had tested, criticized and elaborated Tinto's theory, many more researchers had done works related to Tinto's model. Some of these works are summarized below.

Beekhoven, De Jong and Van Hout (2002) contended a conceptual problem of Tinto based integration theories of college attrition leading to conflicting results because academic and social integration were practically inseparable concepts. Instead, they proposed rational choice theory which was based on personal cost-benefit analysis to enhance the integration model. Using structural equation modeling (SEM) technique with Amos (Analysis of Moment Structures) software, they fit three models (the integration model, rational choice model, and extended model which combined the integration model and rational choice models) to a dataset based on 918 undergraduate students in Netherland. Model fit indices (NFI, TLI and RMSEA) showed that the integration model did not fit the data well and the extended model had a better fit than the rational choice model. The three models explained 18%, 26% and 33% of the variance in the outcome variable—academic progress which was measured by the percentage of required college credits to graduate within five years. Because this study was done in Netherland, the results may not be comparable to the studies done in the U.S. Unlike most studies based on Tinto's model, which were typically focused on the first year in college, Beekhoven's study covered the entire five years of college study and should yield a more complete picture of the persistence process. However, Beekhoven's study was focused on academic progress in terms of percentage of credits completed rather than retention or dropout rate. The longitudinal feature of this study is worth noticing.

Berger and Braxton (1998) sought to elaborate Tinto's (1975) theory of college dropout by illuminating the social integration concept with three organizational attributes—institutional communication, fairness in policy and rule enforcement, and participating in decision making. Tinto failed to lay down the detail mechanism of social and academic integration because these were complicated socialization processes. Berger and Braxton tried to fill the void in Tinto's theory by elaborating the process of social integration through the lens of organizational characteristics. "Theory elaboration entails the application of new concepts borrowed from other theoretical perspectives to explain the focal phenomena" (p. 104). Berger and Braxton tested their path model in a sample of 718 freshmen of a highly selective, private, residential, Research I university. The results showed that all three organizational attributes had direct effects on social integration and had indirect effects on students' intent to persist. Communication and fairness had positive indirect effects, while participation had negative indirect effects. In a follow-up study, Braxton, Milem and Sullivan (2000) used the concept of active learning to elaborate the process of academic integration in Tinto's theory. "Active learning is any class activity that involves students in doing things and thinking about the things they are doing” (p. 571), including discussion, questions faculty asked students in class, debates, role playing, etc. Active learning was different than academic integration because the former preceded and shaped student’s perception of the latter. Academic integration was the process through which the student acquired the values, skills and standards shared by the academic community. So, active learning experience could elaborate the process of academic integration. The results showed that class discussions and higher order thinking activities had direct effects on social integration. Class discussion also had indirect effects on both subsequent institutional commitment and student's intention to persist. Active learning experience could also help students develop friendships and networks of peer support which enabled them to establish membership in the social communities of their college. So, active learning also elaborated the process of social integration. Tinto's (1997) emphasis on “cooperative learning community” illustrated the function of active learning.

Bernard and Amundsen (1989) took Tinto's (1975) theory of student persistence and applied it on the distance learning context. They used discriminant function analysis (DFA) to construct the best combination of predictor variables. Based on a sample of 553 students, who enrolled in the Personal Education Program (PEP) sponsored by the Institute of Canadian Bankers and 49 Canadian universities, Bernard and Amundsen sought to determine how well Tinto's model could predict completers and non-completers at the course level. The total variances explained in the dependent variable are 40% for communication courses, 50% for business administration courses and 58% for accounting courses. This result was better than the results from most studies based on the Tinto-framework in the literature. Different predictor variables had different predictive power in different courses. For example, background characteristics and institutional commitment were important predictors in communication and business administration courses. Goal commitment only affected persistence in accounting courses. Academic integration was important in all courses, particularly in accounting courses and less so in business administration and communication courses. Bernard and Amundsen's study demonstrated an application of Tinto's theory on the distance learning context based on course level student outcome rather than persistence for degree attainment.

Campbell and Campbell (1997) used a matched pairs design to evaluate a faculty/student mentor program within the Tinto framework at a large metropolitan university on the West Coast, in which 339 undergraduates assigned to mentors were paired with non-mentor students with similar characteristics based on gender, ethnicity, GPA and entering enrollment status. The results showed that mentor students had higher GPA (2.45 vs. 2.29), more units completed per semester (9.33 vs. 8.49) and lower dropout rate (14.5% vs. 26.3%) than non-mentor students. The faculty mentor program was a program in which faculty members were encouraged to serve as mentors to undergraduate students. And mentoring was a practice where "a more-experienced member of an organization maintains a relationship with a less-experienced member and provides information, support and guidance so as to enhance the less-experienced member's chances of success in the organization" (p. 727). Academic performance and retention were unrelated to gender and ethnicity of mentor and protégé. The number of and duration of mentor-protégé contacts were found to be positively related with academic performance and negatively related with retention rate.

There were more researchers who had used Tinto's framework to investigate the separation stage in college (Elkins, Braxton, & James, 2000), gender effect on parenthood among African American college students (Leppel, 2002), relationships between organizational success in intercollegiate athletics and overall institutional graduation rates (Mangold, Bean, & Adams, 2003), different retention rates among different groups of transfer students (Koker & Hendel, 2003) and a path analytic model using National Longitudinal Study dataset (Munro, 1981).

Conclusion

Tinto's model for college dropout is basically a sound model tested by many researchers. His theory was based on the concept of person-environment fit and was derived from Durkheim's theory of suicide. Bean's theory of student attrition was based on turnover of work organization, but it shared many similar concepts of Tinto's theory. Bean's theory also included external factors such as opportunity to transfer as well as social-psychological factors such as intention to persist. Cabrera and associates tried to combine Tinto's and Bean's models and included more institutional factors such as role of financial aid and external factors such as influence from significant others. Pascarella and Terenzini took the comprehensive approach to test the validity of Tinto's model as a whole. They also developed many instruments to measure the major components of Tinto's model. Astin did not use Tinto's model to guide his research. Instead, Astin developed his theory of student involvement based on his previous research on student dropout. Student involvement was an all encompassing concept to explain student development in higher education. There were different types and intensity of student involvement. Astin did not build a tight model to explain the relationship between different types of student involvement and how these different types of involvement work together to influence college persistence. Kuh and associates developed their student engagement theory based on Astin's student involvement concept. Kuh also used his theory to develop a whole range of instruments and assessment tools, such as the National Survey of Student Engagement (NSSE). Tinto's theory had definitely elicited more research works in the area of student persistence than any other theory in recent decades. Most of these studies were focusing on the student-level factors such as student characteristics, intention to persist, socioeconomic status, commitment, self-perceived degree of social and academic integration, faculty-student interaction, etc. But different institutions and states may have structural differences that could also affect student persistence in college. Institutional-level research is required to discover these structural factors.

Institutional Level Research on Graduation Rate

So far, much has been said about the effects of individual characteristics and behavior on student persistence. But the institutional characteristics are also important sources of such influences on student graduation. Gansemer-Topf and Schuh (2006) stated:

> Much of the research on retention has focused on the characteristics or traits (i.e. academic ability or experiences or financial need) of students. Significantly less

> research has examined how institutional behavior rather than student characteristics or experiences are related to retention and graduation (p. 614).

The following discussions were about how student graduation was affected by institutional level factors.

Debate upon Graduation Rate

According to the Integrated Postsecondary Education Data System (IPEDS) definition, graduation rate was calculated as the total number of completers within 150% of normal completion time divided by the number of students in the revised cohort minus any allowable exclusion (Knapp et al., 2008). In IPEDS, graduation information was contained in the graduation rate survey (GRS) component (Thurgood et al., 2003). Graduation rate was the most commonly used measure of institutional performance. Graduation rate was also used in many institutional ranking systems, such as the US News and World Report America's Best Colleges. But not everyone agreed to the use of graduation rate as performance measure of higher education institutions. Bailey, Calcagno, Jenkins, Leinbach and Kienzl (2006) listed two reasons for rejecting the use of graduation rate to measure the performance of community colleges. First, many of the students who came to community colleges did not seek degrees or transferred to a baccalaureate institutions. Second, many factors that thwarted students' graduation were beyond the control of the colleges such as family and work responsibilities and deficient academic preparation.

Gillmore and Hoffman (1997) proposed to use the graduation efficiency index (GEI) as an accountability measure to replace the traditional time to degree measure, such as graduation rate. GEI of a student was defined as the ratio of minimum required credits for the degree after subtracting the transfer credits divided by the sum of enrollment census day credits. Using GEI, Gillmore and Hoffman analyzed the data from all graduates of University of Washington who received a bachelor degree during the 1993-94 academic year, among whom 2,539 were transfer students and 2,414 were non-transfer students. The average GEI was 85% with a standard deviation of 15%. A two-way ANOVA showed that the two main effects of degree type and transfer status as well as their interaction effect on GEI were all statistically significant at the .001 level. The effect size was about 11.5%. B.A. graduates had higher GEI than B.S. graduates (87% vs. 81%). Transfer students had lower GEI than non-transfer students (80% vs. 87%). Transfer had more impact on B.S. students (16% increase in GEI) than on B.A. students (8% increase in GEI). Another one-way ANOVA showed that transfer credits explained 36% of the variance in GEI. A three-way ANOVA (sex by degree type by transfer status) showed that overall female students had higher GEI than male students, but the difference was not statistically significant in B.S. degrees. Transfer had no significant effect on GEI at differing levels of degree type and gender. The effect size was less than 3%. Correlational analysis showed that GEI and time to degree had about 14% to 23% shared variance at differing levels of degree type and transfer status, indicating that the two measures were empirically distinct. According to Gillmore and Hoffman (1997), efficiency was defined as the ratio of the effective or useful output to the total input in any system. In the context of higher education, the output referred to the minimum required degree credits and the input referred to the credits attempted. The traditional measure of efficiency was a time to degree measure, which used time as the input. For example, graduation rate was the ratio of students who graduate within a period of time (e.g., four years or six years) compared with the total number of students who enroll as first semester freshmen. The main problem of the time to degree approach was that time was not the best indicator of educational activity. Degree credit could better represent the educational effort and activity. Furthermore, the time to degree approach as an accountability measure had some negative consequences. For example, more students needed to work part-time because of higher tuition and living costs. Measured by graduation rate as their efficiency index, many community colleges were punished by admitting these nontraditional students who took longer to graduate or may never get their degrees.

In addition to the NCES graduation rate, Jacoby (2006) devised the overall degree ratio and the net graduation rate to account for the effects of transfer students and part-time students on graduation rate. The NCES graduation rate was based on the ratio of first-time, first-year (FTFY) students who graduate within 150% of normal completion time relative to the FTFY cohort. The net graduation rate was the same as NCES graduation rate but the FTFY cohort was reduced by the number of students who had transferred to other institutions. The overall degree ratio was based on the number of students who graduated in a given year relative to a college's total FTE student enrollment.

Given the above debate about the use of graduation rate as an institutional performance measure, the NCES graduation rate provided by IPEDS was still by far the most widely used measure. Several limitations should be heeded when IPEDS data were used to study graduation rates. First, IPEDS did not include measurement of student ability and motivation as well as most student-level characteristics, except for gender and ethnicity information aggregated at the institution level. Second, IPEDS did not provide any tracking information about the whereabouts of transfer students, weakening the ability to study the success or failure of transfer students. Third, IPEDS did not account for the graduation or dropout of part-time students. Although IPEDS had its limitations, it provided the institution's summary graduation data for subgroups based on gender, ethnicity, athletic affiliation, etc. IPEDS was the only national dataset sufficient for institution-level analysis of community college graduation rates. It could be used to discover differences among colleges because it contained data about most of the higher education institutions in the United States.

Benchmarking for Peer Comparison

Put into context, graduation rate could be a valid measure to compare performance of one institution with its peers. Taken out of context, graduation rate could be very misleading to compare completely different institutions, such as four-year Carnegie I research universities vs. two-year community colleges.

Astin (1997) warned that an institution’s retention rate could be a very misleading indicator of its capacity to retain students because more than half of the variance in the retention rate was attributed to students’ characteristics prior to enrollment rather than to any differential institutional effect. Only longitudinal studies could control for student’s input characteristics in predicting retention. He argued that an institution’s effectiveness in retaining students should be measured by its actual retention rate compared with its expected retention rate. Astin used logistic regression to predict the probability of completing a degree within 4, 6, or 9 years based on the entering freshmen in the fall of 1985 in 365 baccalaureate-granting institutions which participated in the Cooperative Institutional Research Program's (CIRP) annual survey. The expected probabilities to graduate were calculated for each student using the regression formulae. Then, the expected retention rate of an institution was calculated by summing all expected probabilities of the students attending that institution. Three retention rates were calculated from students in cohort who completed their degrees in 4, 6 and 9 years respectively. The predictor variables were students' high school grades, admissions test scores, sex and race. Other possible independent variables included socioeconomic status, religion, hedonism and political orientation. The multiple R was about .35 indicating that about 12% of the variance in the dependent variable was explained by the independent variables. Astin advised that institutions should use his regression formulae to compute their own expected retention rates. Then, they should compare their actual retention rates with their expected retention rates. If an institution's actual rate was higher than its expected rate, that institution was performing better than what it was expected in comparison with all its peer institutions that were included in the regression analysis. The reverse was also true for the under-performing institutions. Using this approach could help an institution benchmark its performance against its peer institutions. Astin's approach assumed that a homogeneous group of peer institutions could be identified prior to the analysis. Outliers could drastically change the regression lines and increase the prediction error.

Bailey (2006) also advocated using both actual and predicted graduation rates to identify comparable peer groups for benchmarking and put the interpretation of graduation rates in appropriate contexts. Bailey employed data mining technique by using Clementine software to split the IPEDS data into groups based on control and level of the institutions. A multiple regression model was created for each subgroup to predict the graduation rate in that group by 51 predictor variables. Most of the predictors came from the enrollment and institutional characteristics surveys. Pearson correlation was calculated between the actual and predicted graduation rates as a measure of model fit in a group. Further split of groups was justified by improving the Pearson correlation. Finally, eight models were created for eight subgroups of data. Although this approach appeared to be systematic and logical, the critical assumptions of multiple regression were completely left out. The normality assumption and multicollinearity assumption of multiple regression must be met in each subgroup data to avoid bias estimation. However, these assumptions may be violated in the split datasets based on the regression results because regression results were required to split the dataset. It was not clear how this circular dependency was handled. Furthermore, several issues needed to be considered in using the data mining technique to evaluate graduation rates. First, data mining was a exploratory method based on a particular sample. The resulted models may not be generalizable to explain other samples. Second, multiple regression models relied on several assumptions such as normality and independent predictors which were not discussed in the article. Third, the models must make theoretical sense but no interpretation of the models was offered in the article.

Goenner and Snaith (2003) argued that past studies on student attrition were primarily focused on the effects of student characteristics and largely ignored the role of institutional characteristics. They used both student and institutional characteristics as predictors in a multiple regression model to predict the graduation rate based on a sample of 258 Carnegie I research universities. The results showed that both student and institutional characters accounted for significant amount of variances in the graduation rates. The total amount of variance explained were 79%, 77% and 78% in four-, five- and six-year graduation rates respectively. The institutional characteristics included in this study were percentage of full-time faculty, total educational and general expenditures, student-faculty ratio, weighted tuition and fees. The student characteristics were percentage of students in the top 10% of high school class, 25th percentile of student SAT scores, percentage of out-of-state students and average age of the students. Assuming that Carnegie I research universities formed a homogeneous group. The regression model generated in this study can served as the benchmarking tool to compare performance of institutions within the group.

Blose (1999) used logistic regression to compute the expected graduation rates of the State University of New York (SUNY) based on student characteristics (such as gender, race, age and family income) and academic performance measures (such as student's high school average, rank in high school and SAT/ACT scores). He then compared the actual and expected graduation rates to evaluate the relative performance of institutions. The idea was to create a logistic regression model to predict students' graduation probability based on a set of student attributes and data from all institutions. Then, the model was applied to each institution to calculate its predicted graduation rates based on its student profiles. The institution's predicted graduation rate was used to compare with its actual graduation rate. The underlying rationale of this method was that institutions with better prepared students should have higher graduation rates than institutions with less prepared students and vice versa.

Goenner and Snaith (2004a) contended that the performance evaluation of an institution based on comparing its actual graduation rate against the predicted rate from a regression model was not only determined by the institution's graduation rates but also by the accuracy of the model. Model specification should be guided by theory but researchers were still left uncertain about what variables should be selected. Goenner and Snaith used the Bayesian model averaging (BMA) technique implemented by the *bicreg* function in S-Plus software to account for this uncertainty in model specification. Compared with traditional variable selection methods (minimizing Mallow's Cp, Efroymson's stepwise method and maximizing adjusted R^2), BMA achieved a lower predicted mean squared error. Astin's (1991) input-environment-output (IEO) theory was used as the guiding theory. The results showed that average student age, percentage of students who were in top 10% high school rank, SAT score of lowest quartile, percentage of male students, urban location were all very strong predictors. Percentage of student ethnic groups had no influence on the prediction of graduation rate, except for Native

American students. Religious affiliation had weak effect. Percentage of faculty with a doctoral degree and alumni giving both had marginal positive effects only.

Effects of Student Demographics on Graduation Rates

In IPEDS, student demographic information was measured at the aggregate level, averaging over all the students within an institution. These student demographics included gender and ethnicity, which characterized the graduation rates and degree completion rates, as well as the average age variable. The average age of students was negatively related to graduation rates because older students were further removed from the materials learned in secondary school and may also have additional family and work burdens than traditional students (Goenner & Snaith, 2003). Students' non-traditionality was measured by the percentage of part-time, the percentage of commuter and the average age of students. These three measures were related to social attachment of student involvement in campus life. Other demographics included urbanization, institutional size and religious affiliation (Scott et al., 2006). In a study, Scott, Bailey and Kienzl (2006) used the Oaxaca decomposition technique to partition the effects on graduation rates into two components, one due to the predictor variables only and the other due to group difference only. The grouping of institutions was based on public and private sector distinction. The results showed that most effects on graduation rates were explained by the predictor variables such as student characteristics and selectivity. With all these predictor variables held equal, public institutions were slightly more efficient than the private institutions in terms of graduation rate.

Another student demographic information (not available in IPEDS) that had impacts on graduation rate was student's socioeconomic status (SES). Astin and Oseguera (2004) defined student's SES by parental income level and parental educational level. The 25th percentile and 75th percentile of parental income were computed to classify the parental income level as highest 25%, middle 50% or lowest 25%. In the CIRP survey, educational level was defined by a seven-category continuum ranging from grammar school to graduate degree. The parental educational level was defined in a three-category scale: Low as both parents never attended college, High as both parents had college degrees and Middle as the remaining combinations. As generally expected, students' SES impacted academic outcomes by affecting educational aspiration and the resources available to the students in the college years. Students' SES was also correlated to other student attributes such as academic preparedness and personal goals in education.

Effects of Institutional Selectivity on Graduation Rates

As a quality measure, institutional selectivity had enormous impacts on the institution's graduation rate. Astin and Oseguera (2004) defined institutional selectivity narrowly as the mean SAT score (verbal plus mathematical composite) of the entering freshman class. The institutional selectivity as reflected in the relative ordering of institutions remained constant over considerable periods of time. The highly selective, least selective and middle selective institutions were defined by the top 10%, bottom 30% and remaining 60% of the institutions. Using this definition, Astin and Oseguera (2004) examined the income group representation in the most selective institutions from 1985 to 2000 as follow: (1) a steady increase in the representation of high-income students; (2) a steady decrease in the representation of middle-income students; and (3) little change in the representation of low-income students. The inequity of educational opportunities among students at different SES levels had increased during recent decades, despite the expansion of remedial efforts such as student financial aid, affirmative action and outreach programs. The underlying reasons were not clear but were partially attributed to the increasing competitiveness among prospective college students for admission to the most selective institutions.

Those in favor of affirmative action argued for helping economically disadvantaged and minority students attend highly selective institutions to correct the decline in equity in the American higher education system as Astin and Oseguera had described. However, some used the "mismatch" hypothesis to argue the opposite. The "mismatch" hypothesis stated that minority students who attended selective postsecondary institutions had lower graduation rates than their counterparts who attended nonselective institutions because they were put in environment with academic standards higher than what they were prepared to meet (Alon & Tienda, 2005). "The mismatch hypothesis is not about racial and ethnic differences in graduation within institutions but, rather, about same-group comparisons across institutions that differ in the selectivity of their admissions" (p. 305). Those who opposed the "mismatch" hypothesis argued that students attending higher tracks and/or better schools made greater scholastic gains regardless of the students' prior achievements. Selective institutions provided better opportunities for learning than the nonselective institutions. Therefore, attending selective institutions could help minority students offset their disadvantage and develop better cognitive skills. To test the "mismatch" hypothesis, Alon and Tienda (2005) used the bivariate probit technique to simultaneously estimate a student's probability of being admitted into selective institutions and the student's probability of graduation to avoid biased estimation because the determinants of these two probabilities had much in overlap. Due to the nature of "mismatch" hypothesis, group comparisons were conducted between matching samples, where students with similar attributes were selected from the selective and nonselective institutions. The results showed that students attending selective institutions had higher probability of graduation than students attending nonselective institutions after the students' attributes were controlled in the matching samples. This increase in probability of graduation was consistent among students in different ethnic groups (White, Black, Hispanic and Asian). Therefore, the "mismatch" hypothesis was rejected.

Effects of Financial Aid on Graduation Rates

Financial aid was one of the most controversial institutional attributes that affect graduation rates because many researchers had generated conflicting results in this area. IPEDS consisted of the Student Financial Aid (SFA) survey component which contained detailed financial aid information, such as average amount received, percentage and number of recipients of grants and loans. Some researchers defined the institutional socioeconomic status as the Pell grants divided by undergraduate enrollment (Pike et al., 2006). Both figures could be derived from IPEDS data.

Dowd and Coury (2006) used logistic regression to examine the effect of financial aid, primarily federal loans, on persistence and associate's degree attainment within the five-year period of the survey. Dowd and Coury's study was based on a sample of 694 students, who began their studies in public two-year institutions, from National Postsecondary Student Aid Study conducted 1989-90 (NPSAS/90) and the Beginning Postsecondary Students, Second Follow-up (BPS 90/94) to study. The results showed that loans had a negative effect on persistence and no effect on degree attainment. The findings were attributed to the high uncertainty of degree completion and the negative affective component of indebtedness among community college students. However, the loan variables may be correlated with student attribute variables and academic variables, but these correlations were not reported. The interactions of these variables could mask the loan effects on persistence. Effects of other types of financial aid also needed to be examined.

Wohlgemuth, Whalen, Sullivan, Nading, Shelley and Wang (2007) used logistic regression to predict the likelihood of a student being retained from each of four years and the outcome of graduation at the end of years four, five and six based on a sample of 3,610 students from the fall 1996 entering class at a mid-western research extensive university. The predictor variables were in four categories: demographic characteristics (age, gender, ethnicity, in-state residency), ability (high school rank, ACT score), environmental (university athlete, university honors program, first-generation student) and financial aid data (gift, loan and work-study). The results showed the importance of including financial aid variables when examining retention and graduation. Gift aid and work-study aid played key roles in year one. This may translate into effective financial aid policies using more gift aid and work-study aid in the first year and more load aid in later years. The research of Wohlgemuth et al. was conducted at the student level but it showed clear evidence for the effects of financial aid on student retention.

Chen and DesJardins (2008) used discrete-time Logit modeling to examine the effect of student aid and the effect of time on dropout behavior among students at different income-levels. The authors noted that previous research about the effects of student aid on dropout behavior lacked the temporal dimension in analysis and the investigation of aid impacts by income levels. The sample included 6,733 students in two-year institutions from the Beginning Postsecondary Students survey (BPS:96/01). The results showed that dropout risks varied over time and low-income students were more responsive to Pell grants but not to other types of aid with respect to dropout risks. The dropout risk for the students from high income families was only 60% of that for low income students. Students whose parents had a bachelor's degree or above were only 64% as likely to dropout as those students whose parent completed high school or less. The predicted probability of dropout for low and middle income students (both without Pell grants) were 57% and 16% respectively. However, the predicted probability of dropout for low and middle income students (both with Pell grants received) were 21% and 25% respectively. So, receiving a Pell grant helped attenuate the income-dropout relationship, particularly for the low income students. This result was particularly alarming because over the years there was a trend of dramatic shift in college student aid from grants to loans. From 1994 to 1995, the total student loans increased by 130% while the grant aid increased by only 86%. The larger the ratio, the lower was the SES of undergraduate students attending the institution. Further research could focus on the effects of the amount of financial aid on dropout risk.

Alon (2005) used a procedure called Instrumental Variable Probit to separate the effect of aid eligibility from the influence of aid amounts on academic outcomes. The blending of these two effects has led to inconsistent results in prior researches on the impact of financial aid on academic outcomes. The results showed that the negative relationship between grant eligibility and graduation masked the positive impact of financial aid on graduation. The eligibility of grants, loans and work-study decreases the probability of graduation in six years by 40%, 18% and 47% respectively. However, the amount received on grants, loans and work-study increases the probability of graduation in six years by 6%, 4% and 23% respectively. Alon hypothesized that financial aid should positively affect college outcomes by reducing the need of students to direct time away from academic activities. However, financial aid exerted different effects on different income groups of students because aid eligibility status of the students may indicate other un-modeled factors that could independently affect the student outcomes in different groups. This was a model misspecification problem because some variables that could affect the outcomes were not included in the model.

Besides the common use of entering students' SAT/ACT scores as indicators of institutional selectivity, some researchers also used tuition to reflect institutional selectivity. Tuition reflected both institutional resources and selectivity (Scott et al., 2006). The weighted average tuition and fees represented the cost of not graduating in a given time frame. Delayed graduation led to higher tuition costs. Tuition may also reflect perceived quality of the institution. So, tuition was positively related to graduation rates (Goenner & Snaith, 2003).

Effects of Institutional Expenditures on Graduation Rates

The effects of institutional expenditures on graduation could cause confusion to researchers because these effects were not direct effects but were indirect effects. In other words, the effects of institutional expenditures manifested through the associated educational programs and services provided to the students. On this issue, Pike, Kuh and Hayek (2006) asserted, “To date, the few studies of expenditures and college outcomes have produced inconsistent findings, making it impossible to derive a robust theoretical or conceptual framework for guiding research in this area” (p. 849).

Using logistic regression to analyze the data from the College Board’s American Survey of Colleges and IPEDS, Scott, Bailey and Kienzl (2006) found positive effects on graduation rates using the following predictors: SAT scores, proportion of female students and instructional expenditures per full-time equivalent (FTE) student.

Gansemer-Topf and Schuh (2006) employed multiple regression to examine the effects of institutional selectivity and expenditures on retention and graduation rates of 466 private Baccalaureate Liberal and General institutions using data from the Integrated Postsecondary Education Data System (IPEDS), the US News and World Report America's Best Colleges of 2001, and Barron's Profiles of American Colleges of 2001. Discriminant analysis was used to classify institutions into two subgroups based on selectivity (high versus low). Regression analyses were conducted on each group to predict their retention and graduation rates using institutional expenditures as predictors.

The categories of institutional expenditures were instruction, academic support, student services, institutional support and institutional grants. The goal was to determine the effects of institutional expenditures on retention and graduation rates at differing levels of institutional selectivity. The results showed that institutional expenditures accounted for 63% of the variance in retention rates, half and one third of which was explained by institutional selectivity in the high selectivity group and low selectivity group respectively. Institutional selectivity and the expenditures in instruction and institutional grants were the most important predictors. The findings indicated that institutional expenditures were a much more important factor to predict retention and graduation rates for less selective institutions than more selective institutions. Using percentage institutional expenditures as predictors, Gansemer-Topf and Schuh roughly produced the same results, indicating that effects of institutional expenditures on retention and graduation rates were similar in wealthy and non-wealthy institutions alike. The institutional expenditures per student were computed by dividing the amount of expenditures of each category by the institution's full-time equivalent (FTE) enrollment.

Ryan (2004) examined the impact of institutional expenditures on six-year cohort graduation rates at 363 Carnegie-classified Baccalaureate I and II institutions based on IPEDS dataset for 1996. Ordinary least square (OLS) regression was used to analyze the data. The expenditure variables were calculated as per full-time equivalent (FTE) student measures. Log transformations were applied to the expenditure variables based on the principle of diminishing marginal productivity of inputs in production theory. The control variables included academic preparation, gender, ethnicity, age, institutional size, living on campus, institutional affiliation and institutional control. The regression model accounted for 75% of the variance in the six-year graduation rates. The results showed that instructional and academic support expenditures produced a positive significant effect on cohort graduation rates. Student service expenditures did not appear to have a positive or significant effect on degree attainment. Institutional support expenditures had an insignificant negative effects on graduation rates, probably because of the negative implications of certain regulatory burdens, litigation and other mandatory requirements.

In another study, Ryan (2005) examined the relationship between institutional expenditures and student engagement based on data from 142 colleges and universities. The data came from the Integrated Postsecondary Education Data System (IPEDS), the National Survey of Student Engagement (NSSE) and *U.S. News and World Report's* “America's Best Colleges.” OLS multiple regression was used to predict student engagement using institutional expenditures as predictors. The regression model accounted for 36% of the variance in student engagement. The results showed that administration expenditures were negatively related to student engagement. However, expenditures in the instructional, academic support and student service categories did not have a significant relationship with student engagement. The explanation of these relationship was yet to be explored in further research.

Pike, Kuh and Hayek (2006) conducted research on the relationship between different types of expenditures and student engagement and compared these relationships between first-year and senior students attending public and private institutions. The data were drawn from various sources. Student engagement data came from the National

Survey of Student Engagement (NSSE) in spring 2001. Institutional characteristics and expenditures came from the 2000–2001 IPEDS dataset. And institutional selectivity measure was based on *U.S. News* ratings. “Six types of expenditure measures were obtained from the IPEDS finance survey: (1) instruction, (2) research, (3) public service, (4) academic support, (5) student services and (6) institutional support” (p. 856) . In order to account for the relationship between institutional size and expenditures, the six expenditure measures were divided by undergraduate FTE enrollment. In addition, log transformations of these measures were utilized to account for the diminishing marginal productivity of inputs. The results showed that institutional characteristics and expenditures were significantly and positively related to all five NSSE benchmarks, accounting for 32% of the variance in the dependent variables in the first-year group and accounting for 22% in the seniors group attending public institutions. Similar results were obtained for the private institutions. The results also indicated that attending a doctoral-research university was negatively related to student engagement. Money did not appear to be an important factor in creating a supportive, affirming campus environment. Pike, Kuh and Hayek (2006) proposed that the effects of expenditures on student outcomes were indirect because they were mediated by levels of student engagement. They also believed that the relationship was contingent on a variety of institutional and individual characteristics such as institutional control and student class level. The results and effect sizes of Pike, Kuh and Hayek’s research were consistent with Ryan’s (2005) results. Although these studies were not on graduation rate but on student engagement, as stated earlier, student engagement was positively related to student persistence.

Institutional Characteristics Related to Social Environment

Past literatures on college retention indicated that academic and social attachment were the two most important factors affecting persistence and attainment (Pascarella & Terenzini, 1991). So, institutional and social policy designed to increase retention were often focused on strengthening student attachment through student services and quality residential life. Pascarella and Terenzini (1991) found the following factors to have positive impact on graduation rate: entering SAT scores, family income, private and residential institutions and other institutional characteristics promoting social integration such as residential campus. Institutional size was negatively related to graduation rate.

Astin (1997) also found that several institutional factors which had impact on retention rate were student's major field, percentage of new students living in residence halls during freshmen year and institutional size. Institutions with more students in business, psychology, or other social sciences tended to have higher retention rate whereas institutions with more students in engineering tended to have lower retention rate. Institutions with more freshmen students living in residence halls tended to have higher retention rate and vice versa. Institutional size tended to have a negative effective on retention.

Based on the fixed characteristics and state fixed-effect, Bailey et al. (2006) found that colleges located in urban areas had 3.7% lower graduation rates than those located in suburban areas. Based on the compositional characteristics, larger community colleges, especially those with more than 2500 FTE students, had a 9% to 13% lower graduation rate than do smaller colleges.

Scott, Bailey and Kienzl (2006) used the American Survey of Colleges (ACS; The College Board, 1999) and IPEDS datasets to build a regression model on six-year graduation rates based on predictors such as institutional resources, student academic characteristics, the traditionality of student attendance patterns, race/ethnicity and gender. The purpose of Scott, Bailey and Kienzl's study was to assess institutional performance. The growth of non-traditional students, who were usually characterized as older and commuting, over the past few decades may necessitate the modification of Tinto's college dropout theory which was focused on social and academic integrations as the two main factors for retention. While traditional students were more engaged by social and residential life on campus, non-traditional students were more affected by age and goals. Public institutions tended to have more commuters and older students than the private institutions.

Institutional Characteristics Related to Academic Environment

Just as some institutional characteristics were related to the social environment, other institutional characteristics were related to the academic environment in college. Both had impacts on graduation rate in different ways. The institutional characteristics related to the academic environment included percentage of full-time faculty and faculty to student ratio. Both indicators could be derived from the IPEDS data.

According to Goenner and Snaith (2003), the percentage of full-time faculty may reflect the institutional inputs into the production process both quantitatively and qualitatively. Full-time faculty may have more time available for teaching and academic advising. Full-time faculty may also be more involved in faculty responsibilities than part-time faculty who may have more competing roles and responsibilities to juggle. This percentage was positively related to graduation rates. Student-faculty ratio was positively related to graduation rates. Astin (1993) argued that the student-faculty ratio was a weak negative predictor of graduation rate by affecting the student's satisfaction and perception of institutional quality. But Goenner and Snaith (2003) suspected that this ratio may be positively correlated with some kind of academic support systems such as advisement, tutoring and honors programs.

Jacoby (2006) used multiple regression analysis to study the effects of part-time faculty ratio and faculty-student ratio on graduation rates of all 1,209 public communities in the United States. The data came from the IPEDS 2001 dataset. Other predictor variables included tuition, percentage of students who received financial aid, minority student percentages, part-time student ratio, college size and some state level predictors. The effect size was about 37%, half of which were explained by state level predictors. This was an indication of a need of using multi-level analysis to analyze the effects of institutional predictors and state level predictors and their interaction. The results showed significant negative effect of part-time faculty ratio and positive effects of faculty-student ratio on graduation rates. Colleges which had high part-time faculty ratio and low faculty-student ratio had the lowest graduation rates. Colleges which had low part-time faculty ratio and high faculty-student ratio had the highest graduation rates. Benjamin (2002) reasoned that part-time faculty tended to be less available and may use less challenging instructional methods. Over-reliance on part-time faculty may hinder students' social and academic integration because of less student-faculty interaction both in quantity and quality. This would adversely affect student outcomes and graduation rates. “Schools that seek to stretch their instructional dollars by increasing their part-time faculty ratio will find this counterproductive if they are held accountable for higher graduation rates” (Jacoby, 2006, p. 1097).

Three reasons had been mentioned for using institutional-level data, as opposed to student-level data, to analyze the effects of part-time faculty on graduation rates. First, institutions were held accountable for their graduation rates as a performance indicator. Second, institutions were a natural unit to study because many decisions regarding educational programs, resource allocation and policy were made at the institutional level. Third, the full-time and part-time distinction about faculty was made at the institutional level (Jacoby, 2006).

Conclusion: Institutional Model of College Performance

So far, many institutional attributes have been explored concerning their effects on graduation rates or institutional performance. Jacoby (2006) summarized as follows. Tuition was expected to have negative effect on graduation rates because it increased the financial costs for the students to go to college. Financial aid received by the students should had positive effect on graduation rates. But the percentage of students receiving financial aid may be an indicator of lower income students who tended to have lower graduation rate. Urbanization may have negative effect of graduation rates because it provided more alternative opportunities to students. Large school size should have negative influence on graduation rates. Part-time student ratio should negatively impact graduation rates because many part-time student were not seeking degree certificates.

While these results were important to the understanding of the puzzle of what may be causing the wide differences in graduation rates among different institutions and how graduation rates should be interpreted, however, each of these institutional attribute taken alone would not be sufficient to understand the whole picture of institutional performance. Effort needs to be made in future research to examine all the institutional attributes relevant to explaining graduation rates and institutional performance in a tight and theory based model, like Tinto's model. This kind of institutional model is important in benchmarking an institution's performance because it provides a mechanism not only to compare the outcome variable but also to compare the predictor variables and their interrelationships. Such model can be subject to rigorous testing technique such as structural equation modeling (SEM). This kind of model, however, is difficult to build because there are many interrelationships among the institutional-level predictors as well as between the institutional-level predictors and student-level predictors. One approach to make this task more manageable is to first build the institutional model based on the basic structure of Tinto's model; and second, connect the institutional model with Tinto's model using multi-level SEM. The basic structure of Tinto's model includes the precollege/background variables, initial and subsequent commitment variables, college integration variables and the persistence variable. These variables are interrelated in a longitudinal process. There are several advantages of using this structure to build the institutional model of college attainment. First, Tinto's model is a tested model and using its structure to build the institutional model will minimize the specification error. Second, both models explain the same underlying reality which is students' outcomes through their social and academic experiences in college. Therefore, both models should have similar structure although the institutional model is at the aggregate level and should have a wider context. Third, most of the constructs in Tinto's model can be measured at the institutional level. For example, the institutional SES can be measured by the percentage of students receiving Pell grants. Institutional size, urbanization and residential status are related to the social environment. Faculty to student ratio and percentage of full-time faculty are related to the academic environment. Fourth, the two models are easier to be connected by multi-level SEM because they have similar structures.

Finally, Archibald and Feldman (2008) cautioned that universities are multi-product firms. There was no single outcome measure that was good enough to measure the performance of universities. Because different types of degrees may take vastly different resources to complete, their graduation rates may not be readily comparable. So, graduation rates should be compared within certain context such as degree type and type of institutions. This caution was even truer in building a model to measure institutional performance because any model was a simplification of reality and most will agree that colleges and universities were very complex institutions.

Multi-level Research on Student Persistence

Multilevel modeling technique (e.g., HLM or HNLM) had well-established methodological advantages over standard regression techniques for handling multi-level nested datasets. It was a powerful technique to analyze the effects on the dependent variable from different level of predictors, such as individual level and institutional level (Kim & Conrad, 2006). Other levels included state level and regional level. Traditional statistical methods were single-level and the unit of analysis was usually at the individual level. One common way to handle multilevel data was to disaggregate group-level information to the individual levels. But this leads to two problems (Luke, 2004).

> First, all the un-modeled contextual information ends up pooled into the single individual error term of the model (Duncan, 1998). This is problematic because individuals belonging to the same context will presumably have correlated errors, which violated one of the basic assumptions of multiple regression. The second problem is that by ignoring context, the model assumes that the regression coefficients apply equally to all contexts (p. 7).

Two-Level Research: Student and Institution

A few researchers had used the hierarchical linear modeling (HLM) technique to study student outcomes in higher education. Strauss and Volkwein (2002) examined student performance and intellectual growth at 51 public institutions of higher education in the State University of New York System (SUNY), of which 23 were four-year institutions with 2,576 students and 28 were two-year institutions with 5,082 students. Student-level data were collected by surveys and institutional-level data were derived from the 1996-1997 IPEDS datasets. Data were analyzed using SPSS statistical software and hierarchical linear modeling (HLM) statistical software. Strauss and Volkwein's study had two goals: (1) to examine the structural/organizational characteristics that influence student performance and intellectual growth; and (2) to compare the results of this examination using both traditional OLS regression and HLM. The two dependent variables were: (1) student perceptions of growth from students' self-assessment and (2) faculty perceptions of student learning measured by the cumulated GPA. The independent variables were: (1) student precollege characteristics (such as age, gender, ethnicity, SES, SAT score and high school rank); (2) structural/organizational characteristics of institutions (such as size, wealth, complexity, mission and selectivity); (3) financial need/aid as an objective measure of student need and socioeconomic status; (4) goal clarity and encouragement scale; (5) academic experiences and interactions with agent of socialization scale; (6) institutional environment/climate scale; (7) student effort and involvement; and (8) institutional commitment. The results showed that most of the variance in the outcome variable was explained by the student level predictors. HLM analysis revealed a steeper slope for percentile rank and classroom experiences, indicating that high school rank and classroom experiences were more predictive of cumulated GPA at four-year than two-year institutions. "Hierarchical models allow researchers to arrive at more accurate results by taking into account the nested structures of the institution's subenvironrnents" (p. 134). HLM was based on OLS regression, but the regression coefficients could be treated as random effects by including an error term for the level 1 (student effects) in the level 2 (institution) model. The result was a decomposition of variance of the dependent variables into within institution and between institution effects. The level 1, or student variables, were "nested" within the level 2 units, the individual institutions. Because trustees and government officials were turning to performance indicators as signs of institutional effectiveness and as justification of education funding, it was especially important to know if particular structural/organizational characteristics were significantly associated with positive student persistence, learning and growth.

Multi-level research is also powerful to uncover the institutional impacts on minority students' performance in college. African American students scored far below their White counterparts on undergraduate admission tests. Black students at Historically Black Colleges and Universities (HBCUs) tended to have even lower high school GPAs and SAT scores compared with Black students attending Historically White Colleges and Universities (HWCUs). Black students attending HBCUs also tended to come from families with lower socioeconomic status than those of their counterparts attending HWCUs. The quality of the faculty, facilities, available academic programs and opportunities for advanced study were often poorer at HBCUs. Kim and Conrad (2006) used hierarchical nonlinear modeling (HNLM) and the Cooperative Institutional Research Program (CIRP) dataset to examine the impact of HBCUs on the academic success among a sample of African American students, including 401 students in 10 HBCUs and 540 students in 34 HWCUs. Bachelor's degree completion was the dichotomous dependent variable. The independent variables were broken into two levels, student-level and institutional-level, to distinguish the effects on degree completion due to individual student characteristics and due to institutional characteristics. The individual-level predictors included high school GPA, SAT scores, age, initial degree aspiration, gender and family socioeconomic status (parental income and mother's education). All individual-level variables were centered around their grand means in order to control for differences in student composition among institutions. "Grand-mean centering equalizes institution-level units on each predictor at the individual level; in other words, institutions are adjusted for the differences of students on each individual-level predictor" (p. 411). The institutional-level predictors included Black college status (vs. White college status), selectivity (mean SAT scores), public vs. private college status and student enrollment, as well as other internal college characteristics. These internal characteristics included expenditures, faculty, curriculum, percentage of total instruction-related expenditures and instruction-related expenditures per full-time-equivalent (FTE) student. The results showed that while no significant difference was found between HBCUs and HWCUs in terms of degree completion among African American students, HBCUs had much lower resources both in terms of students' pre-college academic preparation and in terms of physical resources such as lower faculty salaries. One reason could be the higher student involvement in academic research with faculty in HBCUs. So, HBCUs seemed to be doing a remarkable job to help the less prepared students succeed with less amount of resources.

Two-Level Research: Institution and State

Some state level attributes may have significant impact on institutional performance and graduation rates. For example, the percentage of state population who go to community college had a significant positive effect on graduation rates in community colleges because more qualified or better-prepared students were being produced in the state. The ratio of community college students relative to all postsecondary students in the state had significant negative effects on graduation rates in community colleges because more qualified students would have gone to four-year universities. Some states, such as California and Florida, had significant higher graduation rates in their community colleges. The governance structure or other state policies may have contributed to the differences (Jacoby, 2006).

Volkwein and Tandberg (2008) used *Measuring Up* data from 2000, 2002, 2004 and 2006, to examine the extent to which the state performance grades and changes in grades were associated with the characteristics of each state and its arrangements for higher education governance and control. Time series analysis and OLS regression were used to analyze the data. The conceptual framework used in this study was Input-Process-Output (IPO) model where state characteristics were the inputs, state governance and regulatory practices constituted the processes and the *Measuring Up* grades and changes in grades were the outcomes. The state characteristics included state size, personal income, state wealth/poverty, population growth/mobility, levels of education/demand, private sector strength, state appropriations per capita and state higher education appropriation change. The results showed that state characteristics accounted for the majority of variances in all five performance areas of the *Measuring Up* data (from 43% in Completion to 60% in Affordability) whereas state governance and regulatory practices accounted for only minimal variance (from 0% to 8%). No state characteristic dominated across all performance areas, but state characteristics collectively appeared to have the strongest influences on Affordability and Preparation. Thus different state characteristics appeared to exert differential influences on the *Measuring Up* index scores. However, none of the state governance structure, accountability practices and regulatory behaviors had any statistically significant connection to Completion, Participation and Preparation.

> Affordability appears to be heavily influenced by population size, growth in high school graduates, tax effort …, having an industrial economy … Benefits is positively associated with income per capita … Completion is heavily influenced by private sector enrollment strength, which is consistent with higher graduation rates among private institutions in the aggregate. However, Completion is negatively associated with growth in high school graduates, student mobility and voter turnout. Participation is significantly higher in states with higher per capita income and with a more high tech economy, by negatively associated with voter turnout. Preparation … is positively associated with per capita income and adult degree attainment and negatively associated with population growth (p. 190).

Other Considerations of Student Persistence Research

Single- versus Cross-institution Sample

Most of the studies conducted on student retention were based on single-institution samples. The results of these studies may not be generalizable to other institutions (Caison, 2007). Kuh et al. (2008) had the same concern: “However, most of the research examining the connections between student engagement and college outcomes is based on single institution studies that do not always control for student background characteristics, limiting their generalizability to specific institutions or institutional types” (p. 542). Of course, institutional-level research would not have this problem because institution was the unit of analysis and a sample of institutions was used in the analysis.

From the retention professional's perspective, the costs and expertise required to conduct retention research may be formidable. If widely available data, which may not be collected specifically for retention purpose, such as enrollment data could be used to predict student retention, it would be a big advantage to devise retention programs based on these widely available data. Caison (2007) used the information-theoretical approach to demonstrate how to achieve this strategy. She compared the predictive power of four logistic regression models using the Akaike Information Criterion (AIC). Data were collected on a sample of 1,513 freshmen from North Carolina State University. One of the models was developed from a survey using Pascarella and Terenzini's (1980) Institutional Integration Survey (IIS) scales. The other models were based on existing databases of the university, such as Institutional Database (IDB), Student Data File (SDF) and First Year Survey (FYS). The results showed that the models from IDB and FYS outperformed the model from IIS.

Cross-Sectional Versus Longitudinal Research

Student persistence is a longitudinal process because student dropout behavior and integration are developed over a period of time. In fact, Tinto's original conception of his model for college dropout was a longitudinal model. That was why the initial institutional and goal commitments were measured before the students entered college and their subsequent commitments were measured after the social and academic integration processes had taken place in college. However, most researchers used two point measurements mostly one year apart. The rationale was that most college dropouts occurred in the first year of college. The implication was that most retention programs were focused on the pre-college orientation programs and the first year retention programs. However, very few researchers had endeavored to study students' persistence behavior throughout the college years. One reason for that was the limited resources researchers could use. Longitudinal research required more resources because it took longer time to conduct. Longitudinal research also required special analytical methods, such as growth modeling and survival analysis. Most researchers of college persistence were unfamiliar to these techniques. Another approach to do longitudinal research was using qualitative method such as case study and ethnographic research. However, these kind of qualitative research cannot provide the generalizability most researchers of college persistence will want.

Obviously, Tinto was aware of these limitations in his original model. Some years later, Tinto (1988) took an ethnographic turn to describe the longitudinal nature of student departure from college. He borrowed from the "rites of passage" theory of Arnold Van Gennep, a Dutch anthropologist, whose work was related to the rites of membership in tribal societies and the movement of individuals through time in a way that promoted social stability in times of change. Van Gennep described the movement in three stages: (1) separation which involved the separation of the individual from past associations; (2) transition which involved the person's beginning interaction in new ways with members of the new group; and (3) incorporation which involved taking on the new patterns of interaction with members of the new group. Social movement entailed changes from familiar norms to unfamiliar new set of norms, often resulting in feelings of weakness and isolation, a description similar to what Durkheim called “anomic” character of changes. Without early assistance, the individual was left in a state of at least temporary normlessness, which might lead to departure from the new community prior to incorporation. This process was also applicable to college students especially in their first semester in college. According to the theory called stages of student departure, retention required students to break away from past communities in the transition stage. But then it was believed that some if not many students, however, persisted by keeping connected to their past communities, family, church, or tribe. Using Van Gannep’s “rite of passage” methodology recommended by Tinto (1988), Christie and Dinham (1991) conducted a qualitative research to investigate the longitudinal dropout process over five years among 25 freshmen at a large public research university. The “rite of passage” involved three phases: (1) separation from past communities, (2) transition into the new college community and (3) incorporation into the college community. The results were largely confirming to Tinto's theory. They also found that external experiences directly interacted with institutional experiences to influence social integration.

Practical Implications of Student Persistence Research

According to Tinto (2006), current theories of student retention utilized abstractions and variables, such as social and academic integration, which were often difficult to operationalized to guide retention practices in institutions. Other variables, such as student high school experiences and family background, were out of direct control or influence of the institutions. Faculty members did not feel responsible for student retention because it was not connected to student learning which was within faculty’s responsibilities. So, investment in faculty development was not tied to student retention. Most institutions had not been able to translate theory into action in the area of student retention. Three lessons had been learned. First, it was one thing to understand why students leave; it was another to know what institutions could do to help students stay and succeed. Second, it was one thing to identify effective action; it was another to implement it in ways that significantly enhanced student retention over time. Third, low-income students were still less likely to graduate than the high-income students even though the gap between them for access was narrowed.

Concerning retention programs, Tinto (1982) mentioned three characteristics of successful retention programs: (1) they were often longitudinal in nature; (2) they were almost always closely tied to the admission process; and (3) their implementation generally involved a wide range of institutional actors. Concerning orientation programs, Tinto (1988) suggested that institutions of higher education employed various programs to make the separation-transition-incorporation process easier for the new students. Orientation programs were becoming increasingly popular forms of introduction to college life. Other programs included fraternities, sororities, student dormitory associations, student unions, frequent faculty and visiting scholar series, extracurricular programs and intramural athletics. Most orientation programs only focused on a few day event. Better results may be obtained by extending the orientation program to a series of activities spanned over the first semester. Based on Van Gennep's theory, institutions could do well to employ public rituals and ceremonies as part of their retention programs.

In a research about learning communities, Tinto (1997) presented a mixed method (quantitative and qualitative) study of one college, Seattle Central Community College, in its Coordinated Studies Program (CSP) for enriching student classroom experience through learning communities and collaborative learning strategies. The results of CSP students were not only improved retention but also improved learning experience compared with the non-CSP students. In CSP, students registered a set of classes together forming small learning communities in which they strengthened their academic and social integrations at the same time by fostering each other’s learning inside and outside the classroom. The faculty of CSP also structured their curriculum and classroom activities to increase students' active involvement and engagement in learning. As a result, students made more friends and learned better. Courses were offered in packages with organizing themes in a semester to promote coherent interdisciplinary learning. The organizational reforms proposed to improve persistence were: (1) adopted a community model of academic organization that would promote involvement through the use of shared and connected learning; (2) reorganized the first year of college as a distinct unit; and (3) reorganized faculty work to allow them to become cross disciplinary and departmental community also. Two things common to all learning communities were: (1) shared knowledge by which students shared coherent educational experience in array of connected courses and (2) shared learning by which the students were enrolled in several classes together to promote social and intellectual involvement. Three benefits of learning communities were: (1) students connected to their supportive peer groups which extend beyond the classroom; (2) students became more actively involved in classroom learning even after class; and (3) students learned more as they spent more time learning.

In another example, DesJardins (2001) used microeconomic theory to investigate the sensitivity of the price-response function of different ability target group of students to different levels of institutional grant received. The sample included 18,173 students admitted to the University of Iowa from 1997 to 1998. DesJardins used a simulation tool built on Excel spreadsheet to demonstrate the effects on net tuition revenue based upon different assumptions of enrollment yields per $1,000 aid increase and discount amount for each target group. Financial aid was also an important factor to attract highly qualified students. The simulation results showed differential effects of aid amount on the enrollment of different ability group of students. These were important information for strategic planning. Studies about the effects financial aid on enrollment management should be presented in a way college administrators and policy-makers could easily understand. Interactive simulation tool could be very useful to provide instant results based on different assumptions and inputs. This information could facilitate communication, forge consensus and focus on strategic issues among different institution stakeholders. Although this example was not directly related to graduation rates or student persistence, similar approach could be used to project graduation rates or dropout rates at different levels of institutional variables based on certain constraints that could be empirically verified in a structural model.

Conclusion

So far, an extensive review of the literature regarding student persistence and graduation rates has been presented. As these subject matters are better understood in light of the works of many researchers, the complexity of the problems also increases and more works are yet to be done to fully understand the roles of different constructs at different levels (student, institutional, state and regional) and their interrelationships and effects on the outcome variables, namely student persistence and graduation rates.

From a theoretical perspective, Tinto's model for dropout from college was the most successful model and it elicited more research than any other competing model. Tinto (1998) concluded with the following four known effects concerning student persistence. First, involvement mattered. Persistence increased as interaction between students and faculty increased. Second, social and academic integration not only influenced persistence separately but their synergy could generate a greater effect on persistence. Third, social and academic integration had different effects on two-year and four year institutions. Fourth, involvement mattered most during the first year of college.

Many researchers had examined the effects of institutional attributes on graduation rates, but few had studied the interrelationship of these institutional attributes nor developed a theoretical model to explain them as a whole. Tinto's theory could serve as the guiding theory to develop such institutional model. Multi-level modeling technique, such as Multi-level SEM, could help bring Tinto's model and its institutional counterpart to better understand the effects of determinants of student persistence and graduation rate at a hierarchical data structure.

CHAPTER 3

METHODS AND PROCEDURES

The purpose of this study is to develop a model of institutional performance in graduation rates for four-year, public and private not-for-profit, Title IV institutions in the United States. This study validates the institutional model based on the IPEDS dataset using the structural equation modeling (SEM) technique. The institutional model is based on the basic structure of Tinto's (1975) theory of college dropouts. This model explains the process of college persistence in terms of graduation rate and other institutional characteristics derived from the IPEDS dataset. The following areas are discussed in this chapter: (1) research questions, (2) research design, (3) description of the population, (4) analysis of data, (5) validity and reliability, (6) assumption and (7) limitations.

Research Questions and Hypotheses

This study tests the model of institutional performance in graduation rates (see Figure 2) by answering the following research questions. Question 1 is related to finding the differences in graduation rates between groups of institutions based on control, gender, race/ethnicity, state and geographical region. Question 2 is related to testing the measurement models of the unobserved variables (background, finance, academic environment and social environment) by the observed variables. Question 3 is related to testing the structural model represented by the paths between exogenous and endogenous variables (background, finance, academic environment, social environment, commitment and graduation rate).

1. Which groups of institutions have significantly different graduation rates compared with other groups of institutions based on control, geographical region, state, Carnegie classification code, degree of urbanization, religious affiliation and regional accreditation agency of the institutions?
2. What are the validity and reliability of the factor models of student background, student finance, academic environment and social environment to measure the underlying constructs in the institutional model of graduation rates?
3. To what degree does the overall institutional model of graduation rates fit the dataset and its subsets based on the groups of institutions identified by answering the first research question?

Below are the research hypotheses to be tested in this study.

H1. There are significant differences in the graduation rates between groups of institutions based on control, geographical region, state, Carnegie classification code, degree of urbanization, religious affiliation and regional accreditation agency of the institutions.

H2. The validity and reliability of the factor models of student background, student finance, academic environment and social environment are established to measure the underlying constructs in the institutional model of graduation rates.

H3. The institutional model of graduation rates fits the dataset and its subsets based on the groups of institutions identified by answering the first research question.

Research Design

The research design of this study consists of two main components. First, the six-year graduation rate (the dependent variable) is regressed on several grouping variables to identify groups of institutions which have significant different graduation rates than other groups (see research question 1). These groups are used to segregate the dataset into subsets for the next step of analysis. The subgroup datasets should have more homogeneous characteristics and should yield more stable statistical results. Second, a SEM model based on the model of institutional performance in graduation rate is developed and fit on each of the subgroup dataset. This step is broken down into two stages: (1) building and validating the measurement model of the SEM model (see research question 2) and (2) building and validating the structural model of the SEM model (see research question 3). Schumacker and Lomax (2004) comment, "According to the two-step approach, the validity of the measurement model is to be established before proceeding to the second step of evaluating structural model… Essentially, the measurement model is evaluated through confirmatory factor analysis" (p. 887). They summarize the steps for SEM as follows:

> Thompson (2000) provided guidance for conducting structural equation modeling by citing key issues and including a list of 10 commandments for good structural equation modeling behavior: (a) do not conclude that a model is the only model to fit the data, (b) test any respecified model with split-sample data or new data, (c) test multiple rival models, (d) evaluate measurement models first, then structural models, (e) evaluate models by fit, theory and practical concerns, (f) report

multiple model fit indices, (g) meet multivariate normality assumptions, (h) seek parsimonious models, (i) consider a variable scale of measurement and distribution and (j) do not use small samples (pp. 231-232).

These ten steps provide good guidance in developing and evaluating the SEM model in this research.

To answer research question 1, hierarchical multiple regression analysis with planned contrasts are conducted in SPSS software to compare the group mean differences in six-year graduation rate among different groups based on gender, ethnicity, control, geographical regions, states, Carnegie classification code, degree of urbanization, religious affiliation and regional accreditation agencies. These are categorical independent (or grouping) variables and their contrast variables are entered into the regression model hierarchically to examine their effects on the dependent variable by grouping variable and as a whole in the model. The planned contrast variables are coded in orthogonal coding method. “Two comparisons are orthogonal when the sum of the products of the coefficients for their respective elements is zero. As a result, the correlation between such comparisons is zero" (Pedhazur, 1997, p. 376). “The maximum number of orthogonal comparisons possible in a given design is equal to the number of groups minus one...” (p. 377). “The primary implication is that orthogonal contrasts provide non-overlapping information about how the groups differ” (Maxwell & Delaney, 2004, p. 180). Table 1 presents the orthogonal planned contrast variables and their values. The first group of predictor variables for main group effects are A1, B1, B2 and B3. The predictor variables for interaction effects are A1B1, A1B2 and A1B3, which are computed by multiplying the values of the respective contrast variables. The second group of predictor variables for main effects are C1, D1 to D7 and the predictor variables for interaction effects are C1D1 to C1D7. The third group of predictor variables for main effects are C1, E1 to E7 and the predictor variables for interaction effects are C1E1 to C1E7. Similarly, the next four groups of predictor variables are F1 to F5, G1 to G6, H1 to H4 and I1 to I5. The hierarchical regression model with planned group comparisons will identify the groups and their interactions which have significant differences in six-year graduation rates. The results will be used to segregate the dataset into subsets for validating the model of institutional performance (see Figure 2) in different groups of institutions using the SEM group comparison technique.

To answer research question 2, four factor models are developed and tested using confirmatory factor analysis (CFA). These factor models measure the four main constructs used in the SEM model—background, finance, academic environment and social environment. Each factor model is tested on each of the subgroup datasets based on the groups which have significant differences in their six-year graduation rates, using SPSS and Amos statistical software.

To answer research question 3, a SEM model is built by connecting all the components (four constructs, retention rate and graduation rate) in a structural model. The SEM model is tested on each of the subgroup datasets based on the groups, which have significant differences in their six-year graduation rates, using Amos statistical software. The path coefficients in the model indicate the relationships (both magnitude and direction) between the predictor variables and between the predictor variables and the criterion variable (graduation rate). These path coefficients are tested for their statistical significance. The explained variance in the criterion variable indicates the predictive power of the model. The residual variances in the observed variables indicate their measurement error to measure the respective constructs. The residual variances in the endogenous variables indicate their unique variances unexplained by their exogenous variables. The overall fit of the SEM model is evaluated by the model fit indices. Table 2 presents the model fit indices and their interpretation.

Finally, the SEM model is tested simultaneously on multiple subgroup datasets using the group comparison technique in Amos software. Path coefficients, explained variances in endogenous variables and overall predictive power are evaluated across multiple groups of institutions. Although all the subgroup datasets can be compared in one group comparison analysis, the results will be difficult to analyze and the model is more difficult to converge on large number of subgroup datasets. It is better to run several group comparison analyses and specific groups are compared in each analysis. For example, public institutions in New England region are compared with public institutions in Southwest region for their performance in graduation rate.

Table 1

Orthogonal Planned Contrast Variables

Grouping Variables	Contrast Variables						
Gender	A1						
Male	1						
Female	-1						
Ethnicity	B1	B2	B3				
Asian or Pacific Islander	3	0	0				
White non-Hispanic	-1	2	0				
Hispanic	-1	-1	1				
Black non-Hispanic	-1	-1	-1				
Control	C1						
Public	1						
Private (not for profit)	-1						
Geographical Region	D1	D2	D3	D4	D5	D6	D7
New England	7	0	0	0	0	0	0
Mid-East	-1	6	0	0	0	0	0
Great Lakes	-1	-1	5	0	0	0	0
Plains	-1	-1	-1	4	0	0	0
Southeast	-1	-1	-1	-1	3	0	0
Southwest	-1	-1	-1	-1	-1	2	0
Rocky Mountains	-1	-1	-1	-1	-1	-1	1
Far West	-1	-1	-1	-1	-1	-1	-1
State	E1	E2	E3	E4	E5	E6	E7
Massachusetts (MA)	7	0	0	0	0	0	0
Pennsylvania (PA)	-1	6	0	0	0	0	0
California (CA)	-1	-1	5	0	0	0	0
New York (NY)	-1	-1	-1	4	0	0	0
Ohio (OH)	-1	-1	-1	-1	3	0	0
Illinois (IL)	-1	-1	-1	-1	-1	2	0
Florida (FL)	-1	-1	-1	-1	-1	-1	1
Texas (TX)	-1	-1	-1	-1	-1	-1	-1

(*table continues*)

Table 1 (*continued*)

Grouping Variables	Contrast Variables					
Carnegie Classification Code	F1	F2	F3	F4	F5	
Bacc. Colleges—Liberal Arts	5	0	0	0	0	
Research Universities—Extensive	-1	4	0	0	0	
Masters Colleges and Univ. II	-1	-1	3	0	0	
Bacc. Colleges—General	-1	-1	-1	2	0	
Research Universities—Intensive	-1	-1	-1	-1	1	
Masters Colleges and Univ. I	-1	-1	-1	-1	-1	
Degree of Urbanization	G1	G2	G3	G4	G5	G6
Urban fringe of large city	6	0	0	0	0	0
Urban fringe of mid-size city	-1	5	0	0	0	0
Mid-size city	-1	-1	4	0	0	0
Rural	-1	-1	-1	3	0	0
Large city	-1	-1	-1	-1	2	0
Small town	-1	-1	-1	-1	-1	1
Large town	-1	-1	-1	-1	-1	-1
Religious affiliation	H1	H2	H3	H4		
No religious affiliation	4	0	0	0		
Presbyterian Church (USA)	-1	3	0	0		
Roman Catholic	-1	-1	2	0		
United Methodist	-1	-1	-1	1		
Baptist	-1	-1	-1	-1		
Regional accreditation agencies	I1	I2	I3	I4	I5	
New England Assoc. (NEASC)	5	0	0	0	0	
Western Assoc. (WASC)	-1	4	0	0	0	
Middle States Assoc. (MSACS)	-1	-1	3	0	0	
North Central Assoc. (NCACS)	-1	-1	-1	2	0	
Southern Assoc. (SACS)	-1	-1	-1	-1	1	
Northwest Assoc. (NASC)	-1	-1	-1	-1	-1	

Table 2

Model Fit Criteria and Acceptable Fit Interpretation

Model fit criterion	*Acceptable level*	*Interpretation*
Chi-square	Tabled χ^2 value	Compares obtained χ^2 value with tabled value for given *df*
Root-mean-square error of approximation (RMSEA)	< .05	Value less than .05 indicates a good model fit
Normed fit index (NFI)	0 (no fit) to 1 (perfect fit)	Value close to .95 reflects a good model fit. Compare a restricted model with a full model using baseline null model.
Comparative fit index (CFI)	0 (no fit) to 1 (perfect fit)	Value close to .95 reflects a good model fit. Measure the improvement in non-centrality from the restricted model to the full model.
Parsimonious fit index	0 (no fit) to 1 (perfect fit)	Compares values in alternative models
Akaike information criterion (AIC)	0 (perfect fit) to negative value (poor fit)	Compares values in alternative models

Note. From *A Beginner's Guide to Structural Equation Modeling* (p. 81), by R.E. Schumacker and R.G. Lomax, 2004, Mahwah, NJ: Lawrence Erlbaum Associates.

In Table 1, each contrast variable is coded to compare two specific groups or composite groups. For example, A1 is for comparing male with female groups. B1 is for comparing the average of Black non-Hispanic, Asian or Pacific Islander and Hispanic with White non-Hispanic. B2 is for comparing Black non-Hispanic with Hispanic. B3 is for comparing the average of Black non-Hispanic and Hispanic with Asian or Pacific

Islander. C1 is for comparing public and private institutions. D1 is for comparing the average New England, Mid-East, Great Lakes and Plains with the average of Southeast, Southwest, Rocky Mountains and Far West. D2 is for comparing the average of New England and Mid-East with the average of Great Lakes and Plains. D3 is for comparing the average of Southeast and Southwest with the average of Rocky Mountains and Far West. D4 is for comparing New England with Mid-East. D5 is for comparing Great Lakes with Plains. D6 is for comparing Southeast with Southwest. D7 is for comparing Rocky Mountains with Far West. E1 is for comparing the average of MA, PA, CA and NY with the average of OH, IL, FL and TX. E2 is for comparing the average of MA and PA with the average of CA and NY. E3 is for comparing the average of OH and IL with the average of FL and TX. E4 is for comparing MA with PA. E5 is for comparing CA with NY. E6 is for comparing OH and IL. E7 is for comparing FL and TX. Each of these contrasts is designed to compare two specific groups or composite groups based on *a prior* interest, which is also informed by scanning the mean graduation rates of those categories. However, the comparisons are not exhaustive because only *n-1* comparisons are allowed for a category with *n* interested levels. For example, only eight states (MA, PA, CA, NY, OH, IL, FL and TX) are selected for comparisons based on the number of institutions in a state, among which only seven comparisons are allowed.

Description of the Population

The population of this study includes all the public and private not-for-profit, Title IV, four-year institutions in the United States. There are 1,785 institutions, of which 577 (or 33%) are public institutions and 1192 (or 67%) are private not-for-profit institutions (see Table 5). The mean FTE enrollment of public institutions (8,965.74) is more than four times larger than the mean FTE enrollment of private not-for-profit institutions (2,104.51). Table 6 presents the descriptive statistics of six-year graduation rates by geographical regions, in which 9% are from New England, 20% from Mid-East, 11% from Great Lakes, 23% from Plains, 7% from Southeast, 16% from Far West and 14% from other geographical regions. Table 7 presents the descriptive statistics of six-year graduation rates by state, in which 9% are from New York, 6% from California, 7% from Pennsylvania, 4% from Massachusetts, 4% from Texas, 5% from Ohio, 3% from Florida, 4% from Illinois and 60% from other states. Table 8 presents the descriptive statistics of six-year graduation rates by Carnegie classification code, in which 14% are doctoral research institutions, 33% master institutions and 31% baccalaureate institutions. Table 9 presents the descriptive statistics of six-year graduation rates by degree of urbanization, of which 21% are in large city, 27% in mid-size cities, 23% at urban fringe, 25% in small towns and rural areas. Each institution has one six-year graduate rate per gender group and per ethnic group. Table 3 presents the descriptive statistics of six-year graduation rates by gender, in which 45% are male and 55% female. Table 4 presents the descriptive statistics of six-year graduation rates by ethnic groups, in which 10% are Black non-Hispanic, 6% Asian or Pacific Islanders, 8% Hispanic, 68% White non-Hispanic and 8% others. The IPEDS dataset used in this study is a national dataset. No sampling is needed because the population data are included in this study.

Table 3

*Graduation Rate within 150% of Normal Time (Four-Year Institutions) by Gender (*N = *1785 institutions)*

Gender	*n*[a]	% of *n*	*M*	*SD*
Male	568,422	45%	53.83	26.03
Female	694,373	55%	59.89	24.53
Total	1,262,295	100%	56.96	25.45

Source: 2007 IPEDS dataset
a. This number indicates the number of students in cohort by gender.

Table 4

*Graduation Rate within 150% of Normal Time (Four-Year Institutions) by Race/Ethnicity (*N = *1785 institutions)*

Race/ethnicity	*n*[a]	% of *n*	*M*	*SD*
Nonresident alien	25,577	2%	64.85	25.99
Black non-Hispanic	130,997	10%	48.56	25.74
American Indian or Alaska Native	9,684	1%	64.29	30.20
Asian or Pacific Islander	75,411	6%	63.07	25.27
Hispanic	103,701	8%	53.73	25.87
White non-Hispanic	864,491	68%	55.32	19.83
Race/ethnicity unknown	52,934	4%	55.65	24.47
Total	1,262,795	100%	56.96	25.45

Source: 2007 IPEDS dataset
a. This number indicates the number of students in cohort by race/ethnicity.

Table 5

*Graduation Rate within 150% of Normal Time (Four-Year Institutions) by Control of Institutions (*N = *1785, missing = 16)*

Control of institution	*n*	% of *n*	*M*	*SD*
Public	577	33%	45.86	16.16
Private not-for-profit	1192	67%	54.77	20.20
Total	1769	100%	51.87	19.43

Source: 2007 IPEDS dataset

Table 6

*Graduation Rate within 150% of Normal Time (Four-Year Institutions) by Geographic Region (*N = *1785, missing = 16)*

Geographic region	*n*	% of *n*	*M*	*SD*
US Service schools	5	0%	80.18	2.02
New England (CT ME MA NH RI VT)	163	11%	59.32	20.12
Mid East (DE DC MD NJ NY PA)	349	22%	57.50	19.48
Great Lakes (IL IN MI OH WI)	279	16%	52.15	18.63
Plains (IA KS MN MO NE ND SD)	191	11%	52.27	16.11
Southeast (AL AR FL GA KY LA MS NC SC TN VA WV)	411	21%	47.18	17.67
Southwest (AZ NM OK TX)	118	6%	42.87	19.02
Rocky Mountains (CO ID MT UT WY)	49	2%	45.44	16.05
Far West (AK CA HI NV OR WA)	161	10%	56.26	19.88
Outlying areas (AS FM GU MH MP PR PW VI)	43	1%	31.20	16.68
Total	1769	100%	51.87	19.43

Source: 2007 IPEDS dataset

Table 7

*Graduation Rate within 150% of Normal Time (Four-Year Institutions) by State (*N *= 1785, missing = 16)*

State	*n*	% of Total *n*	*M*	*S. D.*
NY New York	157	9%	55.48	22.01
PA Pennsylvania	122	7%	60.88	14.45
CA California	103	6%	58.21	19.82
OH Ohio	82	5%	54.25	18.42
MA Massachusetts	76	4%	62.22	21.18
TX Texas	72	4%	44.62	19.94
IL Illinois	62	4%	53.26	19.08
FL Florida	55	3%	48.98	17.70
NC North Carolina	55	3%	50.01	17.29
MI Michigan	54	3%	46.09	19.29
MO Missouri	50	3%	50.55	14.89
IN Indiana	46	3%	51.87	20.65
GA Georgia	45	3%	44.04	18.22
TN Tennessee	45	3%	47.93	16.84
Others	745	42%		
Total	1,769	100%	51.87	19.43

Source: 2007 IPEDS dataset

Table 8

*Graduation Rate within 150% of Normal Time (Four-Year Institutions) by Carnegie Classification (*N = *1785, missing = 16)*

Carnegie Classification	*n*	% of *n*	*M*	*SD*
15 Doctoral or Research Universities--Extensive	148	8%	69.87	15.93
16 Doctoral or Research Universities--Intensive	100	6%	51.55	16.14
21 Masters Colleges and Universities I	476	27%	48.82	15.51
22 Masters (Comprehensive) Colleges and Universities II	101	6%	48.91	13.04
31 Baccalaureate Colleges--Liberal Arts	214	12%	66.27	18.06
32 Baccalaureate Colleges--General	305	17%	45.30	15.25
Others	380	24%		
Total	1769	100%	51.87	19.43

Source: 2007 IPEDS dataset

Table 9

*Graduation Rate within 150% of Normal Time (Four-Year Institutions) by Degree of Urbanization (*N *= 1785, missing = 16)*

Degree of Urbanization	*n*	% of *n*	*M*	*SD*
1 Large city	378	21%	52.21	21.12
2 Mid-size city	477	27%	53.92	19.22
3 Urban fringe of large city	288	16%	53.76	19.45
4 Urban fringe of mid-size city	131	7%	54.06	17.61
5 Large town	64	4%	47.33	17.67
6 Small town	274	15%	50.69	17.54
7 Rural	100	6%	47.43	17.18
Others	57	3%		
Total	1769	100%	51.87	19.43

Source: 2007 IPEDS dataset

Analysis of Data

Before the SEM model is evaluated on multiple subgroup datasets for group comparisons, some preliminary data analyses need to be done. The preliminary analyses include data screening, check for missing data, check for outliers and check for non-normality of the data. SPSS software is used conduct these analyses. After the preliminary data analyses are done, the measurement model is tested on each subgroup dataset using confirmatory factor analysis (CFA) in Amos software. Then, the SEM model is validated on multiple subgroup datasets simultaneously for group comparisons.

For data screening, descriptive statistics, such as frequency tables, scatterplots, skewness, kurtosis, means and standard deviations are visually inspected to identify any obvious data abnormality, such as non-normal distribution, missing data and outliers. When these kinds of data abnormality are discovered, further analyses and possible remedies are pursued. The Amos software used in this study for SEM analyses can handle the missing data with a efficient algorithm called full information maximum likelihood (FIML) estimation method. "Amos uses full information maximum likelihood estimation in the presence of missing data, so it does not impute or replace values for missing data" (Schumacker & Lomax, 2004, p. 43).

Validity and Reliability

The validity of the SEM model is measured by its measurement model using confirmatory factor analysis (CFA). The factor loadings and communality ratios of the observed variables indicate their validity and reliability in measuring the respective constructs. According to the two-step approach, the measurement model must be established before the SEM model can be evaluated (Schumacker & Lomax, 2004). The model fit indices can only tell how well the model fits the data in terms of how close the model implied variance-covariance matrix is to the observed variance-covariance matrix. The overall validity of the model must be judged by interpreting the path coefficients as well as explained variances in the criterion variable in light of the existing literatures.

Assumptions

As mentioned earlier, the normality assumption in the data is an important assumption for most inferential statistics, including multiple regression and SEM (Schumacker & Lomax, 2004). To meet this assumption, data screening is performed as mentioned earlier. Data transformation may be needed to mitigate the effects from violating these assumptions in some of the variables. Log transformations are applied to expenditure variables based on the principle of diminishing marginal productivity of inputs in production theory (Ryan, 2004). Another assumption is that basic structure of Tinto's (1975) model of college dropout can be represented using institutional attributes. Some of the variables used in the institutional model, such as average age of students and institutional SES, should represent the background construct because they are student attribute aggregated at the institutional level. Other constructs, such as the academic environment and social environment, are more difficult to find suitable institutional variables to represent them. The confirmatory factor analysis technique can evaluate the validity of these constructs being measured by the institutional indicators. Another important assumption for group comparison analysis in the multi-group CFA and SEM is the measurement invariance of the factor models, which can be tested by comparing nested factor models with different equality constraints imposed (Vandenberg & Lance, 2000; Widaman, Reise, Bryant, Windle, & West, 1997).

Limitations

One limitation of this study is not using student-level variables in the model of institutional performance in graduation rate. The implication may be lower predictive power of the model to predict graduation rates. The purpose of this research, however, is to develop an institutional model to evaluate performance across institutions in producing graduates. To achieve this goal, a national dataset which includes all or most institutions is required. Currently, only IPEDS provides such extent of national data, but it does not include student-level variables. There are some student related variables in IPEDS, such as average age of students, gender and ethnicity, but these variables are aggregated at the institutional level. Other datasets can be used to provide student level variables just as some researchers have done before. Most of those studies usually involve comparing students from a small number of institutions. To efficiently analyze multilevel data involving large number of students in large number of institutions, the researcher needs to use multilevel modeling technique such as hierarchical linear modeling (HLM) technique. Regardless, the model of institutional performance is still very useful because it not only can be used to benchmark performance across institutions but also can inform the multilevel model in future research.

CHAPTER 4

RESEARCH RESULTS

The purpose of this study is to develop a model of institutional performance in graduation rates for four-year, public and private not-for-profit, Title IV institutions in the United States. Before the results are presented, the raw data and the screening of them are described. Then, the results are presented to answer the following research questions.

1. Which groups of institutions have significantly different graduation rates compared with other groups of institutions based on control, geographical region, state, Carnegie classification code, degree of urbanization, religious affiliation and regional accreditation agency of the institutions?
2. What are the validity and reliability of the factor models of student background, student finance, academic environment and social environment to measure the underlying constructs in the institutional model of graduation rates?
3. To what degree does the overall institutional model of graduation rates fit the dataset and its subsets based on the groups of institutions identified by answering the first research question?

Description of Raw Data

Preparation of the Data

The Integrated Postsecondary Educational Data System (IPEDS) datasets are public data and can be downloaded from the National Center for Education Statistics

(NCES) website without any licensing requirement. The raw data files are in ASCII format and can be converted into SPSS data files using the SPSS syntax files, which are also available at the NCES website. The IPEDS variables to be used in this study and their definitions are listed in the Appendix. These variables are merged into one SPSS data file from different files for further computations and analyses.

The six-year graduation rates are calculated by dividing the number of students in cohort (*grrace<nn>*) where *grtype* = 3 (i.e., completers within 150% normal time) by the number of students in cohort where *grtype* = 2 (i.e., adjusted cohort).

For the student background construct (*background*), institutional selectivity is measured by the 25th percentile of the combined verbal and math ACT score (*act25* combining *acten25* and *actmt25*). For institutions which reported SAT scores (i.e., *satvr25* and *satmt25*) only, the SAT scores are converted to ACT scores by changing the SAT scale (200 to 800) to the ACT scale (1 to 36). The *act25* variable is used because its scale (2 to 72) is closer to the other observed variables measuring the student background construct. Institutional socioeconomic status (*instses*) is defined as one minus the percentage of federal grant aid recipients (*fgrnt_p*) (Pike et al., 2006). Average age of full-time students (*efage*) is computed from the average of males students (*efage01*) and female students (*efage02*) weighted by number of students in each age group indicated by the *line* variable in the same file. For student attributes, the gender and ethnicity variables are derived from the cohort data (*grrace<nn>*) restructured in univariate format. For the student finance construct, the tuitions and financial aid variables are directly taken from the IPEDS data (*tuition2*, *fgrant_a*, *sgrant_a* and *igrant_a*).

For the academic environment construct (*academic*), faculty-student ratio (*fac2stu*) is the number of full-time instructional faculty (*empcount*) divided by the full-time equivalent enrollment (*fte*). Percentage of full-time faculty (*facftpct*) is the number of full-time faculty members (total of *staff15* and *staff16* for male and female faculty respectively) divided by the total number of faculty members (both full-time and part-time). The full-time/part-time status is indicated by the *line* variable in the same file. Instructional expenditures per student (*insexpfte*) is instructional expenditures (*b013*) divided by full-time equivalent enrollment (*fte*). Academic support expenditures (*acsexpfte*) is the expenditure for support services (*b043*) divided by full-time equivalent enrollment (*fte*).

For the social environment construct (*social*), percentage of full-time students (*enrolftpct*) is the ratio of total undergraduate students (*efrace15* and *efrace16* for male and female students respectively) who are in full-time enrollment (indicated by *section* and *lstudy*). Institutional size is defined as the total enrollment of full-time undergraduate students (*enrolft*) which are also derived from *efrace15*, *efrace16*, *section* and *lstudy*. Dormitory capacity (*dormcap*) is a measure of residential support and is directly taken from the IPEDS data *roomcap*. Student service expenditures (*stuexpfte*) are *b063* divided by *fte*.

The commitment is measured by the ratio of cohort students returning in the year following the cohort year. This ratio is directly taken from the IPEDS data *ref_pcf*. Graduation rate is the six-year graduation rate for four-year institutions calculated from the cohort data.

The grouping variables (*control*, *fips*, *obereg*, *carnegie*, *locale*, *relaffil* and *regaccrd*) are used to distinguish groups of institutions that have significantly different graduation rates than other groups and to segregate the dataset into subsets. Segregated datasets are submitted to the same SEM analysis to discover structural differences between groups of institutions and for benchmarking analysis.

Descriptive Statistics

Table 10 presents the descriptive statistics of the observed variables without any data transformation or imputation. The first seven variables are categorical variables used for grouping the institutions and comparing their group mean differences in graduation rates. Specific categories, rather than all categories, are used to code the orthogonal contrast vectors in Table 1 for specific group comparisons. The mean, standard deviation, skewness and kurtosis are not important for the categorical variables. The next seventeen variables are continuous observed variables which are used in the SEM model. The six-year graduation rate (*gr4*), retention rate (*ret_pcf03*), institutional SES (*instses*), percentage of full-time faculty (*facftpct*) and percentage of full-time enrollment (*enrolftpct*) are percentage and have range from 0 to 100%. The normality (indicated by the skewness and kurtosis) of these continuous variables are discussed in the data screening section later.

Table 10

*Descriptive Statistics of Observed Variables without Data Transformation and Imputation (*N = *1785 institutions)*

Variables	Missing	% Miss.	*Min*	*Max*	*M*	*SD*	Skewness	Kurtosis
control	0	0%	1	2	1.68	.47	-.76	-1.43
obereg	0	0%	0	9	4.08	2.15	.48	-.59
fips	0	0%	1	78	30.73	15.69	.12	-.37
carnegie	0	0%	-3	60	28.85	13.42	.48	.10
locale	0	0%	-3	9	3.26	2.17	.68	-.14
relaffil	0	0%	-2	97	20.59	30.44	.88	-.80
regaccrd	0	0%	-2	11	4.59	3.37	-.21	-.64
gr4	16	1%	3.45	100	51.87	19.43	.18	-.30
ret_pcf03	692	39%	0	100	72.90	15.47	-1.85	6.63
act25	618	35%	2	64	36.34	7.40	.34	1.31
instses	61	3%	0	100	65.36	21.07	-1.11	.88
efage	32	2%	17.50	50.21	22.38	3.10	2.70	11.37
tuition2	28	2%	0	27330	9916.38	7079.16	.48	-.83
fgrnt_a	97	5%	0	11200	2728.28	957.95	2.05	12.07
sgrnt_a	141	8%	0	11514	2391.14	1660.50	1.80	5.43
igrnt_a	113	6%	0	20304	4596.69	3759.34	1.36	1.74
fac2stu	26	1%	.14	129.76	5.62	4.48	16.60	407.97
facftpct	64	4%	1.20	100	64.91	24.31	-.26	-.83
insexpfte	38	2%	35.16	196035.2	6870.94	7240.21	13.12	289.71
acsexpfte	90	5%	21.30	47942.8	1811.64	2429.60	10.37	161.30
enrolftpct	4	0%	4.20	100	81.53	16.42	-1.40	2.30
enrolft	4	0%	6	101713	9673.7	13903.2	2.90	10.16
roomcap	231	13%	1	16195	1430.74	1763.12	3.04	12.86
stuexpfte	69	4%	58.74	22017.16	2023.14	1659.54	4.00	33.01

Source: 2007 IPEDS dataset

Data Screening

Normality Assumption

Table 10 presents the descriptive statistics of the continuous observed variables that are used to build the SEM model before data transformation and imputation are performed. These variables are screened for normality, outliers and missing values. Most inferential statistics and statistical testing rely on the normality assumption in the data. Non-normality of data can be univariate (involving single variables) and multivariate (involving configuration of multiple variables). Skewness, kurtosis and histograms are examined to ensure the univariate normality in the data. Skewness and kurtosis between -1 and 1 indicate that the individual variables are close to normal distribution. Several variables are found to be highly skewed and leptokurtic (more peaked than normal curve). Natural logarithmic transformation is performed on seven variables (*efage*, *insexpfte*, *acsexpfte*, *enrolptpct*, *enrolft*, *dormcap* and *stuexpfte*) to reduce non-normal property, but it will not correct all non-normal problems. Before the transformation, the skewness and kurtosis of these variables are -1.40 to 13.12 and 2.30 to 289.71 respectively. After the transformation, the skewness and kurtosis are -.23 to 1.90 and .69 to 6.10 respectively. Significant reduction in skewness and kurtosis are achieved by the logarithmic transformation. Table 11 presents the descriptive statistics of the observed continuous variables after data transformation and imputation are performed on the data. The ‘lg’ prefix of the variables indicates the natural logarithmic transformation. Data transformation alone, however, cannot eliminate all non-normality problem because some of them are caused by outliers, which is discussed next.

Table 11

*Descriptive Statistics of Observed Continuous Variables with Data Transformation and Imputation (*N = *1785 institutions)*

Variables	Missing[a]	*Min*	*Max*	*M*	*Median*	*SD*	Skewness	Kurtosis
gr4	16	3.45	100.00	51.87	50.97	19.43	.18	-.30
xret_pcf03	16	18.00	100.00	73.44	73.29	11.28	-.31	.75
xact25	57	2.00	64.00	34.75	34.98	7.48	.20	1.16
instses	61	.00	100.00	65.36	71.00	21.07	-1.11	.88
lgefage	32	2.86	3.92	3.10	3.07	.12	1.90	5.20
tuition2	28	.00	27330.00	9916.38	8950.00	7079.16	.48	-.83
xrofgrnt_a	103	294.00	6000.00	2693.00	2622.50	783.22	.72	2.10
xrosgrnt_a	121	108.00	7755.00	2339.12	2264.00	1166.21	.80	1.48
xroigrnt_a	102	.00	20304.00	4571.15	3383.00	3740.19	1.39	1.83
rofac2stu	30	.14	19.76	5.42	5.02	2.31	1.52	5.11
rofacftpct	76	1.20	100.00	60.77	61.38	21.22	-.28	-.49
lginsexpfte	37	3.56	12.19	8.63	8.61	.61	-.30	6.10
xlgacsexpfte	73	3.06	10.78	7.17	7.19	.79	-.23	2.49
enrolftpct	4	4.20	100.00	81.53	85.59	16.42	-1.40	2.30
lgenrolft	4	1.79	11.53	8.34	8.40	1.43	-.56	.71
xlgdormcap	41	.00	9.69	6.58	6.68	1.23	-.65	1.26
lgstuexpfte	69	4.07	10.00	7.36	7.39	.73	-.31	.69

Note. a. These are the remaining number of missing values after imputations are performed. The variables with the 'x' prefix have their missing values imputed using the regression method.
b. The variables with the 'ro' prefix have their outlier values replaced by imputed values using the regression method.

Outliers

Outliers are extreme cases in a variable. They can drastically change the relationship between variables established by the majority of the cases. However, cases that are outliers in one variable may not be outliers in other variables. Outliers can also affect the normality of variables. Table 12 presents the correction of outlier values in six variables (*fac2stu*, *fgrnt_a*, *sgrnt_a*, *igrnt_a* and *facftpct*) before missing values are imputed. The criteria for screening outliers are determined subjectively to reduce non-normality and to keep the number of outlier cases as low as possible. With the outlier cases excluded, the concerned variable is regressed on other variables which are in the same factor model. For example, *fgrnt_a* is regressed on *tuition2*, *sgrnt_a* and *igrnt_a* because they are the indicators of the same factor (*finance*). Then, the concerned variable in the outlier cases are imputed using the regression equation. This will minimize the effect of the imputed values on the relationship between the variables in the factor model. The 'ro' prefix of variables indicates that outliers have been replaced by imputed values.

Missing Data

Finally, missing values are imputed using the regression method. The same procedure is used to impute missing values as to impute the concerned variable in the outlier cases. This method, however, will not entirely eliminate the missing values because the regression method is affected by listwise deletion in handling the missing values as well. The 'x' prefix of the variables indicates the imputation for missing values.

Table 12

*Univariate Outliers Replaced by Imputed Values (*N = *1785 institutions)*

				Before		After	
Variables	Criteria	*n*	% of *n*	Skewness	Kurtosis	Skewness	Kurtosis
fac2stu	> 20%	9	.5%	16.603	407.971	1.524	5.114
fgrnt_a	> 6000	26	1.5%	2.061	12.101	.717	2.094
sgrnt_a	> 8000	116	7.1%	1.802	5.434	.793	1.377
igrnt_a	> 6000	19	3.4%	1.661	5.404	1.050	1.769
facftpct	=100	182	10.6%	-.257	-.832	-.281	-.488
ret_pcf03	=0	18	2%	-1.849	6.627	-.533	.828

Note. The univariate outliers are replaced by imputed values using the regression method to improve the normality of the variables. These criteria are determined subjectively.

The above procedure, however, will not detect the multivariate non-normality but may help reduce it by reducing the univarite non-normality. Multivariate non-normality can be detected by computing the Mahalanobis distance and plotting it with the Chi-square (George, 2001) or by a graphical method (Henson, 1999).

Table 13 presents the bivariate Pearson correlation coefficients, variances and covariances of the seventeen observed continuous variables which are used to build the institutional model of performance in graduation rates. All the correlation coefficients are statistically significant at .01 or .05 levels (2-tailed) except for four of them, which belong to the student finance construct (*finance*) and the social environment construct (*social*).

Table 13

*Bivariate Correlation and Covariance (*N = *1785 institutions)*

Variables	gr4	xret_pcf03	xact25	instses	efage	tuition2
gr4	377.429	.786**	.612**	.461**	-.329**	.502**
xret_pcf03	172.309	127.200	.566**	.401**	-.335**	.402**
xact25	88.009	47.453	56.017	.677**	-.510**	.437**
instses	186.436	94.181	106.077	443.793	-.268**	.296**
efage	-19.498	-11.501	-11.492	-17.086	9.614	-.204**
tuition2	68860.318	31913.505	23119.724	44149.712	-4456.990	50114559.079
xrofgrnt_a	4738.636	2600.854	1574.981	2373.543	-462.340	2094851.686
xrosgrnt_a	5318.615	2327.786	1621.318	5143.373	-214.098	3456417.515
xroigrnt_a	40993.242	20824.218	15887.662	29503.336	-3237.867	22111805.834
rofac2stu	16.395	8.091	5.394	5.907	-1.768	4923.011
rofacftpct	91.907	58.812	49.374	61.456	-23.030	-11720.271
lginsexpfte	6.015	3.292	2.548	5.272	-.589	1987.591
xlgacsexpfte	6.820	3.831	2.532	5.176	-.568	1808.095
enrolftpct	121.488	59.789	46.646	53.427	-25.619	32150.928
lgenrolft	3.219	3.596	2.795	7.651	-1.341	-1176.933
xlgdormcap	7.157	4.986	3.596	8.737	-1.644	422.374
lgstuexpfte	4.878	2.190	1.677	3.446	-.464	3251.600

(*table continues*)

Table 13 (*continued*)

Variables	xrofgrnt_a	xrosgrnt_a	xroigrnt_a	rofac2stu	rofacftpct
gr4	.321**	.240**	.574**	.370**	.228**
xret_pcf03	.305**	.182**	.504**	.314**	.250**
xact25	.272**	.188**	.576**	.326**	.314**
instses	.147**	.215**	.384**	.127**	.143**
efage	-.211**	-.067**	-.315**	-.263**	-.360**
tuition2	.376**	.414**	.836**	.304**	-.077**
xrofgrnt_a	613441.274	.277**	.485**	.251**	.092**
xrosgrnt_a	249957.241	1360045.833	.332**	.141**	-.083**
xroigrnt_a	1409006.868	1444069.919	13989033.746	.377**	.093**
rofac2stu	436.255	365.733	3141.373	5.343	.360**
rofacftpct	1455.894	-2045.630	7316.082	17.219	450.444
lginsexpfte	165.422	161.872	1263.569	.716	2.651
xlgacsexpfte	189.119	160.729	1275.765	.750	2.743
enrolftpct	2709.280	1801.971	18212.867	10.976	124.632
lgenrolft	-1.551	-128.433	160.338	-.945	7.629
xlgdormcap	85.850	-6.526	910.911	-.315	8.638
lgstuexpfte	156.968	283.759	1539.495	.676	-.066

(*table continues*)

Table 13 (*continued*)

Variables	lginsexpfte	xlgacsexpfte	enrolftpct	lgenrolft	xlgdormcap	lgstuexpfte
gr4	.512**	.456**	.383**	.117**	.308**	.351**
xret_pcf03	.482**	.439**	.325**	.226**	.369**	.270**
xact25	.566**	.432**	.393**	.268**	.402**	.310**
instses	.421**	.325**	.158**	.257**	.349**	.230**
efage	-.315**	-.236**	-.507**	-.304**	-.439**	-.208**
tuition2	.466**	.324**	.277**	-.116**	.048*	.627**
xrofgrnt_a	.357**	.320**	.224**	-.001	.094**	.283**
xrosgrnt_a	.239**	.180**	.102**	-.084**	-.005	.339**
xroigrnt_a	.576**	.444**	.319**	.032	.208**	.573**
rofac2stu	.546**	.425**	.296**	-.293**	-.115**	.412**
rofacftpct	.223**	.169**	.368**	.273**	.360**	-.004
lginsexpfte	.369	.651**	.245**	.170**	.287**	.482**
xlgacsexpfte	.301	.619	.159**	.123**	.205**	.396**
enrolftpct	2.386	2.004	269.657	.137**	.324**	.264**
lgenrolft	.147	.134	3.226	2.057	.854**	-.207**
xlgdormcap	.213	.193	6.434	1.481	1.511	-.012
lgstuexpfte	.211	.223	3.104	-.211	-.010	.536

Note. Off-diagonal numbers at the upper right triangle are the Pearson correlation coefficients. Numbers at the diagonal are the variances of the variables. Off-diagonal numbers at the lower left triangle are the covariances.
**. Correlation is statistically significant at the 0.01 level (2-tailed).
*. Correlation is statistically significant at the 0.05 level (2-tailed).

Group Comparisons in Graduation Rates

Group comparisons in graduation rates are conducted by using multiple regression analyses with planned contrasts. Orthogonal coding method is used to create the contrast variables in Table 1. These contrast variables are designed to compare the mean of a specific group with the unweighted mean of other groups. For example, E4 is for comparing the mean graduation rates of New York state with the unweighted mean of the mean graduation rates of four other states (Ohio, Illinois, Florida and Texas). These contrast variables are entered into the regression analysis hierarchically to determine the incremental effects of each grouping variable. For example, D1 to D7 are entered together after C1 is entered to determine the incremental effect (in terms of R^2 change) of the geographical region variable (*obereg*) on top of the effect of the *control* variable. Table 14 presents the summary of hierarchical regression of four-year graduation rates (*gr4*) on nine grouping variables. Table 15 presents the regression coefficients for the predictor contrast variables. There are maximum 24,990 (= 1785×14) graduation rates for 1785 institutions, each of which has 14 graduation rates for different combinations of gender (2 categories) and race/ethnicity (7 categories). The 14818 cases are non-empty cells that represents about 60% of all the cells for all the predictor contrast variables. All the R^2 changes from entering the contrast groups are statistically significant with $F(1, 14816)$ statistics from 108 to 381 at the $p < .001$ level, indicating that all the contrast groups have significantly increased the explained variance in graduation rates. The significant R^2 changes are primarily results of the large sample size. The total explained variance in graduation rates by the contrast variables is 21.3%, of which 34.5%

comes from control of institution (public vs. private not-for-profit), 33.8% from Carnegie classification code (selected codes = 15, 16, 21, 22, 31 and 32), 12.3% from race/ethnicity (Black, Asian, Hispanic and White), 7.9% from geographical regions, 6.6% from gender. The *control* and *carnegie* variables are responsible for most of the explained variance in *gr4*.

In Table 15, the standardized regression coefficients (Beta weights) and the structure coefficients (r_s^2) are the key statistics to determine the importance of the predictor variables when the *B* weights are statistically significant at .01 level. Beta weights indicate the uniqueness of the predictor variable in explaining the dependent variable. Structure coefficients indicate the proportion of explained variance in the dependent variable attributed to the predictor variables. So, structure coefficients are effect size measures. Both statistics should be high for good predictors. The structure coefficients will not add up to 100% because of the overlap in the explained variance that are attributed to different predictor variables. The more the overlap, the higher is the multicollinearity caused by the inter-relationship between the predictor variables. Multicollinearilty violates one of the basic assumption of multiple regression, that is the independence of predictor variables with each other. The statistics in the last two columns are tolerance and variance inflation factor (VIF), which are measures of multicollinearity. Tolerance is the percentage of variance in a predictor variable which is not redundant with all other predictor variables. A tolerance less than 10% indicates a multicollinearity problem. VIF is the ratio of a variable’s total variance in standardized terms to its unique variance. If VIF is greater than 10, the variable is likely to be redundant (Kline, 1998).

Table 14

*Hierarchical Regression Summary for Grouping Contrasts (*N *= 1785 institutions)*

Grouping	*R*	R^2	Adj R^2	*SE*	ΔR^2	ΔF	*df1*	*df2*	*p*
gender	.119[a]	.014	.014	25.282	1.41%	212.10	1	14816	<.001
race	.201[b]	.040	.040	24.945	2.63%	135.35	3	14813	<.001
control	.338[c]	.114	.114	23.970	7.36%	1230.74	1	14812	<.001
obereg	.362[d]	.131	.130	23.745	1.69%	41.20	7	14805	<.001
state	.367[e]	.134	.133	23.705	0.34%	8.25	7	14798	<.001
carnegie	.454[f]	.206	.205	22.700	7.21%	268.67	5	14793	<.001
locale	.459[g]	.211	.209	22.642	.44%	13.72	6	14787	<.001
relaffil	.461[h]	.212	.210	22.623	.15%	7.07	4	14783	<.001
regaccrd	.462[i]	.213	.211	22.611	.11%	4.15	5	14778	<.001

Note. Dependent variable = gr4
a. Predictors: (Constant), A1
b. Predictors: (Constant), A1, B3, B1, B2
c. Predictors: (Constant), A1, B3, B1, B2, C1
d. Predictors: (Constant), A1, B3, B1, B2, C1, D7, D3, D2, D1, D5, D4, D6
e. Predictors: (Constant), A1, B3, B1, B2, C1, D7, D3, D2, D1, D5, D4, D6, E4, E2, E5, E7, E1, E6, E3
f. Predictors: (Constant), A1, B3, B1, B2, C1, D7, D3, D2, D1, D5, D4, D6, E4, E2, E5, E7, E1, E6, E3, F5, F3, F1, F2, F4
g. Predictors: (Constant), A1, B3, B1, B2, C1, D7, D3, D2, D1, D5, D4, D6, E4, E2, E5, E7, E1, E6, E3, F5, F3, F1, F2, F4, G3, G2, G1, G6, G4, G5
h. Predictors: (Constant), A1, B3, B1, B2, C1, D7, D3, D2, D1, D5, D4, D6, E4, E2, E5, E7, E1, E6, E3, F5, F3, F1, F2, F4, G3, G2, G1, G6, G4, G5, H4, H2, H3, H1
i. Predictors: (Constant), A1, B3, B1, B2, C1, D7, D3, D2, D1, D5, D4, D6, E4, E2, E5, E7, E1, E6, E3, F5, F3, F1, F2, F4, G3, G2, G1, G6, G4, G5, H4, H2, H3, H1, I4, I5, I2, I1, I3

Table 15

*Hierarchical Regression Variables for Grouping Contrasts (*N *= 1785 institutions)*

Variables	B	*SE*	Beta	r_s^2	*t*	*p*	Tolerance	VIF
Intercept	55.965	.539			103.814	<.001		
A1	-2.879	.186	-.113	6.24%	-15.475	<.001	.998	1.002
B1	2.664	.140	.140	8.97%	19.088	<.001	.989	1.011
B2	1.082	.173	.046	.87%	6.264	<.001	.983	1.017
B3	2.744	.326	.062	1.71%	8.419	<.001	.988	1.013
C1	-6.994	.270	-.269	32.12%	-25.944	<.001	.497	2.013
D1	.517	.307	.049	5.75%	1.682	.093	.062	16.101
D2	1.685	.289	.184	2.10%	5.837	<.001	.053	18.713
D3	.746	.290	.052	1.88%	2.572	.010	.128	7.815
D4	.440	.173	.029	.28%	2.536	.011	.397	2.516
D5	1.394	.235	.060	.82%	5.937	<.001	.525	1.905
D6	1.386	.444	.051	.04%	3.120	.002	.201	4.976
D7	.635	.897	.008	.42%	.708	.479	.423	2.365
E1	.097	.163	.006	2.16%	.595	.552	.453	2.205
E2	.203	.170	.013	1.58%	1.192	.233	.429	2.333
E3	.114	.377	.006	.98%	.303	.762	.124	8.055
E4	.557	.245	.020	.21%	2.271	.023	.658	1.520
E5	.195	.355	.005	.17%	.550	.582	.537	1.862
E6	-1.170	.498	-.030	.18%	-2.350	.019	.325	3.081
E7	-.487	1.041	-.005	.66%	-.467	.640	.416	2.406

(*table continues*)

Table 15. (*continued*)

Variables	B	*S.E.*	Beta	r_s^2	*t*	*p*	Tolerance	VIF
F1	1.544	.104	.121	20.86%	14.807	<.001	.793	1.262
F2	3.824	.127	.246	15.66%	30.142	<.001	.797	1.255
F3	-.606	.216	-.022	4.06%	-2.806	.036	.841	1.189
F4	-1.223	.228	-.047	1.60%	-5.363	<.001	.703	1.423
F5	1.575	.372	.036	5.20%	4.230	<.001	.734	1.362
G1	-.172	.080	-.018	.34%	-2.144	.032	.778	1.286
G2	.353	.127	.022	.16%	2.787	.005	.870	1.149
G3	.237	.100	.020	.29%	2.361	.018	.738	1.354
G4	.070	.248	.002	.17%	.282	.778	.770	1.300
G5	-1.424	.239	-.055	.05%	-5.946	<.001	.616	1.623
G6	1.709	.535	.028	.00%	3.193	.001	.676	1.480
H1	-.265	.124	-.023	5.87%	-2.133	.033	.463	2.161
H2	.572	.306	.015	.01%	1.865	.062	.840	1.191
H3	1.244	.323	.034	1.21%	3.850	.002	.700	1.428
H4	.876	.750	.009	.82%	1.169	.242	.895	1.117
I1	.495	.402	.035	5.67%	1.231	.218	.066	15.073
I2	.976	.396	.048	2.09%	2.465	.014	.139	7.218
I3	-1.420	.476	-.087	2.48%	-2.981	.003	.062	16.028
I4	-.120	.361	-.006	.10%	-.332	.740	.191	5.229
I5	1.340	.983	.026	.72%	1.363	.173	.143	6.980

Note. Dependent variable = gr4

The intercept (55.965) is the unweighted mean of the means of all comparison groups. It is statistically significant with $t = 103.814$ at $p<.001$. All the t statistics in Table 15 has a degree of freedom (df) of 39. The unstandardized regression coefficient (B weight) is the mean difference between the contrasting group means specified by the contrast variable. For example, the B weight of contrast variable A1 is -2.879, which is roughly the mean difference of the male group mean (53.83) and female group mean (59.89), that is -3.03 = (53.83-59.89)/2. The difference between -2.879 and -3.03 is due to interaction effects between A1 and other contrast variables. Further regression analysis does not indicate significant interaction effects between the contrast variables at .05 level. The B weights reported in Table 15 are main effects of the contrasting groups.

Gender and Race

The contrast variable A1 is for comparing the group mean difference between male and female students in graduation rate. The B weight is statistically significant with $t = -15.147$ at $p<.001$. The relatively large Beta weight (-.113) and moderate r_s^2 (6.24%) indicate that A1 is a good predictor for group mean differences in graduation rates.

The contrast variables B1, B2 and B3 are for comparing the group mean differences between the racial/ethnic groups in graduation rates. The B weights for B1, B2 and B3 are all statistically significant with $t = 19.088$, 6.264 and 8.419 respectively at $p<.001$. B1 is for comparing the Asian group and the mean of three other groups (White, Hispanic and Black). The relatively large Beta weight (.140) and moderate r_s^2 (8.97%) indicate that B1 is a good predictor for group mean differences in graduation rates. However, the small Beta weights (.046 and .062) and r_s^2 (.87% and 1.71%) for B2 and

B3 indicates that they are not good predictors. Only the Asian group has significantly higher graduation rates than the other racial/ethnic groups.

Control, Geographical Regions and States

The contrast variable C1 is for comparing the group mean difference between the public and private not-for-profit institutions in graduation rates. The *B* weight is statistically significant with t = -25.944 at p<.001. The large Beta weight (-.113) and r_s^2 (32.12%) indicate that C1 is the best predictor for group mean differences in graduation rates.

The contrast variables D1 to D7 are for comparing the group mean differences in graduation rates between the institutions in different geographical regions. D1 is for comparing the group mean in New England and the means of group means in other geographical regions (i.e., Mid-East, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains and Far West). D2 is for comparing the group mean of Mid-East and the means of group means from the rest of geographical regions (i.e., Great Lakes, Plains, Southeast, Southwest, Rocky Mountains and Far West). Likewise, D3 to D7 are for comparing the group means between the next region with the rest of the regions in the same order. This order is organized in descending order of graduation rates. The *B* weights for D1 and D7 are not statistically significant at .05 level. Although the *B* weights for the other geographical region contrast variables are statistically significant at .05 level, only D2 has relatively moderate Beta weight (.184) and small r_s^2 (2.10%). These results indicate that the geographical region contrast variables are not good predictors for group mean differences in graduation rates. For the same reason, the state contrast variables, E1 to E7, are not good predictors for group mean differences in graduation rates either. Contrast variables D1 to D7 also have low Tolerance and high VIF, indicating that they likely redundant predictors to the other predictor variables.

Carnegie Classification Code

The contrast variables F1 to F5 are for comparing the group mean differences in graduation rates between the institutions in different Carnegie classification groups. F1 is for comparing the group mean between baccalaureate liberal arts colleges and the means of group means in the other selected Carnegie classification groups (i.e., extensive research universities, masters colleges and universities II, general baccalaureate colleges, intensive research universities and masters colleges and universities I). F2 is for comparing the group mean in extensive research universities and the means of group means in the rest of the Carnegie classification groups (i.e., masters colleges and universities II, general baccalaureate colleges, intensive research universities and masters colleges and universities I). Likewise, F3 to F5 are for comparing the group means between the next Carnegie classification group with the rest of the groups in the same order. This order is organized in descending order of graduation rates. The *B* weights for F3 is not statistically significant at .001 level. Although the *B* weights for the other Carnegie classification contrast variables are statistically significant at .001 level, only F1 and F2 have relatively large Beta weight (.121 and .246) and moderate r_s^2 (20.86% and 15.66%). These results indicate that F1 and F2 are good predictors for group mean differences in graduation rates. Baccalaureate liberal arts colleges and extensive research universities are likely to have significantly higher graduation rates when compared with other Carnegie classification group of institutions.

Other Contrast Variables

The other contrast variables are G1 to G6 for comparing institutions in different degree of urbanization, H1 to H4 for comparing institutions with different religious affiliation and I1 to I5 for comparing institutions under different regional accreditation agencies. Only the *B* weights for G5 and G6 are statistically significant at .001 level. All of these contrast variables have small Beta weights and r_s^2, indicating that they are not good predictors for group mean differences in graduation rates. Contrast variables I1 to I4 also have low Tolerance and high VIF, indicating that they likely redundant predictors to the other predictor variables.

The research question 1 is answered by the above analyses. All the groups compared by the contrast variables have statistically significant different graduation rates except for the groups compared by the contrast variables: D1, D7, E1, E2, E3, E5, E7, G4, H2, H4, I1, I4 and I5 (see Table 15). However, the groups compared by C1, F1 and F2 have the most different graduation rates.

Measurement Models

According to the two-step approach, measurement models are created and tested using confirmatory factor analysis (CFA) before the whole model is submitted to structural equation modeling (SEM) analysis. The CFA is conducted on the four factor models (*background*, *finance*, *academic* and *social*) for five grouping variables (*control*, *carnegie*, *locale*, *region* and *state*) using the Analysis of Moment Structure (Amos) version 16 software.

Student Background

Figure 3 presents the factor model for the student background (*background*) construct which is measured by three indicators (*xact25*, *instses* and *efage*). The regression weights (*r_a1*, *r_a3* and 1), intercepts (*i_a1*, *i_a2* and *i_a3*) and unique variances (*var_a0*, *var_a1*, *var_a2* and *var_a3*) are parameters to be estimated in the model. The 1 indicates that *instses* is the marker variable whose scale is used to identify *background*'s scale. Table 16 to Table 20 present the CFA summaries for *background* by the five grouping variables. The parameters are presented in separate columns for each group of institutions. The *B* weights and Beta weights (β) are unstandardized and standardized regression weights. The intercepts (*Int*) are the means of the indicators. The unique variances (*var*) of the indicators are unpredicted by *background*. The multiple R^2 are the lower bound on the reliability of the indicators. The Chi-squared (χ^2) and fit indices (CFI, NFI and RMSEA) are measures of model fit. An equality constraint (*var_a1* = *var_a3*) is imposed for each group to avoid non-positive definite matrices.

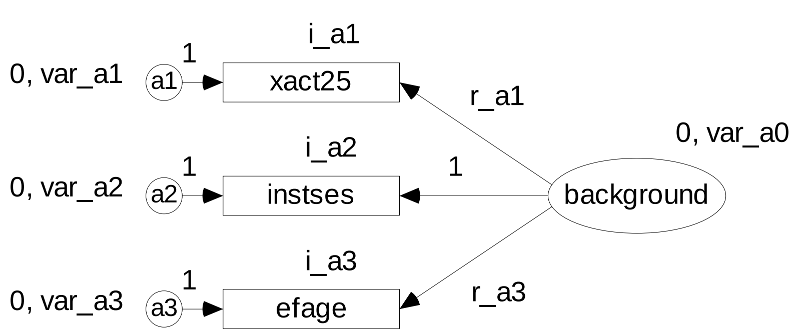

Figure 3. Factor model for student background.

All the χ^2 are statistically significant at .001 level, indicating that the factor model fits the data. But χ^2 alone is not an accurate measure of model fit because it is heavily influenced by the sample size (*n*). CFI and NFI are both greater than or close to .95, indicating that the model fits the data well. RMSEA is more useful to evaluate complex model because it incorporates no penalty for model complexity and tends to favor models with many parameters. RMSEA is not an important fit index here because the CFA factor model is a simple model.

The Beta weights (β) and the multiple R^2 together are key statistics to determine the importance of an indicator for its factor. The closer the Beta weight and the R^2 are to 1, the more important is the indicator. The 25th percentile of ACT score (*xact25*) is the best indicator for *background*, followed by institutional SES (*instses*) and average age of students (*efage*). The *background* can explain 85% to 95% of the variance in *xact25*, 20% to 60% of the variance in *instses* and 20% to 70% of the variance in *efage*.

Table 21 presents the tests of measurement invariance. The small ΔCFI (absolute value $\leq$ .01) indicates metric invariance across groups by control and degree of urbanization. Based on the intercepts in Table 16, the students body in public institutions seem to have higher SES (66.73% vs. 64.40%), lower ACT score (33.95 vs. 34.99) and younger in average age (21.99 vs. 22.57). Students from doctoral and research universities seems to have higher SES and higher ACT scores.

The above results answered research question 2 such that validity and reliability are established for the student background factor based on the multiple R^2 and the fit indices (NFI and CFI) across the five groupings of institutions.

Table 16

CFA Summary for Student Background by Control of Institution

Parameters	All	Public	Private
n	1785	577	1208
B_{r_a2}	1	1	1
B_{r_a1}	.469*	.458*	.471*
B_{r_a3}	-.110*	-.066*	-.121*
β_{r_a2}	.750	.675	.730
β_{r_a1}	.940	.969	.936
β_{r_a3}	-.540	-.491	-.563
$\text{Int}_{instses}$	65.18*	66.73*	64.40*
Int_{xact25}	34.65*	33.95*	34.99*
Int_{efage}	22.38*	21.99*	22.57*
var_a0	229.41*	150.97*	269.41*
var_a2	219.55*	180.39*	235.80*
var_a1	6.67*	2.06*	8.51*
var_a3	6.67*	2.06*	8.51*
$R^2_{instses}$	.511	.456	.533
R^2_{xact25}	.883	.939	.875
R^2_{efage}	.292	.241	.317

Note. $\chi^2(3) = 152.33$*, CFI = .953, NFI = .953, RMSEA = .118
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 17

CFA Summary for Student Background by Carnegie Classification Code

Parameters	All	Doctoral	Master	Baccalaureate
n	1785	248	577	520
B_{r_a2}	1	1	1	1
B_{r_a1}	.469*	.871*	.433*	.469*
B_{r_a3}	-.110*	-.125*	-.098*	-.088*
β_{r_a2}	.715	.586	.675	.753
β_{r_a1}	.940	.984	.919	.964
β_{r_a3}	-.540	-.617	-.467	-.559
$\text{Int}_{instses}$	65.18*	75.77*	66.53*	64.03*
Int_{xact25}	34.65*	40.24*	33.64*	35.64*
Int_{efage}	22.38*	21.21*	22.45*	21.91*
var_a0	229.41*	71.82*	128.24*	272.30*
var_a2	219.55*	137.38*	153.20*	207.51*
var_a1	6.67*	1.82*	4.43*	4.59*
var_a3	6.67	1.82*	4.43*	4.59*
$R^2_{instses}$	.292	.380	.218	.313
R^2_{xact25}	.883	.968	.844	.929
R^2_{efage}	.511	.343	.456	.568

Note. $\chi^2(4) = 79.75$*, CFI = .972, NFI = .971, RMSEA = .078
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 18

CFA Summary for Student Background by Degree of Urbanization

Parameters	All	Doctoral	Master	Baccalaureate
n	1785	384	480	294
B_{r_a2}	1	1	1	1
B_{r_a1}	.469*	.485*	.542*	.527*
B_{r_a3}	-.110*	-.138*	-.131*	-.110*
β_{r_a2}	.715	.707	.680	.718
β_{r_a1}	.940	.926	.948	.944
β_{r_a3}	-.540	-.573	-.584	-.512
$\text{Int}_{instses}$	65.18*	64.43*	69.04*	68.50*
Int_{xact25}	34.65*	34.75*	35.79*	34.73*
Int_{efage}	22.38*	22.87*	22.22*	22.36*
var_a0	229.41*	241.81*	169.85*	214.42*
var_a2	219.55*	242.63*	197.02*	201.55*
var_a1	6.67*	9.39*	5.58*	7.29*
var_a3	6.67*	9.39*	5.58*	7.29*
$R^2_{instses}$	.292	.328	.341	.262
R^2_{xact25}	.883	.858	.899	.891
R^2_{efage}	.511	.499	.463	.515

Note. $\chi^2(4) = 138.92$*, CFI = .948, NFI = .947, RMSEA = .107
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 19

CFA Summary for Student Background by Geographical Region

Parameters	All	New England	Mid East	Great Lakes	Plains[a]	South East	South West	Far west
n	1785	164	361	279	191	412	119	162
B_{r_a2}	1	1	1	1	1	1	1	1
B_{r_a1}	.469*	.724*	.473*	.576*	.025*	.414*	.603*	.660*
B_{r_a3}	-.110*	-.154*	-.092*	-.213*	-.030	-.098*	-.102*	-.176*
β_{r_a2}	.715	.624	.718	.668	.980	.731	.601	.681
β_{r_a1}	.940	.942	.956	.935	.779	.927	.949	.956
β_{r_a3}	-.540	-.510	-.534	-.697	-.147	-.506	-.456	-.654
$\mathrm{Int}_{instses}$	65.18*	71.57*	64.99*	69.29*	65.54*	62.28*	64.01*	69.79*
Int_{xact25}	34.65*	35.77*	34.54*	36.04*	36.13*	33.47*	34.08*	35.04*
Int_{efage}	22.38*	21.75*	21.61*	22.56*	22.30*	22.72*	22.62*	23.17*
var_a0	229.41*	125.60*	251.20*	130.60*	265.48*	259.21*	133.33*	133.23*
var_a2	219.55*	197.42*	235.77*	161.94*	10.82*	225.53*	236.06*	153.83*
var_a1	6.67*	8.44*	5.31*	6.24*	10.82*	7.30*	5.32*	5.50*
var_a3	6.67*	8.44*	5.31*	6.24*	10.82*	7.30*	5.32*	5.50*
$R^2_{instses}$	.292	.260	.285	.486	.961	.256	.208	.428
R^2_{xact25}	.883	.886	.914	.874	.606	.859	.901	.913
R^2_{efage}	.511	.389	.516	.446	.025	.535	.361	.464

Note. $\chi^2(9) = 200.09$*, CFI = .937, NFI = .9135, RMSEA = .078
*. Parameters are statistically significant at the 0.001 level (2-tailed).
a. An additional equality constraint is imposed to avoid estimation problems caused non-positive definite matrices (*var_a1 = var_a2 = var_a3*).

Table 20

CFA Summary for Student Background by State

Parameters	All	CA	FL	IL	MA	NY	OH	PA	TX
n	1785	104	55	62	76	167	82	122	73
B_{r_a2}	1	1	1	1	1	1	1	1	1
B_{r_a1}	.469*	.664*	.372*	.501*	.792*	.375*	.555*	.672*	.972*
B_{r_a3}	-.110*	-.162*	-.111*	-.148*	-.169*	-.070*	-.285*	-.136*	-.164*
β_{r_a2}	.715	.685	.858	.856	.652	.764	.564	.728	.392
β_{r_a1}	.940	.954	.939	.975	.955	.950	.887	.963	.936
β_{r_a3}	-.540	-.613	-.632	-.789	-.565	-.493	-.703	-.587	-.408
$\mathrm{Int}_{instses}$	65.18*	67.68*	62.70*	68.35*	73.50*	58.47*	67.52*	70.59*	66.62*
Int_{xact25}	34.65*	34.92*	32.80*	36.70*	36.61*	34.42*	36.14*	34.54*	34.80*
Int_{efage}	22.38*	23.24*	23.64*	22.07*	21.71*	21.55*	22.55*	21.44*	22.43*
var_a0	229.4*	164.6*	395.1*	207.7*	127.6	402.6*	105.9	115.5*	47.9
var_a2	219.6*	185.7*	141.3*	75.5*	172.8*	287.6*	227.3*	102.6*	263.0*
var_a1	6.7*	7.2*	7.3*	2.8*	7.8*	6.2*	8.8*	4.0*	6.4*
var_a3	6.7*	7.2*	7.3*	2.8*	7.8*	6.2*	8.8*	4.0*	6.4*
$R^2_{instses}$	.292	.376	.400	.623	.320	.243	.494	.345	.166
R^2_{xact25}	.883	.910	.882	.950	.911	.902	.787	.928	.876
R^2_{efage}	.511	.470	.737	.733	.425	.583	.318	.530	.154

Note. $\chi^2(9) = 131.17^*$, CFI = .946, NFI = .944, RMSEA = .073
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 21

Test of Measurement Invariance for Student Background

Models	*df*	χ^2	NFI	CFI	Δdf	$\Delta\chi^2$	ΔCFI
control							
Configural invariance	3	152.33*	.953	.953			
Metric invariance	5	199.33*	.938	.939	2	47.00*	-.01
Scalar invariance	8	285.90*	.911	.913	3	86.57*	-.03
Invariant unique variance	10	579.61*	.820	.822	2	293.71*	-.09
Invariant factor variance	11	675.34*	.790	.792	1	95.74*	-.03
carnegie							
Configural invariance	4	79.75*	.971	.972			
Metric invariance	8	155.95*	.943	.945	4	76.20*	-.03
Scalar invariance	14	340.01*	.875	.879	6	184.06*	-.07
Invariant unique variance	18	412.95*	.849	.854	4	72.94*	-.03
Invariant factor variance	20	508.04*	.814	.819	2	95.10*	-.04
locale							
Configural invariance	4	138.92*	.947	.948			
Metric invariance	8	146.08*	.945	.947	4	7.16	.00
Scalar invariance	14	167.83*	.936	.941	6	21.75*	-.01
Invariant unique variance	18	204.10*	.923	.929	4	36.27*	-.01
Invariant factor variance	20	209.34*	.921	.928	2	5.24	.00

(*table continues*)

Table 21 (*continuted*)

Models	*df*	χ^2	NFI	CFI	Δdf	$\Delta\chi^2$	ΔCFI
region							
Configural invariance	9	200.09*	.935	.937			
Metric invariance	21	433.20*	.860	.864	12	233.11*	-.08
Scalar invariance	39	565.45*	.817	.827	18	132.25*	-.04
Invariant unique variance	51	1258.72*	.592	.603	12	693.27*	-.23
Invariant factor variance	57	1301.00*	.579	.591	6	42.29*	-.01
state							
Configural invariance	9	131.17*	.944	.946			
Metric invariance	23	201.65*	.913	.921	14	70.48*	-.03
Scalar invariance	44	314.33*	.865	.881	21	112.67*	-.05
Invariant unique variance	58	424.84*	.818	.839	14	110.51*	-.05
Invariant factor variance	65	442.01*	.810	.834	7	17.17*	-.01

Note. Configural invariance = same pattern of fixed and free factor loadings for each group; Metric invariance = Configural invariance plus same factor loadings for like items across groups; Scalar invariance = Metric invariance plus same intercepts for like items across groups; Invariant unique variance = Scalar invariance plus same unique variances for like items across groups; Invariant factor variance = Invariant unique variance plus same factor variances across groups (Vandenberg & Lance, 2000). * p<001.

Student Finance

Figure 4 presents the factor model for the student finance (*finance*) construct which is measured by four indicators: in-state tuition (*tuition2*), average amount of federal grant aid received (*xrofgrnt_a*), average amount of state grant aid received (*xrosgrnt_a*) and average amount of institutional grant aid received (*xroigrnt_a*). The regression weights (*r_b2*, *r_b3*, *r_b4* and 1), intercepts (*i_b1*, *i_b2*, *i_b3* and *i_b4*) and unique variances (*var_b0*, *var_b1*, *var_b2*, *var_b3* and *var_b4*) are parameters to be estimated in the model. The 1 indicates that *tuition2* is the marker variable whose scale is used to identify *finance*'s scale. Table 22 to Table 26 present the CFA summaries for *finance* by the five grouping variables. The parameters are presented in separate columns for each group of institutions. The *B* weights and Beta weights (β) are unstandardized and standardized regression weights. The intercepts (*Int*) are the means of the indicators. The unique variances (*var*) of the indicators are unpredicted by *finance*. The multiple R^2 are the lower bound on the reliability of the indicators. The Chi-squared (χ^2) and fit indices (CFI, NFI and RMSEA) are measures of model fit.

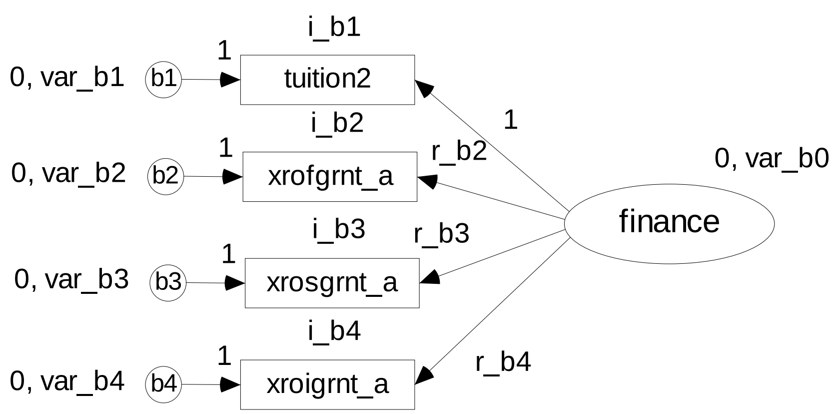

Figure 4. Factor model for student finance.

All the χ^2 are statistically significant at .001 level, indicating that the factor model fits the data. CFI and NFI are both greater than or close to .95, indicating that the model fits the data well. RMSEA is not an important fit index here because the CFA factor model is a simple model.

The average amount of institutional grant aid received (*xroigrnt_a*) is the best indicator for *finance* because of its large Beta weights (.672 to .978) and multiple R^2 (.451 to .953). The second best indicator for *finance* is the average amount of federal grant aid received (*xrofgrnt_a*), which has Beta weights (.232 to .977) and multiple R^2 (.054 to .954).

Based on the sum of the intercepts from Table 22, the average costs for attending a private not-for-profit institution is 1.7 times higher than attending a public institution. For all the groups other than public group, the percentages of the four intercepts to their totals are very similar: 50% to 55% from tuition and 10% to 15%, 10% to 15% and 20% to 30% from federal, state and institutional grant aid respectively. This may reflect the shares of financial burdens for affording higher education from the four constituents: students, federal government, state governments and the institutions.

Table 27 presents the tests of measurement invariance. The small ΔCFI (absolute value ≤ .01) indicates metric invariance across groups by Carnegie classification and degree of urbanization. The ΔCFI is not large for other grouping variables.

The above results answered research question 2 such that validity and reliability are established for the student finance factor based on the multiple R^2 and the fit indices (NFI and CFI) across the five groupings of institutions.

Table 22

CFA Summary for Student Finance by Control of Institution

Parameters	All	Public	Private
n	1785	577	1208
B_{r_b1}	1	1	1
B_{r_b2}	.060*	.653*	.078*
B_{r_b3}	.071*	1.063*	.057*
B_{r_b4}	.556*	1.946*	.726*
β_{r_b1}	.885	.232	.872
β_{r_b2}	.484	.431	.486
β_{r_b3}	.385	.478	.246
β_{r_b4}	.944	.672	.961
$\text{Int}_{\text{tuition2}}$	9931.62*	2770.17*	13388.15*
$\text{Int}_{\text{xrofgrnt\_a}}$	2687.19*	2469.55*	2786.13*
$\text{Int}_{\text{xrosgrnt\_a}}$	2328.47*	1803.94*	2590.82*
$\text{Int}_{\text{xroigrnt\_a}}$	4513.13*	2084.16*	5629.59*
var_b0	39787229*	135880	28120373*
var_b1	10973170*	2394529*	8824868*
var_b2	467626*	253222*	556398*
var_b3	1155167*	519886*	1401277*
var_b4	1509581*	625340*	1219893
R^2_{tuition2}	.784	.054	.761
$R^2_{\text{xrofgrnt\_a}}$	.234	.186	.237
$R^2_{\text{xrosgrnt\_a}}$	.148	.228	.060
$R^2_{\text{xroigrnt\_a}}$	.891	.451	.924

Note. $\chi^2(6) = 218.08$*, CFI = .954, NFI = .953, RMSEA = .100

*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 23

CFA Summary for Student Finance by Carnegie Classification Code

Parameters	All	Doctoral	Master	Baccalaureate
n	1785	248	577	520
B_{r_b1}	1	1	1	1
B_{r_b2}	.060*	.065*	.047*	.060*
B_{r_b3}	.071*	.046*	.094*	.065*
B_{r_b4}	.556*	.523*	.417*	.638*
β_{r_b1}	.885	.954	.919	.898
β_{r_b2}	.484	.663	.419	.502
β_{r_b3}	.385	.366	.480	.342
β_{r_b4}	.944	.976	.937	.946
$\mathrm{Int}_{tuition2}$	9931.62*	8998.72*	8922.34*	13075.69*
$\mathrm{Int}_{xrofgrnt\_a}$	2687.19*	2944.28*	2618.81*	2760.08*
$\mathrm{Int}_{xrosgrnt\_a}$	2328.47*	2228.80*	2354.98*	2517.66*
$\mathrm{Int}_{xroigrnt\_a}$	4513.13*	5445.51*	4042.74*	6055.47*
var_b0	39787229*	73165453*	36385048*	40295834*
var_b1	10973170*	7275989*	6652901*	9653844*
var_b2	467626*	392723*	380697*	437344*
var_b3	1155167*	1009756*	1082630*	1298463*
var_b4	1509581*	995885	872669*	1915162
$R^2_{tuition2}$	.784	.910	.845	.807
$R^2_{xrofgrnt\_a}$	.234	.439	.176	.252
$R^2_{xrosgrnt\_a}$	.148	.134	.230	.117
$R^2_{xroigrnt\_a}$	.891	.953	.879	.896

Note. $\chi^2(8) = 211.68$*, CFI = .962, NFI = .960, RMSEA = .090
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 24

CFA Summary for Student Finance by Degree of Urbanization

Parameters	All	Large City	Mid-size City	Urban Fringe
n	1785	384	480	294
B_{r_b1}	1	1	1	1
B_{r_b2}	.060*	.055*	.064*	.073*
B_{r_b3}	.071*	.060*	.058*	.074*
B_{r_b4}	.556*	.584*	.566*	.619*
β_{r_b1}	.885	.844	.871	.864
β_{r_b2}	.484	.395	.515	.525
β_{r_b3}	.385	.305	.321	.367
β_{r_b4}	.944	.942	.978	.939
$\mathrm{Int}_{tuition2}$	9931.62*	10867.95*	9669.27*	11812.84*
$\mathrm{Int}_{xrofgrnt\_a}$	2687.19*	2851.15*	2660.37*	2753.30*
$\mathrm{Int}_{xrosgrnt\_a}$	2328.47*	2512.54*	2322.57*	2653.96*
$\mathrm{Int}_{xroigrnt\_a}$	4513.13*	4672.28*	4584.60*	5193.32*
var_b0	39787229*	34201731*	40649094*	36829332*
var_b1	10973170*	13816097*	12975067*	12537360*
var_b2	467626*	560247*	468317*	514329*
var_b3	1155167*	1213762*	1202831*	1296767*
var_b4	1509581*	1482516	597928	1893828
$R^2_{tuition2}$	.784	.712	.758	.746
$R^2_{xrofgrnt\_a}$	.234	.156	.265	.276
$R^2_{xrosgrnt\_a}$	.148	.093	.103	.134
$R^2_{xroigrnt\_a}$	.891	.887	.956	.882

Note. $\chi^2(8) = 231.70$*, CFI = .950, NFI = .948, RMSEA = .098
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 25

CFA summary for student finance by geographical region

Parameters	All	New England	Mid East	Great Lakes
n	1785	164	361	279
B_{r_b1}	1	1	1	1
B_{r_b2}	.060*	.055*	.064*	.073*
B_{r_b3}	.071*	.060*	.058*	.074*
B_{r_b4}	.556*	.584*	.566*	.619*
β_{r_b1}	.885	.844	.871	.864
β_{r_b2}	.484	.395	.515	.525
β_{r_b3}	.385	.305	.321	.367
β_{r_b4}	.944	.942	.978	.939
$\mathrm{Int}_{tuition2}$	9931.62*	10867.95*	9669.27*	11812.84*
$\mathrm{Int}_{xrofgrnt\_a}$	2687.19*	2851.15*	2660.37*	2753.30*
$\mathrm{Int}_{xrosgrnt\_a}$	2328.47*	2512.54*	2322.57*	2653.96*
$\mathrm{Int}_{xroigrnt\_a}$	4513.13*	4672.28*	4584.60*	5193.32*
var_b0	39787229*	34201731*	40649094*	36829332*
var_b1	10973170*	13816097*	12975067*	12537360*
var_b2	467626*	560247*	468317*	514329*
var_b3	1155167*	1213762*	1202831*	1296767*
var_b4	1509581*	1482516	597928	1893828
$R^2_{tuition2}$	.784	.712	.758	.746
$R^2_{xrofgrnt\_a}$	.234	.156	.265	.276
$R^2_{xrosgrnt\_a}$	.148	.093	.103	.134
$R^2_{xroigrnt\_a}$	.891	.887	.956	.882

(table continues)

Table 25 (*continued*)

Parameters	Plains	Southeast	Southwest	Farwest
n	191	412	119	162
B_{r_b1}	1	1	1	1
B_{r_b2}	.052*	.068*	.057*	.039*
B_{r_b3}	.112*	.114*	.122*	.087*
B_{r_b4}	.409*	.600*	.418*	.396*
β_{r_b1}	.977	.807	.870	.969
β_{r_b2}	.462	.454	.379	.418
β_{r_b3}	.599	.499	.653	.494
β_{r_b4}	.856	.933	.929	.839
$\mathrm{Int}_{tuition2}$	9515.43*	7983.58*	6101.08*	10889.55*
$\mathrm{Int}_{xrofgrnt\_a}$	2497.07*	2561.69*	2577.42*	2912.29*
$\mathrm{Int}_{xrosgrnt\_a}$	2263.88*	2310.27*	1961.78*	2749.16*
$\mathrm{Int}_{xroigrnt\_a}$	4064.63*	3963.80*	2891.77*	5032.56*
var_b0	32983194*	22622136*	21645060*	65345862*
var_b1	1576593	12134224*	6968538*	4312789*
var_b2	330423*	401905*	425301*	467196*
var_b3	740941*	892830*	432015*	1514449*
var_b4	2017313*	1215380	598711	4312789*
$R^2_{tuition2}$	.954	.651	.756	.938
$R^2_{xrofgrnt\_a}$	.214	.206	.144	.175
$R^2_{xrosgrnt\_a}$	.358	.249	.427	.244
$R^2_{xroigrnt\_a}$	.732	.870	.863	.704

Note. $\chi^2(17) = 323.39$*, CFI = .947, NFI = .944, RMSEA = .069
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 26

CFA Summary for Student Finance by State

Parameters	All	CA	FL	IL	MA
n	1785	104	55	62	76
B_{r_b1}	1	1	1	1	1
B_{r_b2}	.060*	.040*	.077*	.059	.071*
B_{r_b3}	.071*	.099*	.152*	.050	-.008
B_{r_b4}	.556*	.386*	.613*	.476*	.671*
β_{r_b1}	.885	.969	.787	.901	.897
β_{r_b2}	.484	.413	.471	.419	.552
β_{r_b3}	.385	.554	.580	.339	-.081
β_{r_b4}	.944	.832	.997	.814	.969
$\mathrm{Int}_{tuition2}$	9931.62*	11088.65*	9038.11*	12839.18*	15241.86*
$\mathrm{Int}_{xrofgrnt\_a}$	2687.19*	2986.15*	2704.73*	2662.46*	3001.90*
$\mathrm{Int}_{xrosgrnt\_a}$	2328.47*	2993.81*	2585.21*	3866.04*	2051.31*
$\mathrm{Int}_{xroigrnt\_a}$	4513.138	5306.48*	3510.80*	5066.82*	7380.57*
var_b0	39787229*	74648545*	24032067*	29201772*	52492585*
var_b1	10973170*	4926448*	14721910	6795405	12747484
var_b2	467626*	580335*	500574*	478241*	595174*
var_b3	1155167*	1652970*	1098698*	555566*	533415*
var_b4	1509581*	4926448*	48632*	3372561	1514341
$R^2_{tuition2}$	.784	.938	.620	.811	.805
$R^2_{xrofgrnt\_a}$	.234	.171	.222	.176	.305
$R^2_{xrosgrnt\_a}$	.148	.307	.336	.115	.006
$R^2_{xroigrnt\_a}$	.891	.693	.995	.662	.940

(table continues)

Table 26 (*continued*)

Parameters	NY	OH	PA	TX
n	167	82	122	73
B_{r_b1}	1	1	1	1
B_{r_b2}	.024	.046*	.049*	.069*
B_{r_b3}	.044*	.044*	.052*	.126*
B_{r_b4}	.594*	.491*	.574*	.435*
β_{r_b1}	.922	.966	.971	.866
β_{r_b2}	.230	.385	.485	.437
β_{r_b3}	.380	.448	.702	.815
β_{r_b4}	.930	.879	.918	.941
$\text{Int}_{tuition2}$	11050.11*	11401.34*	12993.47*	6481.06*
$\text{Int}_{xrofgrnt\_a}$	3004.76*	2563.60*	2762.21*	2558.57*
$\text{Int}_{xrosgrnt\_a}$	2376.18*	1477.42*	2628.47*	2188.36*
$\text{Int}_{xroigrnt\_a}$	5051.89*	4691.99*	5688.89*	3094.40*
var_b0	49306656*	39743880*	43667817*	20956986*
var_b1	8649892	2819120*	2686317*	6975650*
var_b2	502909*	474446*	346815*	429444*
var_b3	578322*	302179*	123622*	169002*
var_b4	2697806	2819120*	2686317*	512478
$R^2_{tuition2}$	.851	.934	.942	.750
$R^2_{xrofgrnt\_a}$	.053	.148	.236	.191
$R^2_{xrosgrnt\_a}$	.144	.201	.493	.665
$R^2_{xroigrnt\_a}$	.866	.772	.843	.885

Note. $\chi^2(21) = 277.27$*, CFI = .937, NFI = .933, RMSEA = .070
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 27

Test of Measurement Invariance for Student Finance

Models	*df*	χ^2	NFI	CFI	Δdf	$\Delta\chi^2$	ΔCFI
control							
Configural invariance	6	218.08*	.953	.954			
Metric invariance	9	311.08*	.933	.935	3	93.00*	-.02
Scalar invariance	13	2206.07*	.526	.525	4	1894.98*	-.41
Invariant unique variance	17	2558.58*	.450	.450	4	352.51*	-.08
Invariant factor variance	18	3189.49*	.314	.314	1	630.91*	-.14
carnegie							
Configural invariance	8	211.68*	.960	.962			
Metric invariance	14	273.88*	.949	.951	6	62.20*	-.01
Scalar invariance	22	549.77*	.897	.900	8	275.89*	-.05
Invariant unique variance	30	643.99*	.879	.884	8	94.22*	-.02
Invariant factor variance	32	764.38*	.857	.862	2	120.39*	-.02
locale							
Configural invariance	8	231.70*	.948	.950			
Metric invariance	14	236.31*	.947	.950	6	4.62	.00
Scalar invariance	22	282.84*	.937	.941	8	46.52*	-.01
Invariant unique variance	30	301.50*	.933	.939	8	18.67	.00
Invariant factor variance	32	304.47*	.932	.939	2	2.97	.00

(*table continues*)

Table 27 (*continued*)

Models	*df*	χ^2	NFI	CFI	Δdf	$\Delta\chi^2$	ΔCFI
region							
Configural invariance	17	323.39*	.944	.947			
Metric invariance	35	417.74*	.928	.933	18	94.35*	-.02
Scalar invariance	59	611.24*	.895	.904	24	193.50*	-.03
Invariant unique variance	83	816.65*	.860	.872	24	205.41*	-.04
Invariant factor variance	89	860.42*	.852	.865	6	43.77*	-.01
state							
Configural invariance	21	277.27*	.933	.937			
Metric invariance	42	398.07*	.904	.912	21	120.80*	-.03
Scalar invariance	70	771.53*	.814	.827	28	373.46*	-.09
Invariant unique variance	96	1112.22*	.732	.749	26	340.69*	-.08
Invariant factor variance	103	1135.47*	.726	.745	7	23.25	-.01

Note. Configural invariance = same pattern of fixed and free factor loadings for each group; Metric invariance = Configural invariance plus same factor loadings for like items across groups; Scalar invariance = Metric invariance plus same intercepts for like items across groups; Invariant unique variance = Scalar invariance plus same unique variances for like items across groups; Invariant factor variance = Invariant unique variance plus same factor variances across groups (Vandenberg & Lance, 2000). * p<001.

Academic Environment

Figure 5 presents the factor model for the academic environment (*academic*) construct which is measured by four indicators: faculty-student ratio (*rofac2stu*), percentage of full-time faculty (*rofacftpct*), instructional expenditures per FTE student (*lginsexpfte*) and academic support expenditures per FTE student (*xlgacsexpfte*). The regression weights (*r_c2*, *r_c3*, *r_c4* and 1), intercepts (*i_c1*, *i_c2*, *i_c3* and *i_c4*) and unique variances (*var_c0*, *var_c1*, *var_c2*, *var_c3* and *var_c4*) are parameters to be estimated in the model. The 1 indicates that *rofac2stu* is the marker variable whose scale is used to identify *academic*'s scale. Table 28 to Table 32 present the CFA summaries for *academic* by the five grouping variables. The parameters are presented in separate columns for each group of institutions. The *B* weights and Beta weights (β) are unstandardized and standardized regression weights. The intercepts (*Int*) are the means of the indicators. The unique variances (*var*) of the indicators are unpredicted by *academic*. The multiple R^2 are the lower bound on the reliability of the indicators. The Chi-squared (χ^2) and fit indices (CFI, NFI and RMSEA) are measures of model fit.

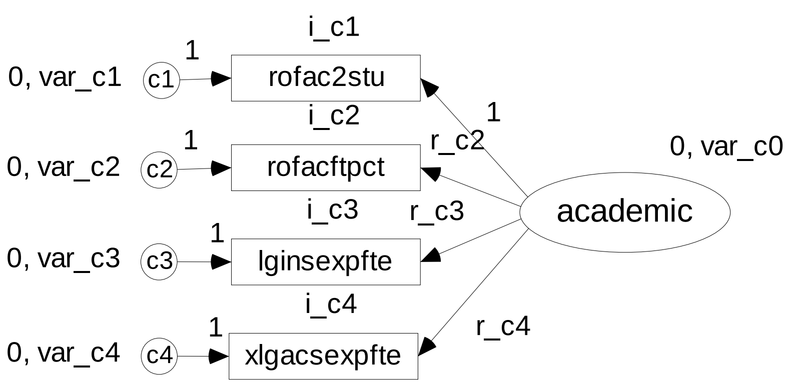

Figure 5. Factor model for academic environment.

All the χ^2 are statistically significant at .001 level, indicating that the factor model fits the data. CFI and NFI are close to .95, indicating that the model fits the data well. RMSEA is not an important fit index here because the CFA factor model is a simple model.

The instructional expenditures per FTE student (*lginsexpfte*) is the best indicator for *academic* because of its large Beta weights (.678 to .995) and multiple R^2 (.460 to .990). The second best indicator for *finance* is the academic support expenditures per FTE student (*xlgacsexpfte*) which has Beta weights (.485 to .883) and multiple R^2 (.286

to .780). The percentage of full-time faculty (*rofacftpct*) is a weak and unreliable indicator due to its small Beta weights and multiple R^2. The faculty-student ratio (*rofac2stu*) is a moderate indicator.

From Table 28, private institutions spend \$543 (or 10%) more per student than public institutions in instructions, but they spend equal amount on academic supports. Also, private institutions have higher faculty-student ratio (5.73% vs. 4.70%) and lower percentage of full-time faculty (56.63% vs. 68.46%) than public institutions. Private institutions are more efficient to create a better academic environment.

From Table 29, doctoral/research universities spend \$3,280 (or 59%) and \$979 (or 76%) more per student in instructions and academic supports respectively compared with the averages from all institutions. However, they have below average faculty-student ratio (5.32% vs. 5.39%) and much more full-time faculty (73.03% vs. 60.61%) than the average of all institutions. On the other hand, baccalaureate institutions spend in instructions and academic supports at the national average, but they have higher faculty-student ratio (6.07% vs. 5.39%) than the national average. Master universities have below average in all four indicators. This shows different academic environments between doctoral/research universities and baccalaureate institutions. The former may have invested a lot of their resources in research projects and research staff without worrying too much about faculty-student ratio. Their better prepared students, who have higher ACT scores (40, or 5 above national average), may have compensated the lower faculty-student ratio. Baccalaureate institutions are more focused on teaching and provide higher faculty-student ratio to help their less prepared students.

From Table 31, New England institutions spend \$1,487 (or 26.6%) and \$510 (or 40%) more per student in instructions and academic supports respectively compared with the national averages. However, their faculty-student ratios and percentages of full-time faculty are both below the national averages. On the other hand, southern regions spend \$600 to \$800 (or 10% to 14%) per student less than the national averages but they have higher percentages of full-time faculty and about average faculty-student ratios.
From Table 32, the states follow the same patterns as the geographical regions as mentioned above in terms of academic expenditures and the ratios.

Table 33 presents the tests of measurement invariance. The small ΔCFI (absolute value ≤ .01) indicates metric invariance across groups by all grouping variables except for state. The ΔCFI is not large for state grouping variable.

The above results answered research question 2 such that validity and reliability are established for the academic environment factor based on the multiple R^2 and the fit indices (NFI and CFI) across the five groupings of institutions.

Table 28

CFA Summary for Academic Environment by Control of Institution

Parameters	All	Public	Private
n	1785	577	1208
B_{r_c1}	1	1	1
B_{r_c2}	4.424*	6.449*	4.823*
B_{r_c3}	.369*	.440*	.345*
B_{r_c4}	.390*	.527*	.374*
β_{r_c1}	.640	.581	.672
β_{r_c2}	.312	.335	.379
β_{r_c3}	.903	.920	.877
β_{r_c4}	.730	.780	.731
$\mathrm{Int}_{rofac2stu}$	5.39*	4.70*	5.73*
$\mathrm{Int}_{rofacftpct}$	60.61*	68.46*	56.63*
$\mathrm{Int}_{lginsexpfte}$	8.63*	8.56*	8.66*
$\mathrm{Int}_{xlgacsexpfte}$	7.16*	7.16*	7.16*
var_c0	2.25*	.86*	2.96*
var_c1	3.25*	1.68*	3.59*
var_c2	409.66*	281.24*	409.38*
var_c3	.07*	.03*	.11*
var_c4	.30*	.15*	.36*
$R^2_{rofac2stu}$	.410	.338	.452
$R^2_{rofacftpct}$	.097	.112	.144
$R^2_{lginsexpfte}$	.816	.846	.769
$R^2_{xlgacsexpfte}$	.534	.608	.534

Note. $\chi^2(6) = 294.08$*, CFI = .922, NFI = .921, RMSEA = .116
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 29

CFA Summary for Academic Environment by Carnegie Classification Code

Parameters	All	Doctoral	Master	Baccalaureate
n	1785	248	577	520
B_{r_c1}	1	1	1	1
B_{r_c2}	4.424*	2.357	2.031	4.650*
B_{r_c3}	.369*	.454*	.307*	.267*
B_{r_c4}	.390*	.561*	.300*	.306*
β_{r_c1}	.640	.583	.690	.860
β_{r_c2}	.312	.142	.096	.456
β_{r_c3}	.903	.815	.918	.891
β_{r_c4}	.730	.866	.535	.758
$\mathrm{Int}_{rofac2stu}$	5.39*	5.32*	4.70*	6.07*
$\mathrm{Int}_{rofacftpct}$	60.61*	73.03*	59.13*	63.68*
$\mathrm{Int}_{lginsexpfte}$	8.63*	9.09*	8.55*	8.65*
$\mathrm{Int}_{xlgacsexpfte}$	7.16*	7.73*	7.04*	7.17*
var_c0	2.25*	1.02*	.98*	3.35*
var_c1	3.25*	1.98*	1.08*	1.18*
var_c2	409.66*	276.42*	430.77*	275.60*
var_c3	.07*	.11*	.02	.06*
var_c4	.30*	.11*	.22*	.23*
$R^2_{rofac2stu}$	.410	.340	.475	.740
$R^2_{rofacftpct}$	.097	.020	.009	.208
$R^2_{lginsexpfte}$	.816	.664	.842	.794
$R^2_{xlgacsexpfte}$	.534	.751	.286	.574

Note. $\chi^2(9) = 268.80^*$, CFI = .927, NFI = .925, RMSEA = .096
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 30

CFA Summary for Academic Environment by Degree of Urbanization

Parameters	All	Large City	Mid-size City	Urban Fringe
n	1785	384	480	294
B_{r_c1}	1	1	1	1
B_{r_c2}	4.424*	3.922*	5.861*	6.957*
B_{r_c3}	.369*	.395*	.402*	.448*
B_{r_c4}	.390*	.399*	.419*	.348*
β_{r_c1}	.640	.612	.612	.579
β_{r_c2}	.312	.286	.390	.454
β_{r_c3}	.903	.916	.915	.995
β_{r_c4}	.730	.721	.765	.605
$\mathrm{Int}_{rofac2stu}$	5.39*	5.54*	5.34*	5.11*
$\mathrm{Int}_{rofacftpct}$	60.61*	53.78*	63.89*	52.76*
$\mathrm{Int}_{lginsexpfte}$	8.63*	8.78*	8.66*	8.66*
$\mathrm{Int}_{xlgacsexpfte}$	7.16*	7.32*	7.19*	7.27*
var_c0	2.25*	2.65*	1.91*	1.78*
var_c1	3.25*	4.44*	3.19*	3.53*
var_c2	409.66*	458.29*	365.04*	330.90*
var_c3	.07*	.08	.06*	.004
var_c4	.30*	.39*	.24*	.37*
$R^2_{rofac2stu}$	.410	.374	.374	.335
$R^2_{rofacftpct}$	.097	.082	.152	.206
$R^2_{lginsexpfte}$	.816	.839	.837	.990
$R^2_{xlgacsexpfte}$	.534	.520	.585	.366

Note. $\chi^2(8) = 174.29$*, CFI = .943, NFI = .941, RMSEA = .084
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 31

CFA Summary for Academic Environment by Geographical Region

Parameters	All	New England	Mid East	Great Lakes
n	1785	164	361	279
B_{r_c1}	1	1	1	1
B_{r_c2}	4.424*	6.619*	4.715*	6.115*
B_{r_c3}	.369*	.317*	.326*	.240*
B_{r_c4}	.390*	.360*	.338*	.272*
β_{r_c1}	.640	.677	.644	.732
β_{r_c2}	.312	.475	.378	.487
β_{r_c3}	.903	.885	.892	.846
β_{r_c4}	.730	.744	.698	.645
$\mathrm{Int}_{rofac2stu}$	5.39*	5.82*	5.52*	5.24*
$\mathrm{Int}_{rofacftpct}$	60.61*	58.08*	54.09*	59.37*
$\mathrm{Int}_{lginsexpfte}$	8.63*	8.86*	8.74*	8.65*
$\mathrm{Int}_{xlgacsexpfte}$	7.16*	7.49*	7.28*	7.13*
var_c0	2.25*	2.59*	2.68*	3.30*
var_c1	3.25*	3.06*	3.78*	2.85*
var_c2	409.66*	389.17*	356.07*	396.17*
var_c3	.07*	.07	.07*	.08*
var_c4	.30*	.27*	.32*	.34*
$R^2_{rofac2stu}$	.410	.458	.414	.536
$R^2_{rofacftpct}$	.097	.225	.143	.237
$R^2_{lginsexpfte}$	.816	.782	.796	.716
$R^2_{xlgacsexpfte}$	.534	.554	.488	.416

(table continues)

Table 31 (*continued*)

Parameters	Plains	Southeast	Southwest	Farwest
n	191	412	119	162
B_{r_c1}	1	1	1	1
B_{r_c2}	5.949*	6.526*	2.971	3.687
B_{r_c3}	.345*	.399*	.311*	.437*
B_{r_c4}	.436*	.427*	.241*	.382*
β_{r_c1}	.578	.578	.824	.697
β_{r_c2}	.382	.389	.305	.260
β_{r_c3}	.866	.849	.879	.964
β_{r_c4}	.749	.675	.694	.732
$\mathrm{Int}_{rofac2stu}$	5.71*	5.48*	4.99*	5.21*
$\mathrm{Int}_{rofacftpct}$	65.04*	66.19*	66.43*	53.83*
$\mathrm{Int}_{lginsexpfte}$	8.55*	8.51*	8.48*	8.81*
$\mathrm{Int}_{xlgacsexpfte}$	7.00*	7.05*	6.96*	7.43*
var_c0	1.70*	1.23*	4.01*	2.37*
var_c1	3.38*	2.45*	1.89*	2.50*
var_c2	351.97*	294.27*	345.92*	445.06*
var_c3	.07*	.08*	.11	.04
var_c4	.25*	.27*	.25*	.30*
$R^2_{rofac2stu}$	.335	.335	.680	.486
$R^2_{rofacftpct}$	.146	.151	.093	.067
$R^2_{lginsexpfte}$	.750	.721	.773	.929
$R^2_{xlgacsexpfte}$	.562	.456	.482	.535

Note. $\chi^2(16) = 189.83$*, CFI = .949, NFI = .945, RMSEA = .056
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 32

CFA Summary for Academic Environment by State

Parameters	All	CA	FL	IL	MA
n	1785	104	55	62	76
B_{r_c1}	1	1	1	1	1
B_{r_c2}	4.424*	4.162*	6.261	6.061	7.173*
B_{r_c3}	.369*	.460*	.289	.364*	.332*
B_{r_c4}	.390*	.421*	.262	.458*	.393*
β_{r_c1}	.640	.715	.534	.769	.655
β_{r_c2}	.312	.344	.396	.423	.455
β_{r_c3}	.903	.957	.678	.771	.848
β_{r_c4}	.730	.794	.529	.770	.719
$\text{Int}_{rofac2stu}$	5.39*	5.02*	4.79*	5.54*	5.88*
$\text{Int}_{rofacftpct}$	60.61*	49.94*	59.16*	61.58*	57.31*
$\text{Int}_{lginsexpfte}$	8.63*	8.82*	8.48*	8.74*	8.96*
$\text{Int}_{xlgacsexpfte}$	7.16*	7.50*	7.09*	7.26*	7.56*
var_c0	2.25*	2.97*	2.13	1.80	2.10
var_c1	3.25*	2.83*	5.35*	1.25*	2.79*
var_c2	409.66*	383.98*	450.37*	304.30*	413.81*
var_c3	.07*	.06	.21	.16*	.09
var_c4	.30*	.31*	.38*	.26*	.30*
$R^2_{rofac2stu}$	.410	.512	.285	.591	.429
$R^2_{rofacftpct}$	.097	.118	.156	.179	.207
$R^2_{lginsexpfte}$	.816	.916	.460	.595	.718
$R^2_{xlgacsexpfte}$	.534	.630	.280	.593	.517

(table continues)

Table 32 (*continued*)

Parameters	NY	OH	PA	TX
n	167	82	122	73
B_{r_c1}	1	1	1	1
B_{r_c2}	4.458*	4.155*	3.659	1.646
B_{r_c3}	.320*	.220*	.415*	.264*
B_{r_c4}	.393*	.210*	.667*	.239*
β_{r_c1}	.654	.677	.454	.821
β_{r_c2}	.424	.389	.150	.145
β_{r_c3}	.862	.955	.761	.830
β_{r_c4}	.768	.485	.883	.698
$Int_{rofac2stu}$	5.66*	5.57*	5.33*	5.02*
$Int_{rofacftpct}$	52.34*	58.91*	57.42*	67.79*
$Int_{lginsexpfte}$	8.71*	8.66*	8.76*	8.51*
$Int_{xlgacsexpfte}$	7.17*	7.01*	7.37*	7.05*
var_c0	3.56*	3.80	.74	3.09*
var_c1	4.76*	4.49*	2.85*	1.50*
var_c2	322.81*	367.81*	429.49*	389.41*
var_c3	.13*	.02	.09*	.10
var_c4	.38*	.55*	.09*	.19*
$R^2_{rofac2stu}$	.428	.459	.206	.674
$R^2_{rofacftpct}$	.180	.151	.023	.021
$R^2_{lginsexpfte}$	.743	.911	.579	.690
$R^2_{xlgacsexpfte}$	.589	.235	.780	.487

Note. $\chi^2(19) = 191.73$*, CFI = .931, NFI = .926, RMSEA = .060
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 33

Test of Measurement Invariance for Academic Environment

Models	*df*	χ^2	NFI	CFI	Δdf	$\Delta\chi^2$	ΔCFI
control							
Configural invariance	6	294.08*	.921	.922			
Metric invariance	9	307.34*	.917	.919	3	13.26	.00
Scalar invariance	13	616.70*	.834	.837	4	309.36*	-.08
Invariant unique variance	17	846.12*	.773	.776	4	229.42*	-.06
Invariant factor variance	18	964.00*	.741	.744	1	117.88*	-.03
carnegie							
Configural invariance	9	267.80*	.925	.927			
Metric invariance	15	315.18*	.912	.915	6	47.38*	-.01
Scalar invariance	23	870.17*	.758	.761	8	554.98*	-.15
Invariant unique variance	31	1218.08*	.661	.666	8	347.91*	-.10
Invariant factor variance	33	1341.40*	.626	.631	2	123.32*	-.04
locale							
Configural invariance	8	174.29*	.941	.943			
Metric invariance	14	186.88*	.937	.941	6	12.60	.00
Scalar invariance	22	286.83*	.903	.909	8	99.94*	-.03
Invariant unique variance	30	330.71*	.888	.897	8	43.89*	-.02
Invariant factor variance	32	343.84*	.883	.893	2	13.13	-.01

(table continues)

Table 33 (*continued*)

Models	*df*	χ^2	NFI	CFI	Δdf	$\Delta\chi^2$	ΔCFI
region							
Configural invariance	16	189.83*	.945	.949			
Metric invariance	34	229.34*	.934	.942	18	39.51	-.01
Scalar invariance	58	556.05*	.839	.853	24	326.71*	-.10
Invariant unique variance	82	608.78*	.824	.844	24	52.73*	-.02
Invariant factor variance	88	648.18*	.813	.834	6	39.40*	-.01
state							
Configural invariance	19	191.73*	.926	.931			
Metric invariance	40	235.04*	.909	.922	21	43.30*	-.02
Scalar invariance	68	361.17*	.861	.883	28	126.14*	-.05
Invariant unique variance	96	520.56*	.799	.830	28	159.39*	-.06
Invariant factor variance	103	556.79*	.785	.819	7	36.23*	-.01

Note. Configural invariance = same pattern of fixed and free factor loadings for each group; Metric invariance = Configural invariance plus same factor loadings for like items across groups; Scalar invariance = Metric invariance plus same intercepts for like items across groups; Invariant unique variance = Scalar invariance plus same unique variances for like items across groups; Invariant factor variance = Invariant unique variance plus same factor variances across groups (Vandenberg & Lance, 2000). * p<001.

Social Environment

Figure 5 presents the factor model for the social environment (*social*) construct which is measured by three indicators: percentage of full-time environment (*enrolftpct*), full-time undergraduate enrollment (*lgenrolft*) and dormitory capacity (*xlgdormcap*). The student service expenditures per FTE student (*lgstuexpfte*) was removed from the factor model due to identification problem. The regression weights (*r_d2*, *r_d3* and 1), intercepts (*i_d1*, *i_d2* and *i_d3*) and unique variances (*var_d0*, *var_d1*, *var_d2* and *var_d3*) are parameters to be estimated in the model. The 1 indicates that *lgenrolft* is the marker variable whose scale is used to identify *social*'s scale. Table 34 to Table 38 present the CFA summaries for *social* by the five grouping variables. The parameters are presented in separate columns for each group of institutions. The *B* weights and Beta weights (β) are unstandardized and standardized regression weights. The intercepts (*Int*) are the means of the indicators. The unique variances (*var*) of the indicators are unpredicted by *social*. The multiple R^2 are the lower bound on the reliability of the indicators. An equality constraint (*var_d2* = *var_d3*) is imposed to avoid non-positive definite estimate problems.

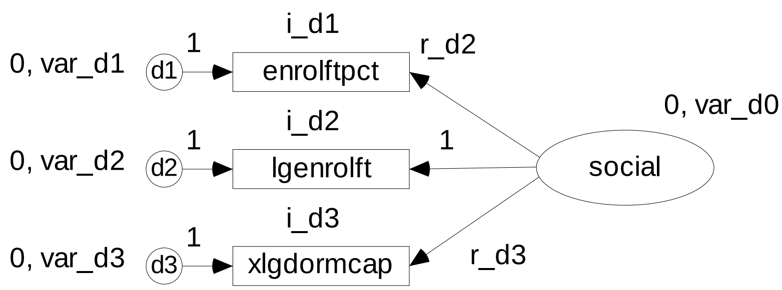

Figure 6. Factor model for social environment.

All the χ^2 are statistically significant at .001 level, indicating that the factor model fits the data. CFI and NFI are less than .95 but greater than .90, indicating that the model does not fit the data well. RMSEA is not an important fit index here because the CFA factor model is a simple model.

The percentage of full-time environment (*enrolftpct*) and the dormitory capacity (*xlgdormcap*) are strong indicators for *social* because of their large Beta weights (.706 to .984) and multiple R^2 (.499 to .968). The full-time undergraduate enrollment (*lgenrolft*) is a weak and unreliable indicator due to its small Beta weights (.044 to .480) and multiple R^2 (.002 to .251).

From Table 34, private institutions have higher percentage of full-time undergraduate students (83% vs. 78%) and more dormitory capacity (21% vs. 11% of full-time enrollment) than public institutions. Public institutions are also much bigger than private institutions because their average enrollment is more than five times bigger than that of the private institutions.. This indicates that private institutions may provide a more collegiate social environment for their students than public institutions.

From Table 35, baccalaureate colleges and doctoral/research universities have higher percentages of full-time students (85% and 84% vs. 78%) than master institutions. Baccalaureate colleges, however, have more dormitory capacity (21% vs. 12% and 13%) than doctoral/research and master institutions. Baccalaureate colleges are also 6.5 and 1.2 times smaller than doctoral/research and master universities based on full-time enrollment. This may indicate that baccalaureate colleges provide a more collegiate social environment for their students.

From Table 36, institutions located at urban fringe areas have greater dormitory capacity (18% vs. 15% and 16%) than institutions located at large cities and mid-size cities, but they have similar average sizes based on full-time enrollment. This may indicate that students who go to colleges at urban fringes may enjoy better campus life than students who go to colleges at large cities. The urban environment may also draw the students away from the social activities on campus.

From Table 37, institutions in New England and the Plains regions have larger dormitory capacity (20% vs. 14%) than institutions in the southeast and far west regions. They have similar percentages of full-time students and similar average sizes.

From Table 38, Texas universities are 50% larger than the national average based on full-time enrollment, have the lowest percentage of full-time students and the smallest dormitory capacity—about 5% lower than the national averages. Massachusetts universities have the largest dormitory capacity—5% higher than the national average—and about average percentage of full-time students and institutional size. New York has twice as many institutions as Texas. But its institutions are 50% smaller and have 10% more full-time students and 5% more dormitory capacity than the Texas institutions.

Table 33 presents the tests of measurement invariance. The small ΔCFI (absolute value ≤ .01) indicates metric invariance across groups by all grouping variables except for control and state. The ΔCFI is not large for the control and state grouping variables.

The above results answered research question 2 such that reliability is established for the social environment factor based on the multiple R^2 but the validity is not established based on the small fit indices (NFI and CFI).

Table 34

CFA Summary for Social Environment by Control of Institution

Parameters	All	Public	Private
n	1785	577	1208
B_{r_d1}	1	1	1
B_{r_d2}	2.757*	7.465*	4.478*
B_{r_d3}	.848*	1.018*	.934*
β_{r_d1}	.937	.880	.931
β_{r_d2}	.226	.472	.309
β_{r_c3}	.915	.883	.922
$Int_{enrolftpct}$	81.53*	78.45*	83.00*
$Int_{lgenrolft}$	8.34*	9.48*	7.80*
$Int_{xlgdormcap}$	6.55*	7.25*	6.22*
var_d0	1.81*	.82*	1.40*
var_d1	255.82*	158.74*	266.06*
var_d2	.251*	.238*	.216*
var_d3	.251*	.238*	.216*
$R^2_{enrolftpct}$	.051	.222	.095
$R^2_{lgenrolft}$	.878	.774	.867
$R^2_{xlgdormcap}$	.838	.780	.850

Note. $\chi^2(3) = 370.89$*, CFI = .926, NFI = .926, RMSEA = .185
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 35

CFA Summary for Social Environment by Carnegie Classification Code

Parameters	All	Doctoral	Master	Baccalaureate
n	1785	248	577	520
B_{r_d1}	1	1	1	1
B_{r_d2}	2.757*	7.871*	9.160*	11.656*
B_{r_d3}	.848*	1.409*	.945*	1.119*
β_{r_d1}	.937	.706	.861	.800
β_{r_d2}	.226	.369	.480	.434
β_{r_c3}	.915	.815	.848	.848
$\text{Int}_{enrolftpct}$	81.53*	84.77*	78.25*	85.77*
$\text{Int}_{lgenrolft}$	8.34*	10.12*	8.91*	8.10*
$\text{Int}_{xlgdormcap}$	6.55*	7.98*	6.89*	6.53*
var_d0	1.81*	.30*	.61*	.30*
var_d1	255.82*	118.26*	169.86*	176.324*
var_d2	.251*	.303*	.210*	.170*
var_d3	.251*	.303*	.210*	.170*
$R^2_{enrolftpct}$	.051	.137	.230	.188
$R^2_{lgenrolft}$	.878	.499	.742	.719
$R^2_{xlgdormcap}$	.838	.664	.720	.640

Note. $\chi^2(3) = 371.54$*, CFI = .902, NFI = .902, RMSEA = .172
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 36

CFA Summary for Social Environment by Degree of Urbanization

Parameters	All	Large City	Mid-size City	Urban Fringe
n	1785	384	480	294
B_{r_d1}	1	1	1	1
B_{r_d2}	2.757*	.534	3.554*	2.186
B_{r_d3}	.848*	.802*	.854*	.828*
β_{r_d1}	.937	.924	.951	.949
β_{r_d2}	.226	.044	.314	.164
β_{r_c3}	.915	.888	.934	.929
$\mathrm{Int}_{enrolftpct}$	81.53*	79.25*	81.46*	79.88*
$\mathrm{Int}_{lgenrolft}$	8.34*	8.16*	8.62*	8.15*
$\mathrm{Int}_{xlgdormcap}$	6.55*	6.24*	6.76*	6.44*
var_d0	1.81*	2.42*	1.91*	1.83*
var_d1	255.82*	347.44*	219.49*	315.79*
var_d2	.251*	.416*	.202*	.200*
var_d3	.251*	.416*	.202*	.200*
$R^2_{enrolftpct}$	.051	.002	.099	.027
$R^2_{lgenrolft}$	.878	.853	.904	.901
$R^2_{xlgdormcap}$	.838	.789	.873	.862

Note. $\chi^2(3) = 430.88$*, CFI = .902, NFI = .902, RMSEA = .191
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 37

CFA Summary for Social Environment by Geographical Region

Parameters	All	New England	Mid East	Great Lakes
n	1785	164	361	279
B_{r_d1}	1	1	1	1
B_{r_d2}	2.757*	3.766*	.848	4.103*
B_{r_d3}	.848*	.962*	.895*	.931*
β_{r_d1}	.937	.953	.953	.914
β_{r_d2}	.226	.263	.071	.297
β_{r_c3}	.915	.950	.942	.902
$Int_{enrolftpct}$	81.53*	81.23*	83.92*	79.37*
$Int_{lgenrolft}$	8.34*	8.17*	8.27*	8.39*
$Int_{xlgdormcap}$	6.55*	6.63*	6.54*	6.54*
var_d0	1.81*	1.53*	1.95*	1.63*
var_d1	255.82*	291.59*	275.45*	282.00*
var_d2	.251*	.153*	.197*	.322*
var_d3	.251*	.153*	.197*	.322*
$R^2_{enrolftpct}$	.051	.069	.005	.088
$R^2_{lgenrolft}$	.878	.909	.908	.835
$R^2_{xlgdormcap}$	.838	.902	.888	.814

(table continues)

Table 37 (*continued*)

Parameters	Plains	Southeast	Southwest	Farwest
n	191	412	119	162
B_{r_d1}	1	1	1	1
B_{r_d2}	3.800*	2.909*	2.451*	3.624*
B_{r_d3}	.730*	.842*	.764*	.774*
β_{r_d1}	.952	.957	.950	.910
β_{r_d2}	.295	.273	.220	.308
β_{r_c3}	.916	.941	.918	.862
$\text{Int}_{enrolftpct}$	79.82*	83.36*	77.82*	81.86*
$\text{Int}_{lgenrolft}$	8.11*	8.39*	8.57*	8.34*
$\text{Int}_{xlgdormcap}$	6.48*	6.64*	6.57*	6.37*
var_d0	1.70*	1.75*	1.96*	2.33*
var_d1	258.94*	184.06*	230.79*	291.15*
var_d2	.174*	.160*	.214*	.482*
var_d3	.174*	.160*	.214*	.482*
$R^2_{enrolftpct}$	.087	.074	.049	.095
$R^2_{lgenrolft}$	.907	.916	.902	.828
$R^2_{xlgdormcap}$	.839	.886	.843	.743

Note. $\chi^2(24) = 1261.25$*, CFI = .795, NFI = .794, RMSEA = .122
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 38

CFA Summary for Social Environment by State

Parameters	All	CA	FL	IL	MA
n	1785	104	55	62	76
B_{r_d1}	1	1	1	1	1
B_{r_d2}	2.757*	4.349*	2.333	2.335	3.181
B_{r_d3}	.848*	.772*	.789*	.895*	.964*
β_{r_d1}	.937	.891	.984	.943	.931
β_{r_d2}	.226	.387	.219	.217	.235
β_{r_c3}	.915	.835	.975	.930	.927
$Int_{enrolftpct}$	81.53*	82.06*	79.50*	83.24*	82.61*
$Int_{lgenrolft}$	8.34*	8.31*	8.01*	8.46*	8.26*
$Int_{xlgdormcap}$	6.55*	6.31*	6.21*	6.67*	6.74*
var_d0	1.81*	2.59*	3.41*	1.63*	1.37*
var_d1	255.82*	277.38*	370.01*	180.89*	235.93*
var_d2	.251*	.669*	.112*	.203*	.209*
var_d3	.251*	.669*	.112*	.203*	.209*
$R^2_{enrolftpct}$	.051	.150	.048	.047	.055
$R^2_{lgenrolft}$	.878	.795	.968	.889	.867
$R^2_{xlgdormcap}$	.838	.698	.950	.865	.859

(*table continues*)

Table 38 (*continued*)

Parameters	NY	OH	PA	TX
n	167	82	122	73
B_{r_d1}	1	1	1	1
B_{r_d2}	-2.381*	2.651	6.718*	4.553
B_{r_d3}	.903*	.877*	.883*	.762*
β_{r_d1}	.946	.950	.965	.929
β_{r_d2}	-.248	.227	.501	.332
β_{r_c3}	.935	.936	.955	.887
$\mathrm{Int}_{enrolftpct}$	87.59*	81.16*	83.03*	76.69*
$\mathrm{Int}_{lgenrolft}$	8.09*	8.17*	8.39*	8.74*
$\mathrm{Int}_{xlgdormcap}$	6.35*	6.42*	6.72*	6.69*
var_d0	2.37*	1.81*	1.31*	1.62*
var_d1	205.33*	234.69*	177.19*	271.45*
var_d2	.279*	.196*	.098*	.257*
var_d3	.279*	.196*	.098*	.257*
$R^2_{enrolftpct}$	.061	.051	.251	.110
$R^2_{lgenrolft}$	.895	.902	.930	.863
$R^2_{xlgdormcap}$	.874	.876	.912	.786

Note. $\chi^2(9) = 354.67$*, CFI = .909, NFI = .908, RMSEA = .124
*. Parameters are statistically significant at the 0.001 level (2-tailed).

Table 39

Test of Measurement Invariance for Social Environment

Models	*df*	χ^2	NFI	CFI	Δdf	$\Delta\chi^2$	ΔCFI
control							
Configural invariance	3	370.89*	.926	.926			
Metric invariance	5	248.66*	.950	.951	2	-122.22*	.02
Scalar invariance	8	1278.65*	.745	.746	3	1029.98*	-.21
Invariant unique variance	10	1309.48*	.739	.740	2	30.83*	-.01
Invariant factor variance	11	1313.97*	.738	.739	1	4.49	.00
carnegie							
Configural invariance	4	375.54*	.902	.902			
Metric invariance	8	407.56*	.894	.895	4	32.03*	-.01
Scalar invariance	14	1293.47*	.662	.664	6	885.90*	-.23
Invariant unique variance	18	1346.77*	.648	.651	4	53.31*	-.01
Invariant factor variance	20	1514.60*	.604	.607	2	167.83*	-.04
locale							
Configural invariance	4	430.88*	.902	.902			
Metric invariance	8	445.61*	.898	.900	4	14.73	.00
Scalar invariance	14	490.67*	.888	.891	6	45.06*	-.01
Invariant unique variance	18	588.60*	.866	.869	4	97.93*	-.02
Invariant factor variance	20	596.93*	.864	.868	2	8.33	.00

(*table continues*)

Table 39 (*continued*)

Models	*df*	χ^2	NFI	CFI	Δdf	$\Delta\chi^2$	ΔCFI
region							
Configural invariance	8	490.25*	.908	.909			
Metric invariance	20	543.93*	.898	.901	12	53.68*	-.01
Scalar invariance	38	488.70*	.908	.915	18	-55.22*	.01
Invariant unique variance	50	774.55*	.855	.863	12	285.84*	-.05
Invariant factor variance	56	784.93*	.853	.862	6	10.39	.00
state							
Configural invariance	9	354.67*	.908	.909			
Metric invariance	23	425.09*	.890	.894	14	70.42*	-.02
Scalar invariance	44	500.02*	.870	.880	21	74.93*	-.02
Invariant unique variance	58	638.55*	.834	.847	14	138.52*	-.04
Invariant factor variance	65	666.48*	.827	.842	7	27.93*	-.01

Note. Configural invariance = same pattern of fixed and free factor loadings for each group; Metric invariance = Configural invariance plus same factor loadings for like items across groups; Scalar invariance = Metric invariance plus same intercepts for like items across groups; Invariant unique variance = Scalar invariance plus same unique variances for like items across groups; Invariant factor variance = Invariant unique variance plus same factor variances across groups (Vandenberg & Lance, 2000). * p<001.

Structural Model

Figure 7 presents the SEM model for the institutional performance of graduation rates. It is constructed by connecting the four measurement models—for *background*, *finance*, *academic* and *social* factors—the retention rate (*xret_pct03*) and the six-year graduation rate (*gr4*). The *B* weights and Beta weights (e.g., *r_a1*) are unstandardized and standardized regression weights. The intercepts (e.g., *i_a1*) are the predicted means of the indicators (e.g., *xact25*). The unique variances (e.g., *var_a1*) of the indicators are variances unpredicted by the factors (e.g., *background*). The 0's on the left of the unique variances are means fixed at zero. An equality constraint (*var_d2* = *var_d3*) is imposed on the model to avoid estimation problems caused by non-positive definite matrices.

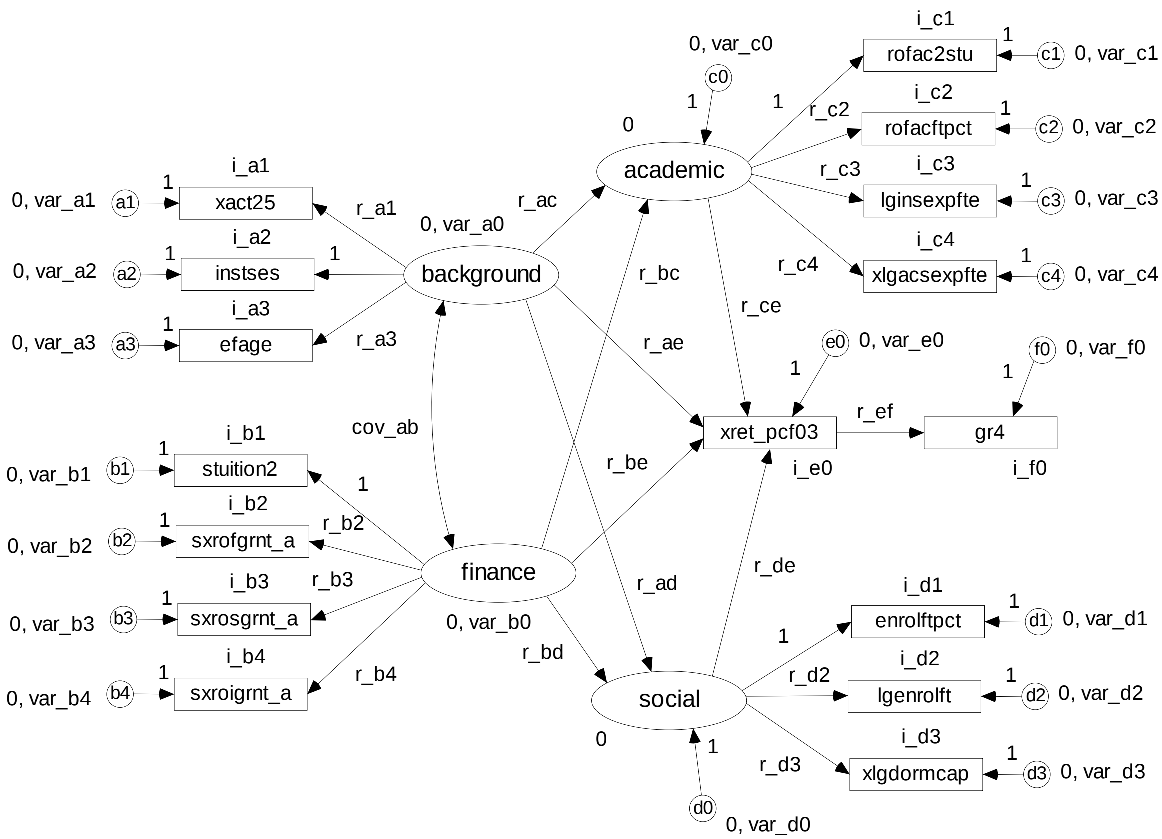

Figure 7. SEM model of institutional performance in graduation rates.

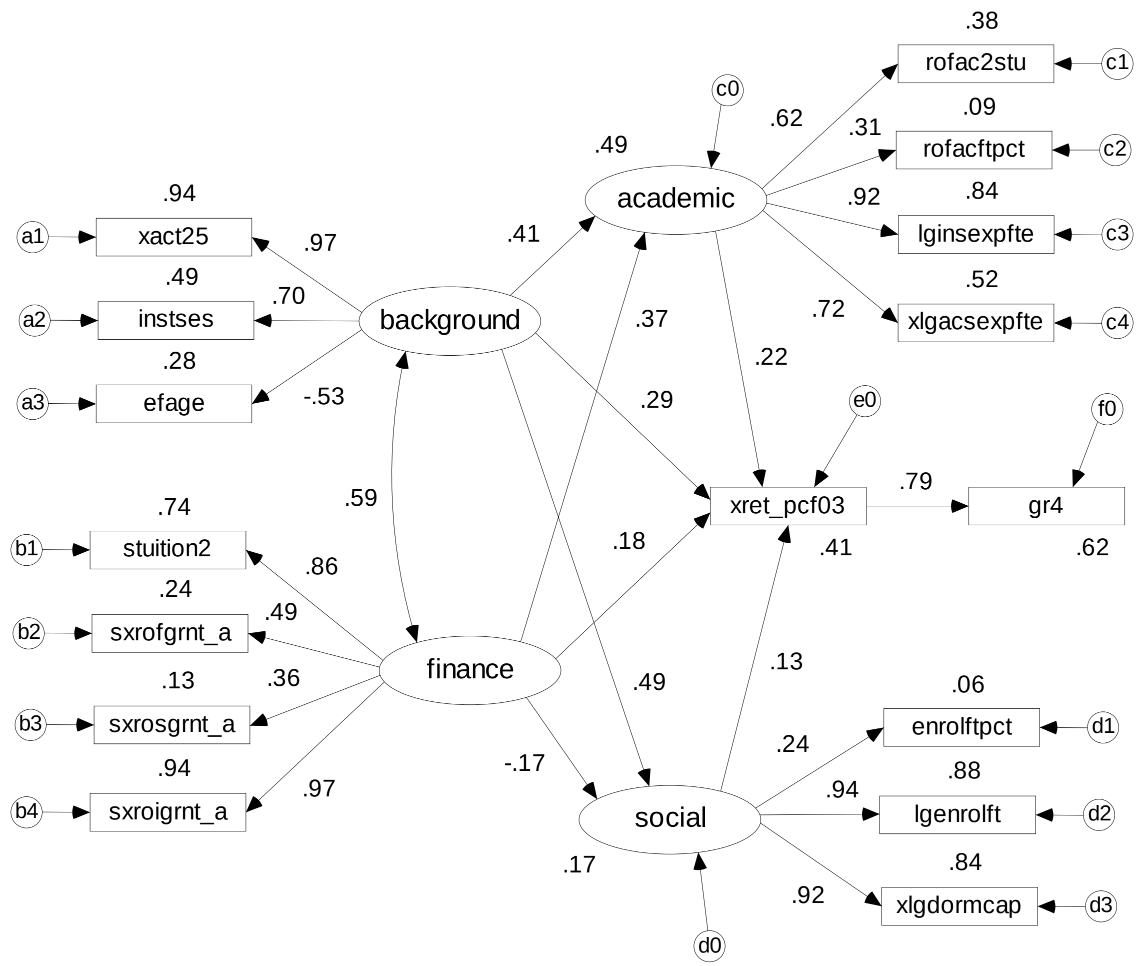

Figure 8. Standardized SEM model of graduation rates for all institutions (*N* = 1785).

Figure 8 presents the standardized results of the SEM model for all public and private not-for-profit, Title IV, four-year institutions. The $\chi^2(291) = 6778.81$, $p<.001$ is statistically significant, indicating that the model fit the data. However, χ^2 alone is not an accurate model fit index because it is heavily influenced by sample size. The fit indices, CFI = .794 and NFI = .787, are less than .95, indicating that the model does not have good fit on the data. However, RMSEA = .079 is close to the .05, indicating that the model may fit the data marginally because RMSEA incorporates no penalty for model complexity and tends to favor models with many parameters. Modification of the model should be considered to improve the overall model fit. However, modification indices cannot be computed to identify the areas to modify because of the missing values in the dataset. An alternative is to make the model stronger by imposing constraints on it. The Amos software can compute the critical ratios for differences of parameters to aid imposing such constraints. When the critical ratio for difference between two parameters is less than 1.96 and greater than -1.96, the hypothesis that the two parameters are equal in the population cannot be rejected at the .05 level (two-tailed). That means, an equality constraint can be imposed on the parameters without significantly increasing the χ^2. For example, the equality constraints (*r_ae* = *r_be* = *r_de*) are imposed for equal effects on the retention rate from *background*, *finance* and *social*. Amos allows creating a different model to impose these constraints on top of the baseline model. The alternative model has two degrees of freedom more than the baseline model because the two equality constraints reduce the number of estimated parameters by 2, i.e., one estimation for three parameters. In this case, the χ^2 are 6778.81 and 6782.98 for the baseline model and alternative model respectively. The χ^2 difference is 4.17 for 2 degrees of freedom. Of course, χ^2 (2) = 4.17 is not statistically significant at the .05 level. More alternative models can be created to test different constraints. For example, the constraint (*r_c3* = *r_c4*) can be imposed for equal weights on instructional expenditures and academic support expenditures and the χ^2 (1) difference is 4.14, *p*=.520. For group comparisons, equality constraints can also be imposed on parameters across groups to test their invariance in different groups. However, this kind of model improvement should not be abused because they can only be validated by testing the model in a different dataset.

The following interpretation is focused on the structural portion of the model, which includes the four factors (*background*, *finance*, *academic* and *social*) plus two observed variables—the retention rate (*xret_pcf03*) and the six-year graduation rate (*gr4*). The four measurement models associated with the four factors are discussed before and will not be discussed here. The numbers on the unidirectional arrows are the Beta (β) weights which indicate the direct causal or predictive effects on the endogenous variables from the exogenous variables. For example, one standard deviation change in *background* will cause a .41 standard deviation change in *academic*. Among the four latent factors, *background* has the largest direct effect on retention (.29) followed by *academic* (.22), *finance* (.18) and *social* (.13). This is contrary to Tinto's (1975) model where the background and input variables have only indirect effect, rather than direct effects, on commitment (measured by retention rates in this study) and graduation rates. An indirect effects is the effect on an endogenous variables from an exogenous variable through other mediating variables. This will be explained later. The correlation marked by the bidirectional arrow between *background* and *finance* (.59) is medium size.

The multiple R^2 are displayed beside the endogenous variable. They can be interpreted as the lower bound on the reliability or the percentages of variance explained in the variables. For example, 41% of the variance in the retention rate (*xret_pcf03*) is explained directly or indirectly by its four latent predictors (*background*, *finance*, *academic* and *social*). Likewise, 62% of the variance in the six-year graduation rate (*gr4*) is explained directly by the retention rate (*xret_pcf03*) and indirectly by the four latent predictors. Compared with the *academic* factor, the *social* factor has a small multiple R^2

(17%) and a small Beta weight (.13) on *xret_pcf03* indicating that *social* is a weak factor in the model for all institutions.

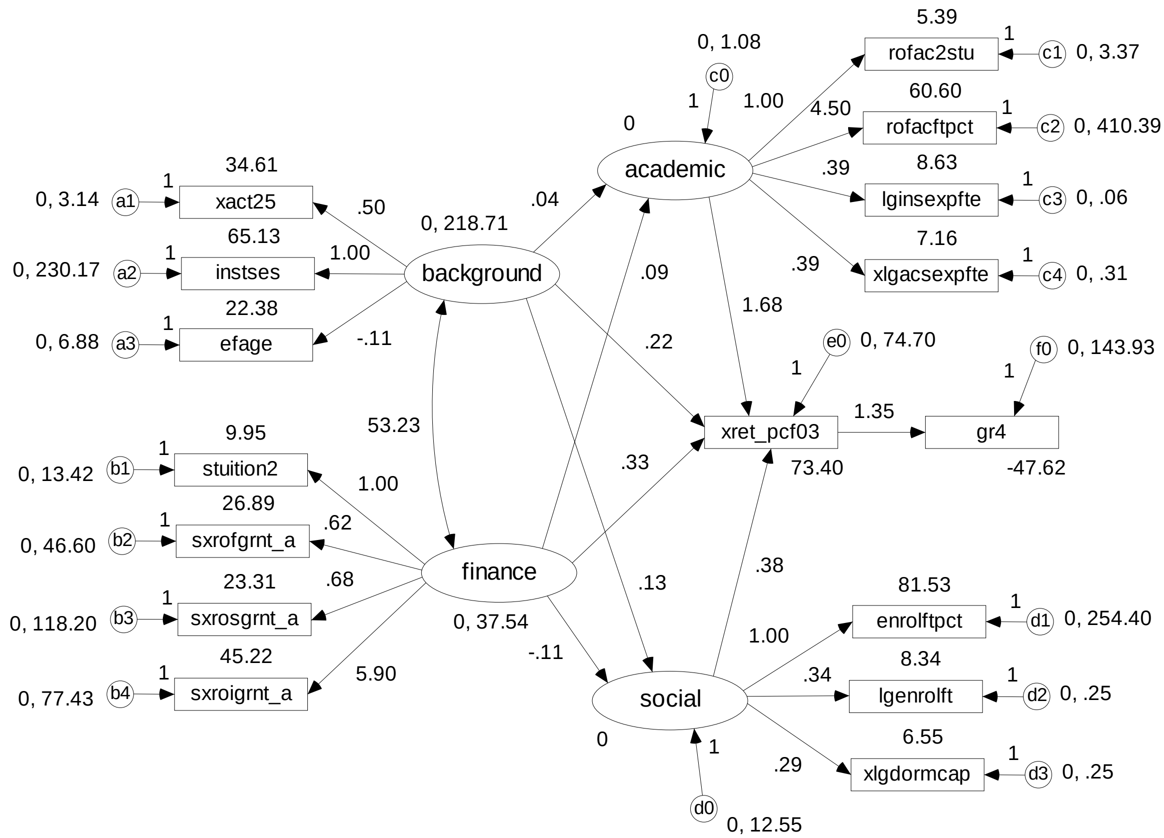

Figure 9. Unstandardized SEM model of graduation rates for all institutions (*N* = 1785).

Figure 9 presents the unstandardized results of the SEM model for all institutions. The numbers on the unidirectional arrows are the unstandardized regression weights (*B* weights). For example, one unit change in retention rate (*xret_pcf03*) will cause a 1.35 units change in the graduation rate (*gr4*). The number 53.23 on the bidirectional arrow is the covariance between *background* and *finance*, beside which are displayed their variances (218.71 and 37.54). The intercepts of the four indicators of the *finance* factor are different than the numbers shown in Table 22 because they are rescaled to be closer to the scales of the other factors. This will help the estimation. The s*tuition2* variable is in the unit of thousand dollars and the other three indicators (*sxrofgrnt_a*, *sxrosgrnt_a* and *sxroigrnt_a*) are in the unit of hundred dollars. The prefix ‘s’ indicates that these four variables are rescaled. The intercept for *xret_pcf03* is 73.40, which is the predicted mean of *xret_pcf03* when its predictors (i.e., the four latent factors) all have a factor mean of 0. Likewise, the intercept for *gr4* is -47.62. The predicted mean of *gr4* is 51.47 (= 73.40 × 1.35 – 47.62) which is close to the actual mean of *gr4* (51.87) in Table 11.

Structural Models with Group Comparisons

The SEM model is fit simultaneously on multiple subgroup datasets representing different groups of institutions based on control, Carnegie classification code, degree of urbanization, geographical region and state. Multi-group SEM is at least partially supported by the metric invariance established earlier on the four latent factors.

Groups by Control

Figure 10 presents the SEM model for public institutions. Figure 11 presents the SEM model for private not-for-profit institutions. Both figures are showing the standardized results of the model. The overall model fit indices (NFI = .787 and CFI = .794) do not indicate good fit on the data. The RMSEA is .079 which may indicate a marginal fit of the model because the multi-group comparison increases the complexity of the model. The following invariant constraints can be imposed to improve the model: *r_ae* = *r1_ae* = *r2_ae*; *r_be* = *r1_be* = *r2_be*; *r_ce* = *r1_ce* = *r2_ce*; *r_de* = *r1_de*; and *r_ef* = *r1_ef* = *r2_ef*. The “*r1*” indicates that the parameters are for group 1 (i.e., public institutions). Likewise, the “*r2*” indicates that the parameters are for group 2 (i.e., private not-for-profit institutions). The χ^2 (9) difference is 17.411, *p*=.043, which is not statistically significant at the .001 level. That means, these invariant constraints do not significantly worsen the model fit at the .001 level but will worsen the model fit at the .05 level. The equal effect constraints on the retention rate from *background*, *finance* and *social* can be extended to the group invariant case (i.e., *r_ae* = *r_be* = *r_de* = *r1_ae* = *r1_be* = *r1_de* = *r2_ae* = *r2_be* = *r2_de*). The χ^2 (8) difference is 24.310, *p*=.002. These constraints can be imposed at the .001 level if they make good theoretical sense.

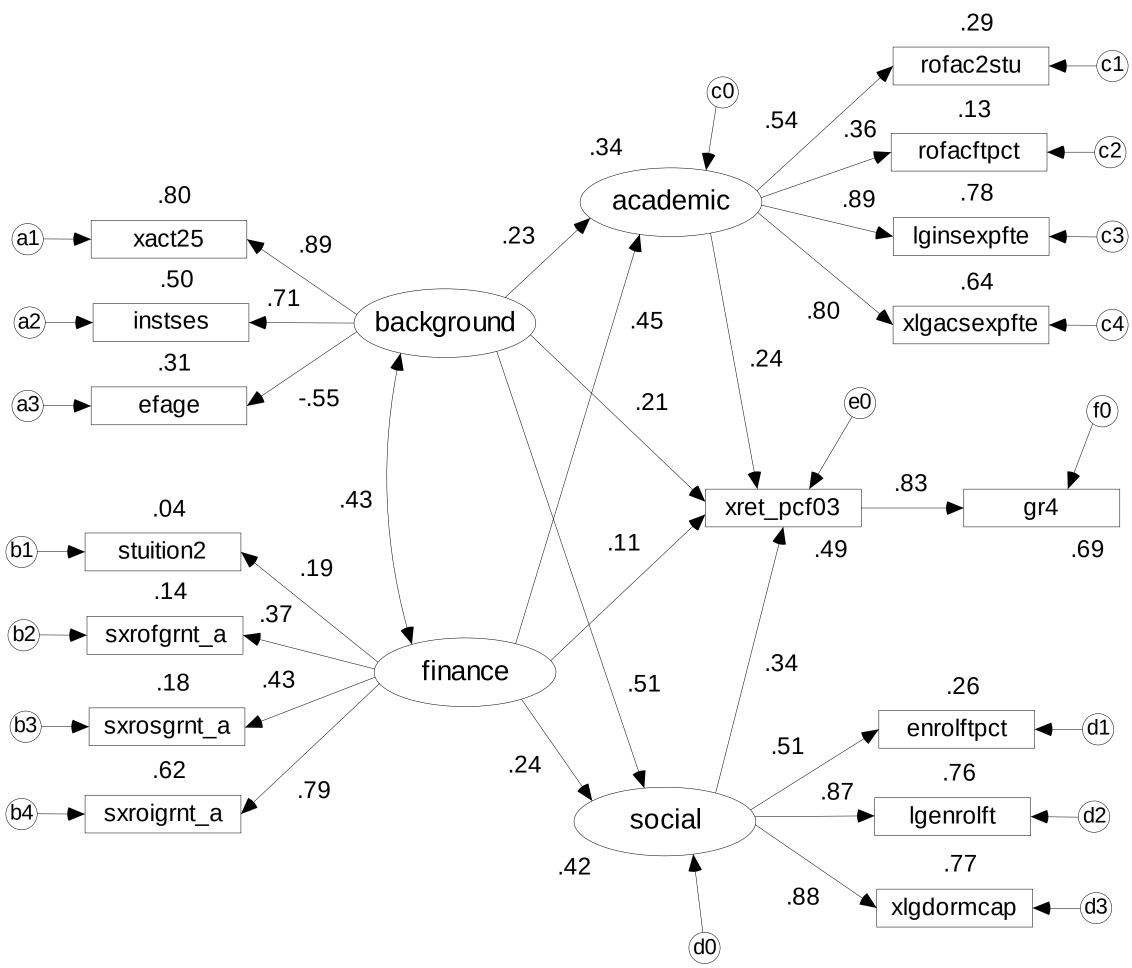

Figure 10. SEM model of graduation rates for public institutions (*N* = 577).

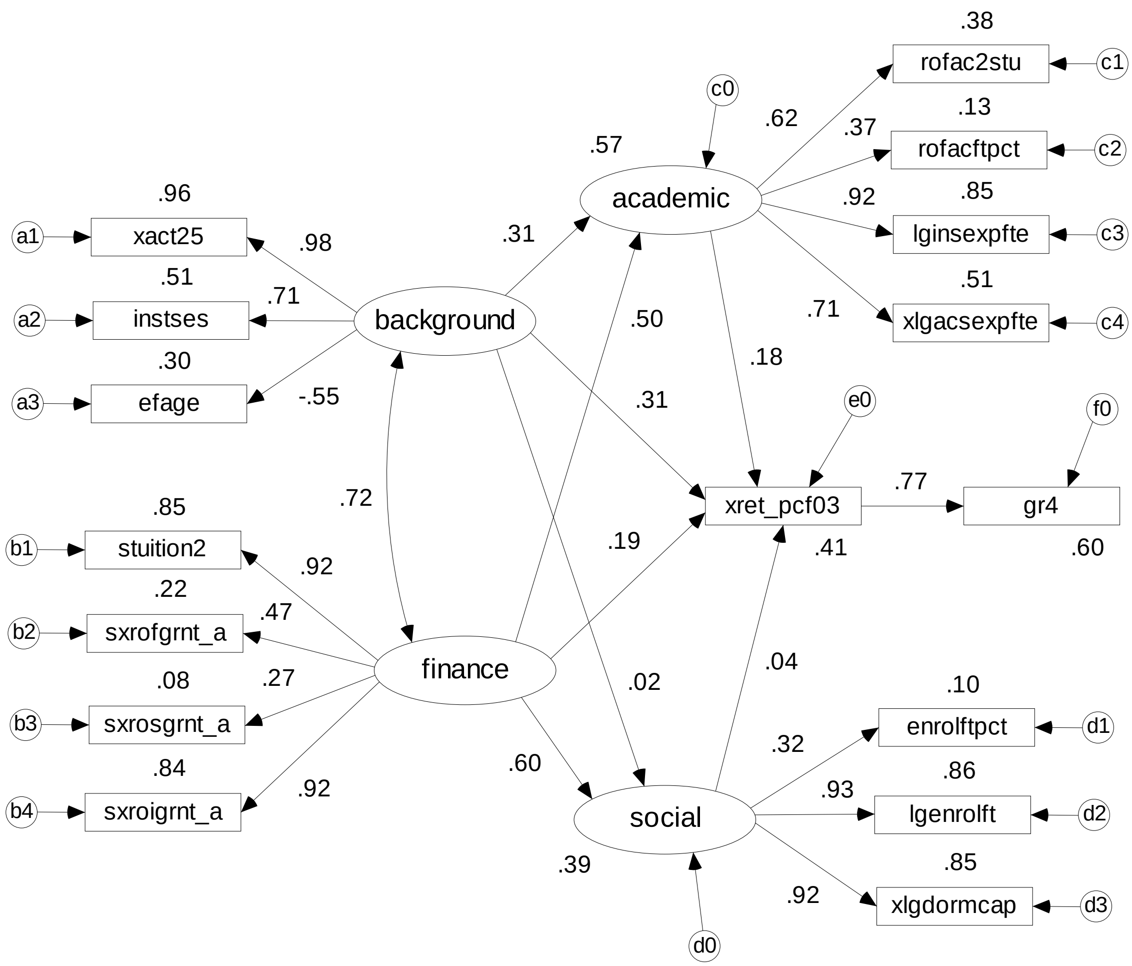

Figure 11. SEM model of graduation rates for private not-for-profit institutions (*N* = 1208).

Table 40 presents the summary of SEM results for group comparison between the public and private not-for-profit institutions. The Beta weights (β) are direct effects on the endogenous variables from their exogenous variables in standardized terms. Particular attention is on comparing the direct effects of the four paths from the two input factors (*background* and *finance*) to the two intermediate factors (*academic* and *social*): *background* to *academic* (β_{r_ac}), *background* to *social* (β_{r_ad}), *finance* to *academic* (β_{r_bc}) and *finance* to *social* (β_{r_bd}). These four parameters indicate how the four factors interact with each other. Figure 12 and Figure 13 present the graphical comparisons of the four direct effects and the four factor means between public and private institutions. Public institutions have much stronger direct effects from *background* to *social* (.508 vs. .022) and much weaker direct effects from *finance* to *social* (.244 vs. .604) than private institutions, indicating that the students' background and the students' finance may have compensatory effects on the social environment between the public an private institutions. On the other hand, private institutions have slightly stronger direct effects from *background* to *academic* (.305 and .231) and from *finance* to *academic* (.503 vs. .450) than the public institutions, indicating that the students' finance has a stronger effect (.503 vs. .305) than the student's background has (.450 vs. .231) on the academic environment in private institutions as well as in public institutions. Private institutions have a much stronger correlation between *background* and *finance* (.719 vs. .427) than public institutions, indicating that public institutions may have served a more diversified student body than the private institutions. Based on the factor means, public institutions have slightly disadvantaged students' backgrounds (60.83 vs. 67.68), much less in students' finances (1.79 vs. 18.92), moderately weaker academic environments (12.99 vs. 16.47) and much stronger social environments (60.25 vs. 32.88) than private institutions. This may mean that public institutions have done a commendable job in creating a competitive academic environment and a great job in creating a much better social environment to attract students with less advantageous background and much less financial resources. On the other hand, private institutions may have provided premium academic environments to attract the richer and more advantageous students.

The next four Beta weights (β_{r_ae}, β_{r_be}, β_{r_ce} and β_{r_de}) are the direct effects of the four factors on the retention rates. They represent, in part, the relative importance of the four factors in predicting the retention rates. However, the indirect effects should also be considered to determine the total effects of each of the four factors on the retention rates. Table 41 presents the direct, indirect and total effects of the four factors on retention rates and graduation rates. Public institutions have stronger direct effects from *social* and *academic* to retention rates (.339 vs. .044 and .235 vs. .185) than the private institutions. Private institutions, however, have stronger direct effects from *background* and *finance* to retention rates (.312 vs. .213 and .192 vs. .107) than the public institutions. But public institutions have stronger indirect effects from background and finance to retention rates (.227 vs. .057 and .189 vs. .120) than the private institutions. Consequently, public institutions have stronger total effects from three of the four factors—except for *finance*— to retention rates than the private institutions. Furthermore, public institutions have stronger total effects from all four factors—*background*, *social*, *finance* and *academic* in that order—to graduation rates than the private institutions. This means that students' background is the most influential factor to retention rates and graduation rates, followed by social environment, students' finance and academic environment for public institutions. Private institutions have similar order of importance in these four factors, only with the social environment ranked the lowest. Despite public institutions, rather than private institutions, can exert more positive influences through the academic and social environments to help their students persist, students' background and students' finance together remain the strongest factor for the students' persistence to graduation in both public and private institutions.

The multiple R^2 ($R^2_{academic}$, R^2_{social}, $R^2_{xret\_pcf03}$ and R^2_{gr4}) are percentages of variance in the four endogenous variables (*academic*, *social*, *xret_pcf03* and *gr4*) predicted in the model. While the model fit indices indicate the global fit of the model, the multiple R^2 indicate the local fit in different parts of the model. The R^2_{gr4} is also a measure of how well the model can be used to predict the six-year graduation rate, which is a performance measure of the institutions. Public institutions have larger explained variances in all four endogenous variables, except for *social* (.344 vs. .566) than the private institutions. This means that the model has larger predictive power for the public institutions than the private institutions. The model explains 68.8% of the variance in graduation rates among the public institutions whereas it explains 60% of the variance in graduation rates among the private institutions.

The four factor score means ($FM_{background}$, $FM_{finance}$, $FM_{academic}$ and FM_{social}) represent the average levels at which the public and private institutions can attain in the four factor areas. Figure 14 and Figure 15 present the graphical comparisons of the four factor score means for the public and the private institutions. Private institutions have greater factor score means than public institutions in all four factors except for the social environment (32.88 vs. 60.22), indicating that public institutions surpass private institutions only in social environment. Private institutions also have wider ranges and larger variances than the public institutions in the four factor scores, indicating that the private institutions vary a lot in the four factor areas.

Table 40

Summary of SEM Results by Control of Institutions

Parameters	All	Public	Private
n	1785	577	1208
β_{r_ac}	.409	.231	.305
β_{r_ad}	.490	.508	.022
β_{r_bc}	.373	.450	.503
β_{r_bd}	-.172	.244	.604
β_{r_ae}	.290	.213	.312
β_{r_be}	.178	.107	.192
β_{r_ce}	.216	.235	.185
β_{r_de}	.130	.339	.044
β_{r_ef}	.786	.829	.775
r_{ab}	.587	.427	.719
$R^2_{academic}$	.486	.344	.566
R^2_{social}	.171	.423	.385
$R^2_{xret\_pcf03}$	.412	.495	.415
R^2_{gr4}	.618	.688	.600
n_{FM}	1557	548	1009
$FM_{background}$	65.27	60.83	67.68
$FM_{finance}$	12.89	1.79	18.92
$FM_{academic}$	15.24	12.99	16.47
FM_{social}	42.51	60.25	32.88

Note. The Beta weights (β) are the standardized regression weights for the paths. The correlation coefficient (r_{ab}) is the Pearson r between *background* and *finance* factors. The multiple R^2 are the percentage of variance explained in the variables. The *FM*s are the factor means predicted by the observed variables in the model. The n_{FM} is the effective sample size for computing the factor means.

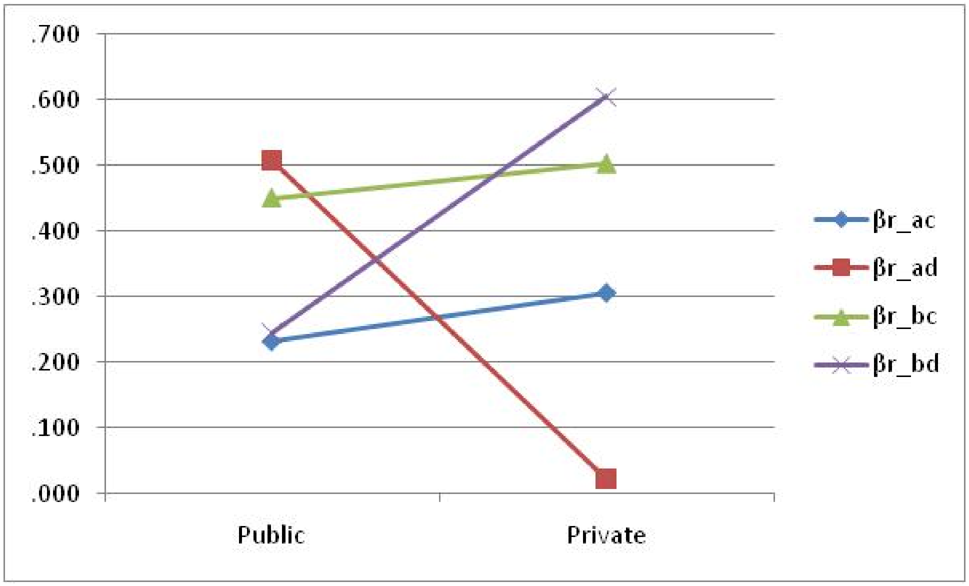

Figure 12. Comparison of direct effects by control of institutions. (*Note*. The four standardized direct effects are background to academic β_{r_ac}, background to social β_{r_ad}, finance to academic β_{r_bc} and finance to social β_{r_bd}.)

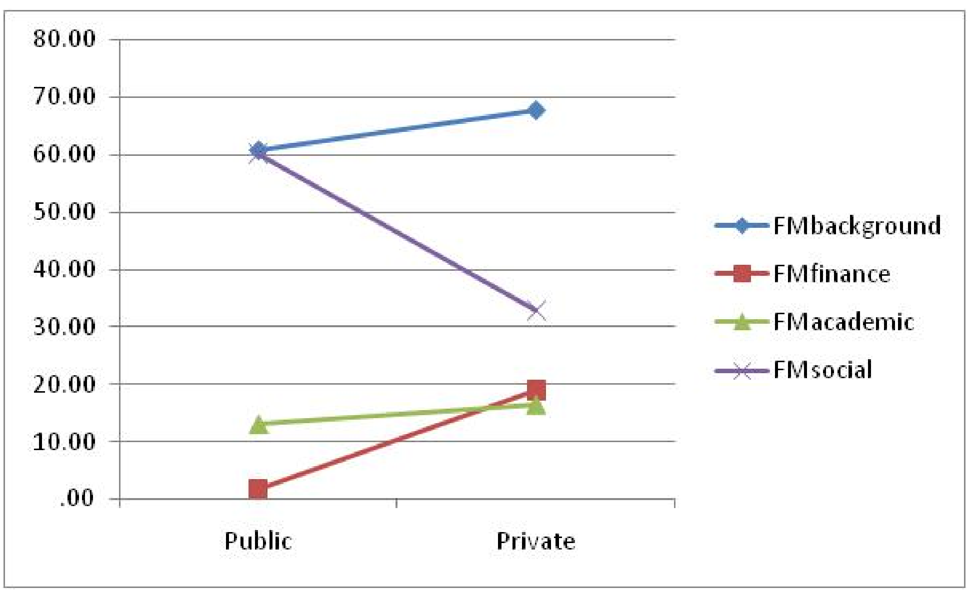

Figure 13. Comparison of factor means by control of institutions.

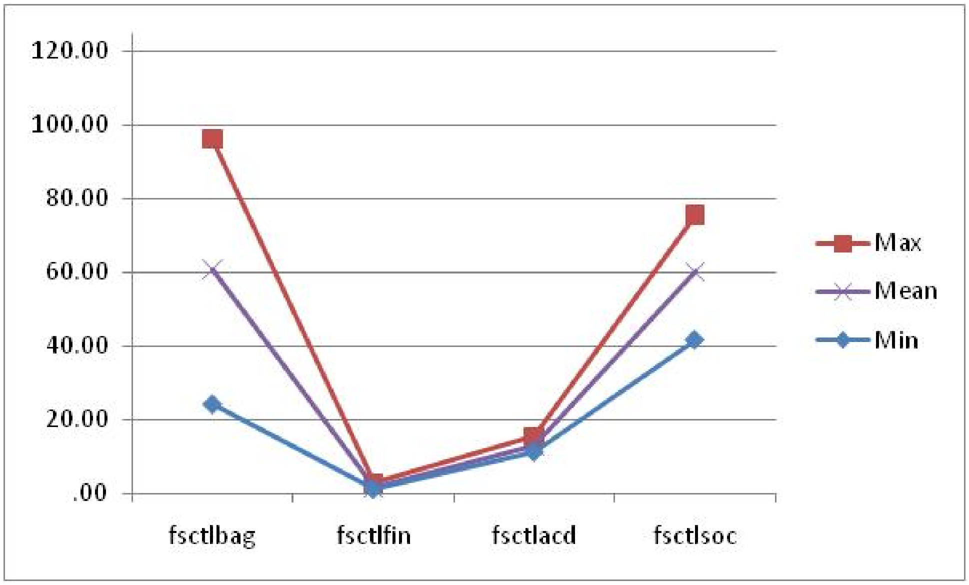

Figure 14. Comparison of factor scores for public institutions (*N* = 548). (*Note*. The four factor scores by control of institutions are for students' background *fsctlbag*, students' finance *fsctlfin*, academic environment *fsctlacd* and social environment *fsctlsoc*.)

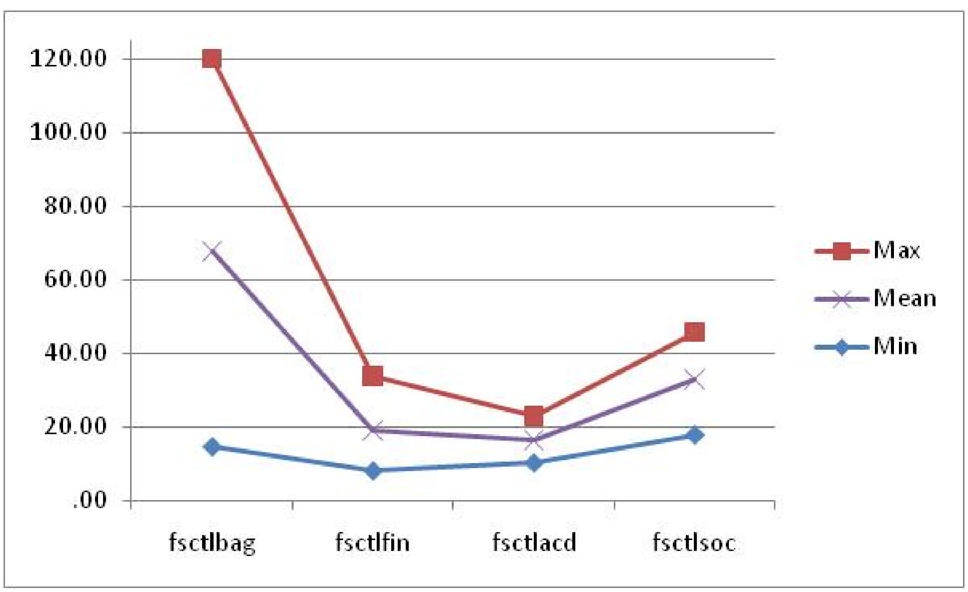

Figure 15. Comparison of factor scores for private institutions (*N* = 1009).

Table 41

Effects on Graduation Rates in SEM Model by Control of Institutions

Effects	All	Public	Private
n	1785	577	1208
Total effects on gr4 by:			
background	.348	.365	.286
finance	.186	.245	.241
social	.102	.282	.034
academic	.170	.195	.143
xret_pcf03	.786	.829	.775
Total effects on xret_pcf03 by:			
background	.442	.440	.369
finance	.236	.296	.312
social	.130	.339	.044
academic	.216	.235	.185
Direct effects on xret_pcf03 by:			
background	.290	.213	.312
finance	.178	.107	.192
social	.130	.339	.044
academic	.216	.235	.185
Indirect effects on xret_pcf03 by:			
background	.152	.227	.057
finance	.058	.189	.120

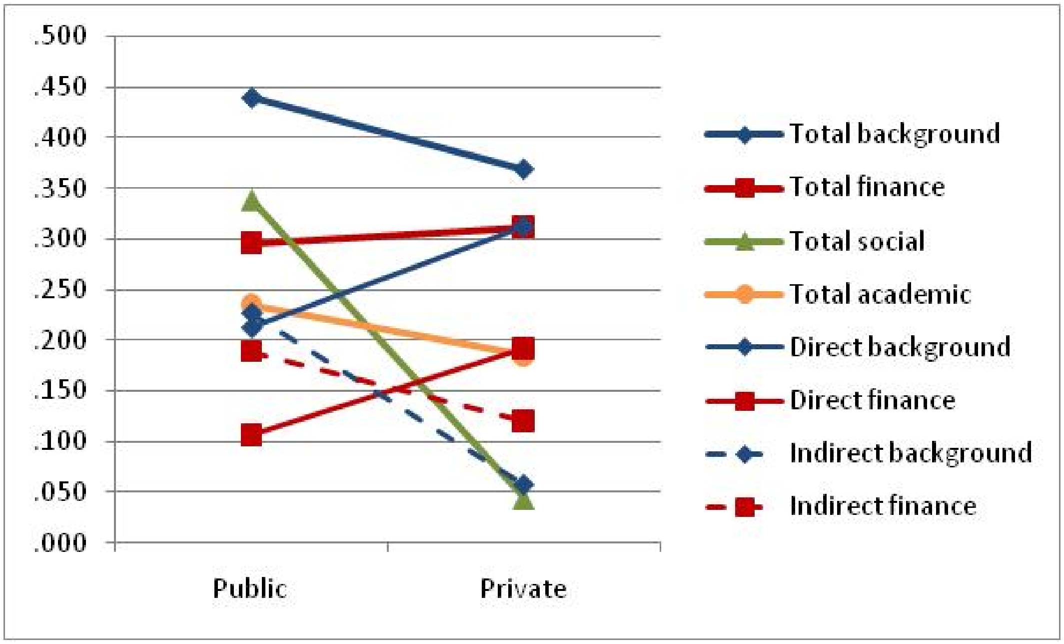

Figure 16. Comparison of direct, indirect and total effects of four factors on retention rates by control of institutions.

Groups by Carnegie Classification Code

From Table 15, control of institutions and Carnegie classification are the two most important grouping variables out of nine predictor variables for explaining the variances in six-year graduation. What has been discussed above is a comparison based on control of institutions by fitting the SEM model on the subgroup datasets of public and private not-for-profit institutions simultaneously. In below, the same SEM model is simultaneously fit on three groups of institutions based on Carnegie classification code—doctoral or research universities (codes 15 and 16), masters colleges and universities (codes 21 and 22) and baccalaureate colleges (codes 31 and 32). Table 42 summarizes the SEM results, including the Beta weights of the structural paths, the multiple R^2 and the factor score means. Again the measurement portion of the model is left out here because they have been discussed earlier. The overall model fit indices are NFI = .785, CFI = .794 and RMSEA = .071, very close to that based on control of institutions. Although NFI and CFI do not indicate good fit on the data, RMSEA may indicate a marginal fit. Surely, equality constraints can be imposed on some parameters of the model to make the model stronger as it has been demonstrated in previous discussion. But these constraints can only indicate possible improvements of the model which itself must be validated by a different dataset.

Figure 17 and Figure 18 present the graphical comparisons of the four direct effects of the four factors and their means between doctoral, masters and baccalaureate institutions. Based on the factor means, doctoral universities have the lowest scores in all four areas (students' background, students' finance, academic environment and social environment) followed by masters universities and baccalaureate colleges. Masters universities have slightly better students' background (74.84 vs. 74.42) and academic environment (22.95 vs. 20.28) than baccalaureate colleges. Students' finance has a stronger direct effect than students' background on the academic environment by the similar extent across all three groups. Comparing the three groups, students' background and students' finance have similar direct effects on the academic environment in doctoral universities and baccalaureate colleges, but these effects are weaker in masters universities. This may mean that the masters universities are doing a better job to create a better academic environment for their students with less regard to their students' background and finance. The doctoral universities and baccalaureate colleges, however, have not done enough to help their students succeed academically without regard to their background and finance. On the other hand, the doctoral universities may have done very little to create a better social environment for their students allowing the strong effects of students' background and students' finance to shape the social environment. Baccalaureate colleges, however, may have done a better job to create a better social environment for their students, particularly in overcoming the negative effects of students' finance. The masters universities are in the middle, particularly in helping the less prepared students than the less resourceful students.

The next four Beta weights (β_{r_ae}, β_{r_be}, β_{r_ce} and β_{r_de}) are the direct effects of the four factors on the retention rates. They represent, in part, the relative importance of the four factors in predicting the retention rates. However, the indirect effects should also be considered to determine the total effects of each of the four factors on the retention rates. Table 43 presents the direct, indirect and total effects of the four factors on retention rates and graduation rates. Figure 22 presents the graphical comparison of the direct, indirect and total effects of the four factors on retention rates. Based on their total effects on retention rates, students' background is the most important factor to influence the retention rates in all three of doctoral, masters and baccalaureate institutions. It is the strongest in doctoral institutions (.797) followed by masters and baccalaureate institutions (.549 and .410). The direct and indirect effects of students' background follow the same pattern. The total effect of students' finance on retention rates follows the reverse pattern of students' background and is the weakest in doctoral institutions (.052) followed by masters and baccalaureate institutions (.236 and .345). This is largely the results of the larger direct effects offset by the negative effects in doctoral and masters institutions.

Baccalaureate institutions have both positive direct and indirect effects. This may indicate that students' background and students' finance have compensatory effects on retention rates just as they have compensatory effects on the social environment. That means when one effect tends to be larger, the other effect tends to be smaller. If this is true, institutions are better off pursuing larger effects on retention rates either from students' background by their admission policies or from students' finance by their student financing policies but not both. The academic environment and social environment only have direct effects on retention rates. Master institutions have the smallest effects (.007) from their academic environment to their retention rates but have the largest effects (.335) from their social environment to retention rates. These two effects are close to each other in doctoral and baccalaureate institutions. This may be resulted from the influence of the indirect effects of students' background and students' finance. Because students' background has a larger effect on the social environment (see Figure 17), the indirect effect of students' background will have a greater impact on the direct effect of social environment. Likewise, students' finance has a larger effect on the academic environment, the indirect effect of students' finance will have a greater impact on the direct effect of academic environment. The academic environment in masters institutions has a smaller effects on retention rates (.007) than the doctoral and baccalaureate institutions because of the influence by the larger negative indirect effects of students' finance (-.210). Likewise, the effects of the social environment are pulled down more by the indirect effect of students' background in doctoral and baccalaureate institutions. If these indirect effects are removed, the social and academic environments should have similar pattern in their effects on retention rates as the students' background, that is higher in doctoral institutions than in masters and baccalaureate institutions.

The multiple R^2 ($R^2_{academic}$, R^2_{social}, $R^2_{xret\_pcf03}$ and R^2_{gr4}) are percentages of variance in the four endogenous variables (*academic*, *social*, *xret_pcf03* and *gr4*) predicted in the model. The R^2_{gr4} is also a measure of how well the model can be used to predict the six-year graduation rate, which is a performance measure of the institutions. The model has more predictive power to predict retention rates and graduation rates in doctoral institutions (74.9% and 83% respectively) than in masters and baccalaureate institutions. The academic environment is better predicted in doctoral and baccalaureate institutions (68.3% and 69.8% respectively) than in masters institutions (28.8%) whereas the social environment is better predicted in the doctoral and masters institutions (50.7% and 54.2%) than in baccalaureate institutions (25.3%).

The four factor score means ($FM_{background}$, $FM_{finance}$, $FM_{academic}$ and FM_{social}) represent the average levels at which the public and private institutions can attain in the four factor areas. Figure 19, Figure 20 and Figure 21 present the graphical comparisons of the four factor score means for the doctoral, masters and the baccalaureate institutions. Doctoral institutions have smallest factor score means for all four factors, particularly in students' background and social environment (45.49 and 50.52 respectively). Masters institutions score the highest in academic environment and baccalaureate institutions score the highest in social environment. The variance of each of the four factor scores is similar in all three groups of institutions, except for larger variance in the students' background in baccalaureate institutions.

Table 42

Summary of SEM Results by Carnegie Classification of Institutions

Parameters	All	Doctoral	Master	Baccalaureate
n	1785	248	577	520
β_{r_ac}	.409	.310	.187	.286
β_{r_ad}	.490	.953	.689	.550
β_{r_bc}	.373	.586	.437	.593
β_{r_bd}	-.172	-.717	-.636	-.063
β_{r_ae}	.290	.455	.316	.246
β_{r_be}	.178	.133	.447	.220
β_{r_ce}	.216	.215	.007	.230
β_{r_de}	.130	.289	.335	.178
β_{r_ef}	.786	.911	.836	.811
r_{ab}	.587	.670	.385	.781
$R^2_{academic}$	.486	.683	.288	.698
R^2_{social}	.171	.507	.542	.253
$R^2_{xret\_pcf03}$	.412	.749	.508	.548
R^2_{gr4}	.618	.830	.698	.658
n_{FM}	1281	241	555	485
$FM_{background}$	69.16	45.49	74.84	74.42
$FM_{finance}$	16.73	12.66	14.47	21.33
$FM_{academic}$	20.48	15.22	22.95	20.28
FM_{social}	61.82	50.52	60.93	68.45

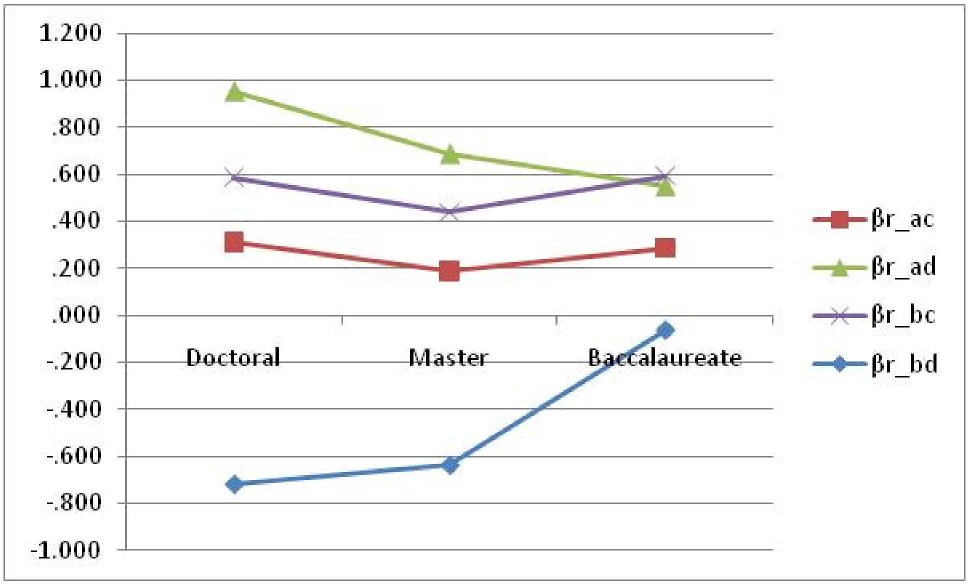

Figure 17. Comparison of direct effects by Carnegie classification of institutions. (*Note*. The four standardized direct effects are background to academic β_{r_ac}, background to social β_{r_ad}, finance to academic β_{r_bc} and finance to social β_{r_bd}.)

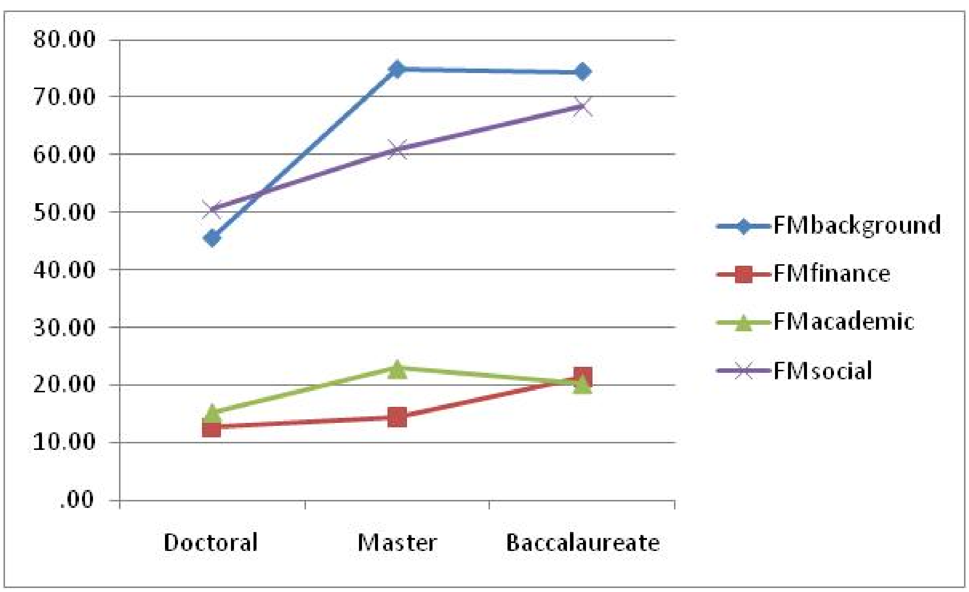

Figure 18. Comparison of factor means by Carnegie classification of institutions.

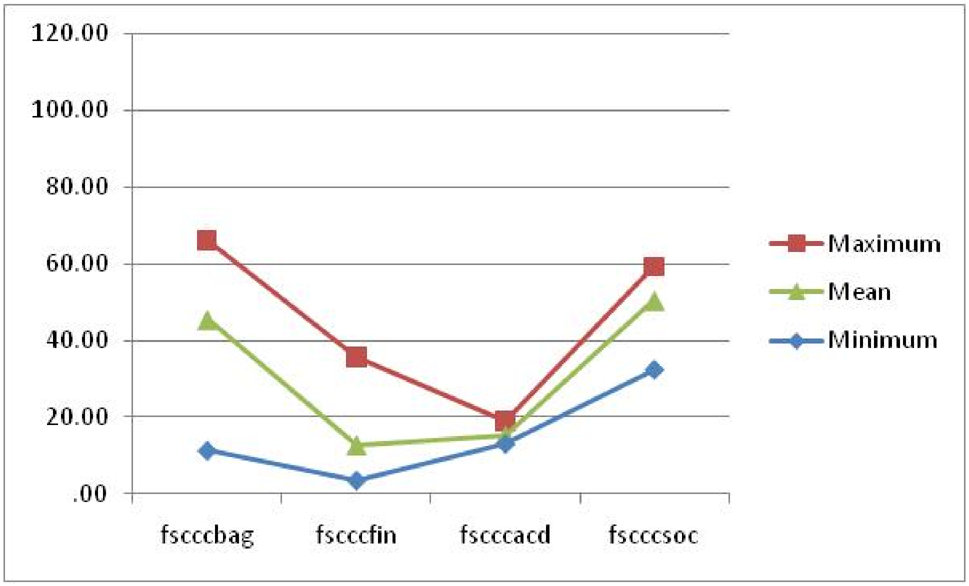

Figure 19. Comparison of factor scores for doctoral/research institutions (*N* = 241). (*Note*. The four factor scores by Carnegie classification of institutions are for students' background *fscccbag*, students' finance *fscccfin*, academic environment *fscccacd* and social environment *fscccsoc*.)

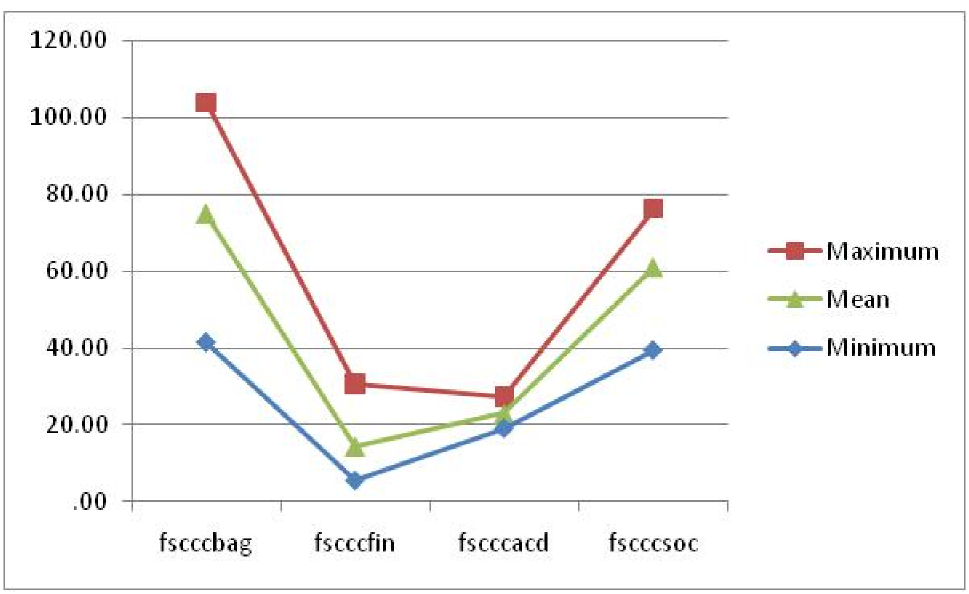

Figure 20. Comparison of factor scores for master institutions (*N* = 555).

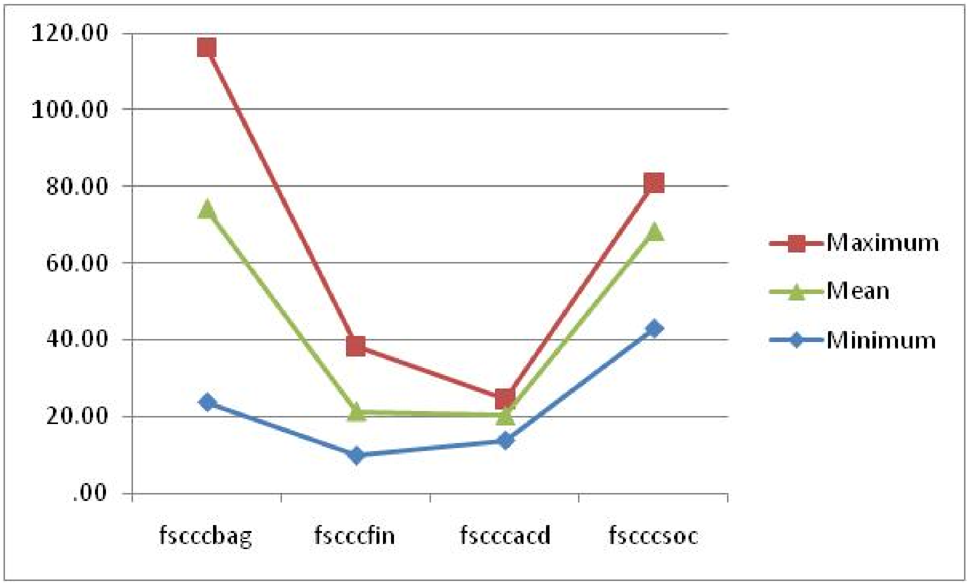

Figure 21. Comparison of factor scores for baccalaureate institutions (N = 485).

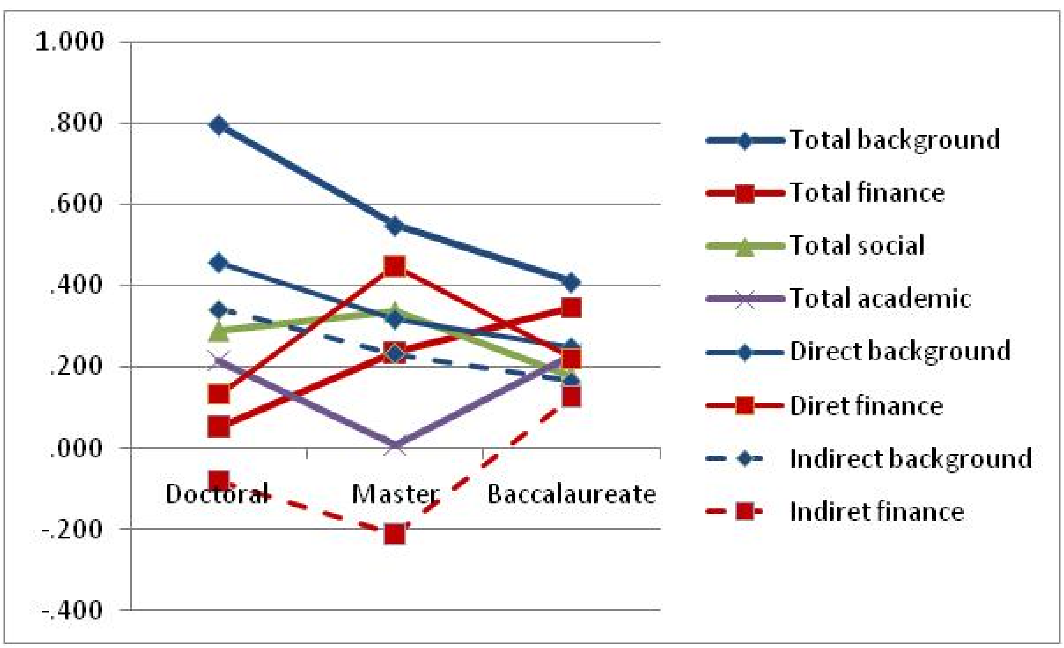

Figure 22. Comparison of direct, indirect and total effects of four factors on retention rates by Carnegie classification of institutions.

Table 43

Effects on Graduation Rates in SEM Model by Carnegie Classification of Institutions

Effects	All	Doctoral	Master	Baccalaureate
n	1785	248	577	520
Total effects on gr4 by:				
background	.348	.726	.459	.332
finance	.186	.047	.198	.280
social	.102	.263	.280	.144
academic	.170	.196	.006	.187
xret_pcf03	.786	.911	.836	.811
Total effects on xret_pcf03 by:				
background	.442	.797	.549	.410
finance	.236	.052	.236	.345
social	.130	.289	.335	.178
academic	.216	.215	.007	.230
Direct effects on xret_pcf03 by:				
background	.290	.455	.316	.246
finance	.178	.133	.447	.220
social	.130	.289	.335	.178
academic	.216	.215	.007	.230
Indirect effects on xret_pcf03 by:				
background	.152	.342	.232	.163
finance	.058	-.081	-.210	.125

Groups by Degree of Urbanization

The SEM model is fit on three groups of institutions in different degree of urbanization—large city with population greater than or equal to 250,000; mid-size city with population less than 250,000; and urban fringe of large city. These three groups are chosen because of the larger number of institutions in the groups. Table 44 summarizes the SEM results, including the Beta weights of the structural paths, the multiple R^2 and the factor score means. Again the measurement portion of the model is left out here because they have been discussed earlier. The overall model fit indices are NFI = .777, CFI = .787 and RMSEA = .070, very close to that based on control of institutions and that based on Carnegie classification code. Although NFI and CFI do not indicate good fit on the data, RMSEA may indicate a marginal fit. The possibility for model improvement is the same as that in previous discussion.

Figure 23 and Figure 24 present the graphical comparisons of the four direct effects of the four factors and their means between the institutions in large cities, mid-size cities and urban fringe of large city. The trend line of β_{r_ac} seems to be parallel and above the trend line of β_{r_bc}, indicating that students' background has a stronger direct effect than students' finance on the academic environment by the similar extent across all three groups. The trend line of β_{r_ad} is a mirror image of trend line of β_{r_bd}, indicating that students' background and students' finance have compensatory effects on the social environment across all three groups. For example, students' background has the largest direct effect on the social environment in the mid-size city institutions (.556) whereas students' finance has the smallest direct effect on the social environment in the mid-size city institutions (-.227). Similarly, the trend line of $FM_{\text{background}}$ seems to be parallel with the trend line of FM_{finance} and the trend line of FM_{academic} seems to be reflective with the trend line of FM_{social}. This indicates that students' background tends to be proportional to students' finance and academic environment tends to be compensatory with social environment.

The next four Beta weights (β_{r_ae}, β_{r_be}, β_{r_ce} and β_{r_de}) are the direct effects of the four factors on the retention rates. They represent, in part, the relative importance of the four factors in predicting the retention rates. However, the indirect effects should also be considered to determine the total effects of each of the four factors on the retention rates. Table 45 presents the direct, indirect and total effects of the four factors on retention rates and graduation rates. Figure 28 presents the graphical comparison of the direct, indirect and total effects of the four factors on retention rates. Based on their total effects on retention rates, students' background is the most important factor to influence the retention rates in all three levels of urbanization, followed by academic environment, students' finance and social environment in that order. The latter threes have the strongest effects in mid-size city institutions (.270, .163 and .299). The effects of academic and social environments are influenced by the indirect effects of students' background and students' finance. If the indirect effects are removed, the shapes of the lines for academic and social environment would be like the line for students' background.

The multiple R^2 (R^2_{academic}, R^2_{social}, $R^2_{\text{xret\_pcf03}}$ and R^2_{gr4}) are percentages of variance in the four endogenous variables (*academic*, *social*, *xret_pcf03* and *gr4*) predicted in the model. The percentages of variances in retention and graduation rates predicted by the model seems to be inversely related with the degree of urbanization, indicating that urbanization has a disrupting effect on the model. Social environment is least explained by the model among the four endogenous variables. Figure 25, Figure 26 and Figure 27 indicate that the factor variances are invariant across the three groups.

Table 44

Summary of SEM Results for Institutions Grouped by Degree of Urbanization

Parameters	All	Large City	Mid-size City	Urban Fringe
n	1785	384	480	294
β_{r_ac}	.409	.427	.503	.460
β_{r_ad}	.490	.305	.556	.478
β_{r_bc}	.373	.254	.348	.351
β_{r_bd}	-.172	.074	-.227	-.041
β_{r_ae}	.290	.427	.236	.310
β_{r_be}	.178	.031	.203	.176
β_{r_ce}	.216	.088	.299	.238
β_{r_de}	.130	.093	.163	.077
β_{r_ef}	.786	.776	.821	.862
r_{ab}	.587	.666	.527	.625
$R^2_{academic}$	.486	.392	.558	.536
R^2_{social}	.171	.129	.227	.205
$R^2_{xret\_pcf03}$	.412	.298	.496	.451
R^2_{gr4}	.618	.602	.673	.743
n_{FM}	977	299	426	252
$FM_{background}$	63.41	64.00	62.35	64.50
$FM_{finance}$	10.27	8.51	9.79	13.18
$FM_{academic}$	16.08	17.50	14.66	16.80
FM_{social}	19.84	5.64	30.39	18.85

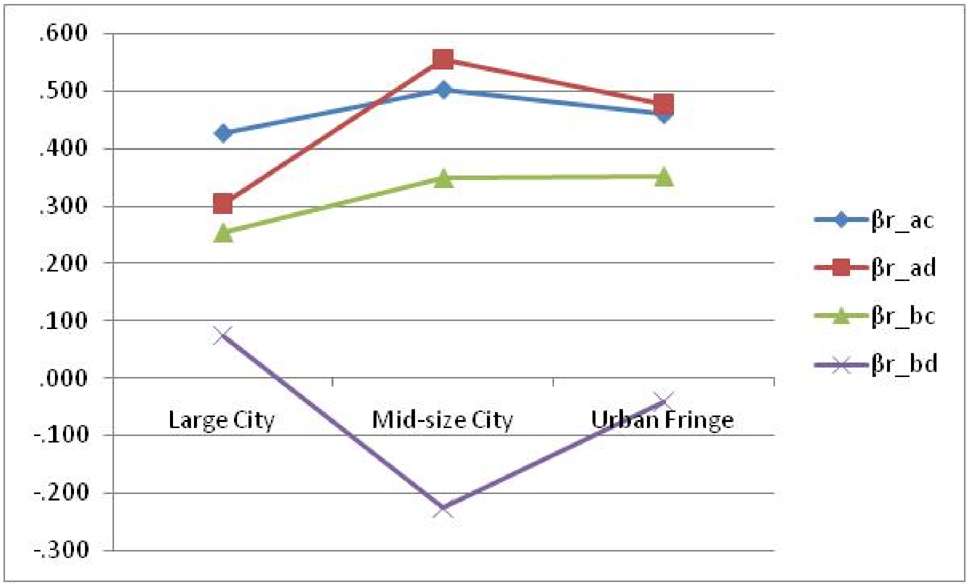

Figure 23. Comparison of direct effects by degree of urbanization. (*Note*. The four standardized direct effects are background to academic β_{r_ac}, background to social β_{r_ad}, finance to academic β_{r_bc} and finance to social β_{r_bd}.)

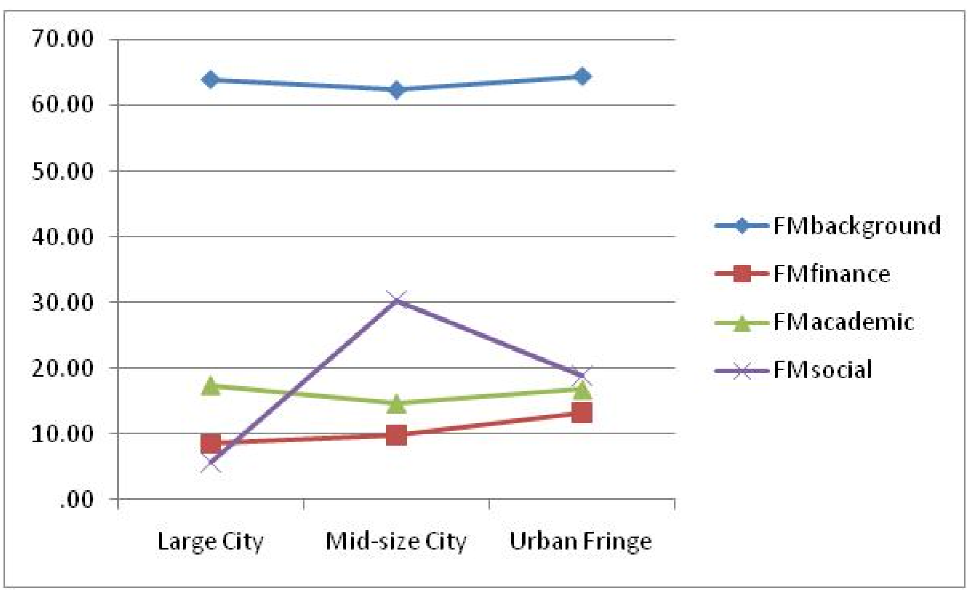

Figure 24. Comparison of factor means by degree of urbanization.

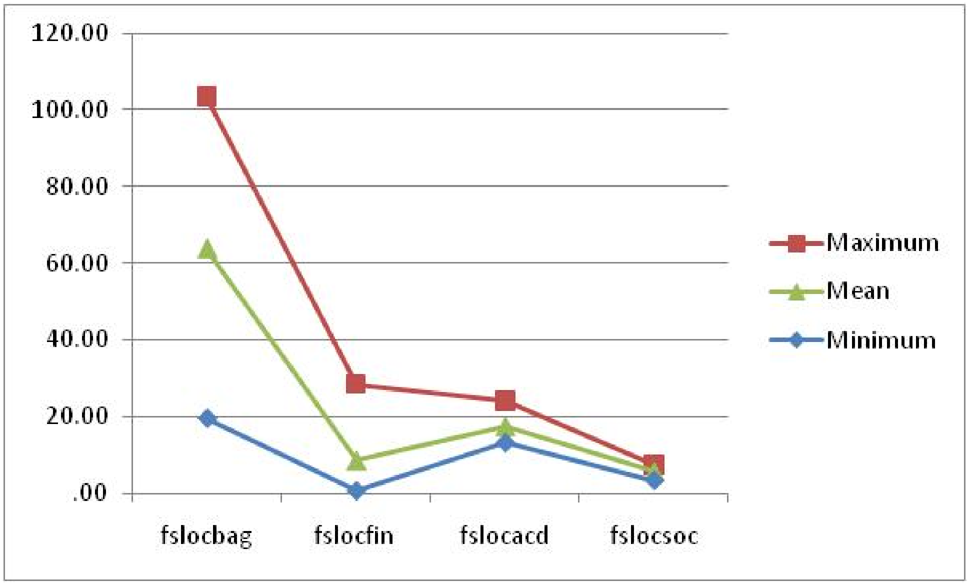

Figure 25. Comparison of factor scores for institutions in large cities (*N* = 299). (*Note*. The four factor scores by degree of urbanization are for students' background *fslocbag*, students' finance *fslocfin*, academic environment *fslocacd* and social environment *fslocsoc*.)

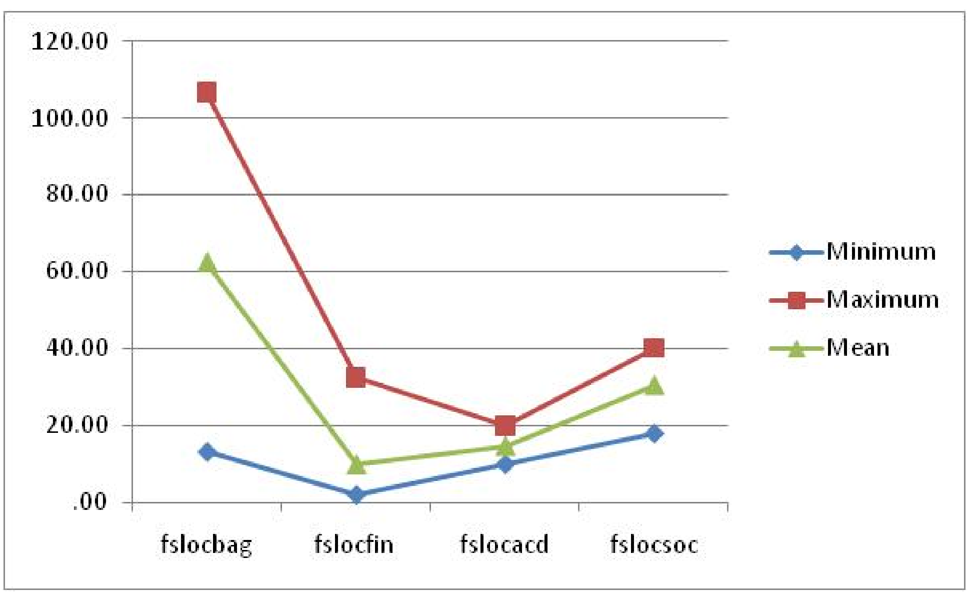

Figure 26. Comparison of factor scores for institutions in mid-size Cities (*N* = 426).

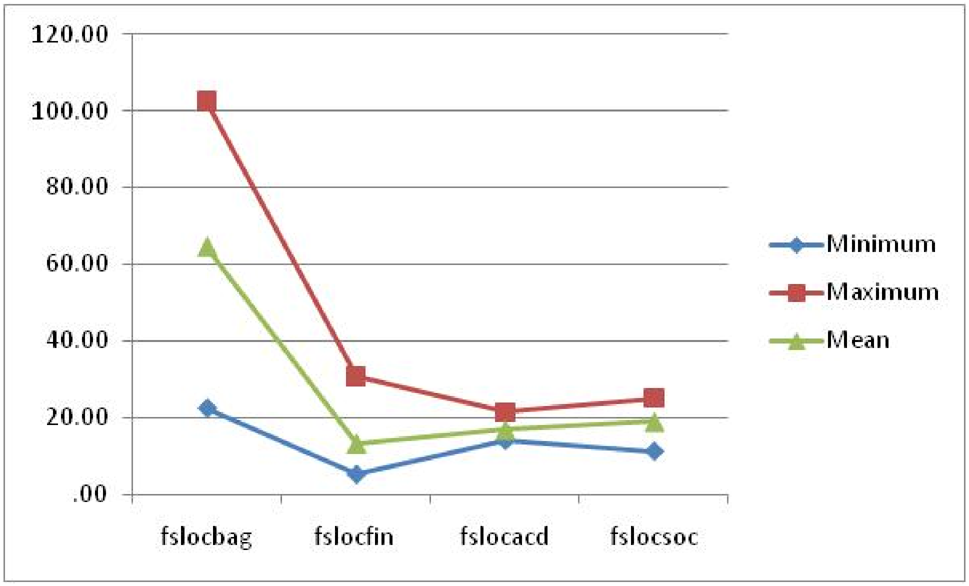

Figure 27. Comparison of factor scores for institutions in urban fringes *(N =* 252*)*.

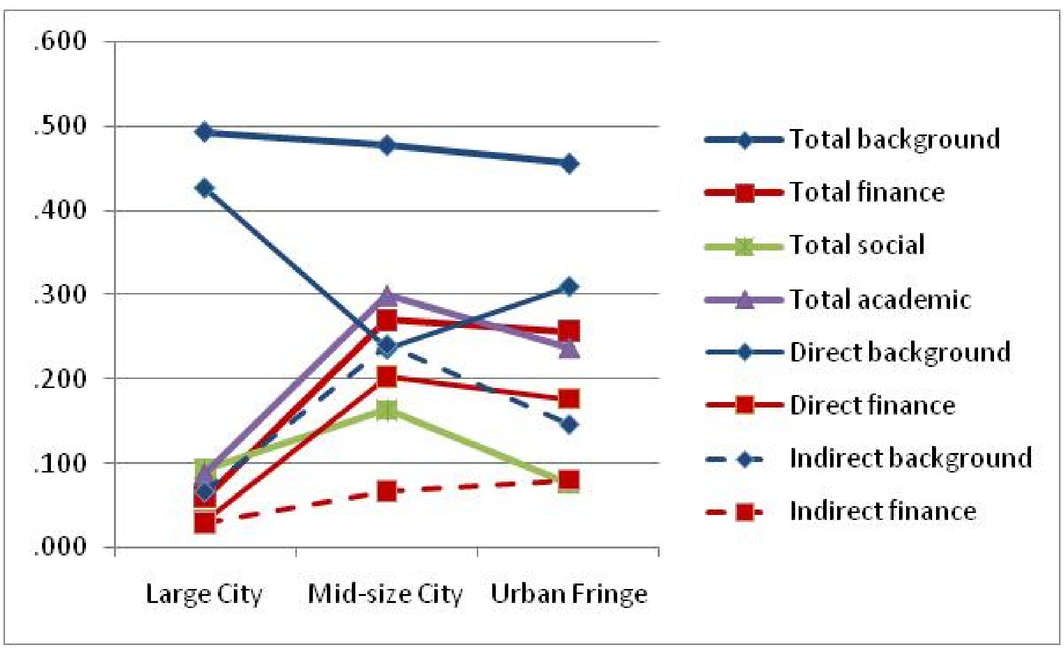

Figure 28. Comparison of direct, indirect and total effects of four factors on retention rates in institutions by degree of urbanization.

Table 45

Effects on Graduation Rates in SEM Model by Degree of Urbanization

Effects	All	Large City	Mid-size City	Urban Fringe
n	1785	384	480	294
Total effects on gr4 by:				
background	.348	.382	.391	.393
finance	.186	.047	.222	.221
social	.102	.072	.134	.066
academic	.170	.068	.245	.205
xret_pcf03	.786	.776	.821	.862
Total effects on xret_pcf03 by:				
background	.442	.493	.477	.456
finance	.236	.060	.270	.257
social	.130	.093	.163	.077
academic	.216	.088	.299	.238
Direct effects on xret_pcf03 by:				
background	.290	.427	.236	.310
finance	.178	.031	.203	.176
social	.130	.093	.163	.077
academic	.216	.088	.299	.238
Indirect effects on xret_pcf03 by:				
background	.152	.066	.241	.146
finance	.058	.029	.067	.080

Groups by Geographical Regions

The SEM model is fit on seven groups of institutions by geographical regions. Table 46 summarizes the SEM results, including the Beta weights of the structural paths, the multiple R^2 and the factor score means. Again the measurement portion of the model is left out here because they have been discussed earlier. The overall model fit indices are NFI = .761, CFI = .778 and RMSEA = .051, very close to the previous results from other groupings of the institutions. Although NFI and CFI do not indicate good fit on the data, RMSEA may indicate a good fit. The possibility for model improvement is the same as that in previous discussion.

Figure 29 and Figure 30 present the graphical comparisons of the four direct effects of the four factors and their means of the institutions in seven geographical regions. The trend line of β_{r_ac} looks like a bumpy road above the trend line of β_{r_bc}, indicating that students' background has a stronger direct effect than students' finance on the academic environment to different extents across all seven regions. The trend line of β_{r_ad} looks like a mirror image of trend line of β_{r_bd}, indicating that students' background and students' finance have compensatory effects on the social environment across all seven regions. Similarly, the trend line of $FM_{\text{background}}$ is above the trend line of FM_{finance} and the trend line of FM_{academic} seems to be a little reflective with the trend line of FM_{social}. This indicates that students' background tends to be proportional to students' finance and academic environment tends to be compensatory with social environment.

The next four Beta weights (β_{r_ae}, β_{r_be}, β_{r_ce} and β_{r_de}) are the direct effects of the four factors on the retention rates. They represent, in part, the relative importance of the four factors in predicting the retention rates. However, the indirect effects should also be considered to determine the total effects of each of the four factors on the retention rates. Table 48 presents the direct, indirect and total effects of the four factors on retention rates and graduation rates. Figure 31 presents the graphical comparison of the direct, indirect and total effects of the four factors on retention rates. Based on their total effects on retention rates, students' background is the most important factor to influence the retention rates in all regions and is slightly more influential in New England and Mid East (.593 and .546 respectively). Students' finance has a weaker effect on retention rates than students' background consistently, particularly in the Southwest region (-.017). The trend lines for these two effects seems reflective at the two ends and parallel in the middle, indicating that students' background and students' finance may be compensatory in New England, Mid East and Southwest but proportional in Great Lakes, Plans and Southeast. The effect academic environment has a big "dip" in Mid East (-.038) and a big "peak" in Plains (.422), which may be influenced by the indirect effects of students' background (.015 and .217) and students' finance (-.006 and .106). Comparing the trend lines of the effects of academic and social environments, the two effects seems to be compensatory at least in Great Lakes, Plains, Southeast and Southwest. Overall, the four factors seem to affect the retention rates differently in different geographical regions.

The multiple R^2 (R^2_{academic}, R^2_{social}, $R^2_{\text{xret\_pcf03}}$ and R^2_{gr4}) are percentages of variance in the four endogenous variables (*academic*, *social*, *xret_pcf03* and *gr4*) predicted in the model. Figure 32 presents the comparisons of these four multiple R^2. The model has a larger predictive power in Mid East, Great Lakes, Plains and Southwest (73.7%, 79.4%, 74.4% and 68.3%) than in New England, Southeast and Far West (56.7%, 50.4% and 50.9%). Again, the lines for social and academic environments seem to be reflective, so the two factors may be compensatory to each other.

Table 46

Summary of SEM Results for Institutions Grouped by Geographical Regions

Parameters	All	New England	Mid East	Great Lakes	Plains	South East	South West	Far West
n	1785	164	361	279	191	412	119	162
β_{r_ac}	.432	.601	.410	.446	.445	.430	.310	.575
β_{r_ad}	.537	.412	.258	.599	.698	.588	1.006	.577
β_{r_bc}	.354	.282	.398	.359	.287	.389	.149	.099
β_{r_bd}	-.209	.006	.075	-.289	-.372	-.166	-.693	-.337
β_{r_ae}	.315	.267	.532	.403	.259	.384	.471	.338
β_{r_be}	.170	.046	.163	.210	.082	.115	-.103	.186
β_{r_ce}	.201	.376	-.038	.169	.422	.197	.319	.110
β_{r_de}	.116	.242	.117	.076	.042	.084	-.055	.224
β_{r_ef}	.786	.753	.858	.891	.862	.710	.827	.713
r_{ab}	.599	.795	.667	.516	.490	.483	.617	.659
$R^2_{academic}$	.496	.711	.544	.493	.406	.498	.176	.415
R^2_{social}	.198	.174	.098	.264	.371	.279	.633	.190
$R^2_{xret\_pcf03}$	.416	.609	.451	.491	.456	.414	.340	.429
R^2_{gr4}	.618	.567	.737	.794	.744	.504	.683	.509
n_{FM}	1475	141	293	245	178	376	102	140
$FM_{background}$	66.19	51.99	73.47	57.02	71.43	77.70	57.13	50.28
$FM_{finance}$	10.80	10.69	9.51	15.07	12.61	8.71	7.21	12.06
$FM_{academic}$	16.89	17.51	17.50	20.73	16.10	13.82	17.53	17.08
FM_{social}	24.10	29.38	7.34	32.89	31.28	24.01	20.81	32.03

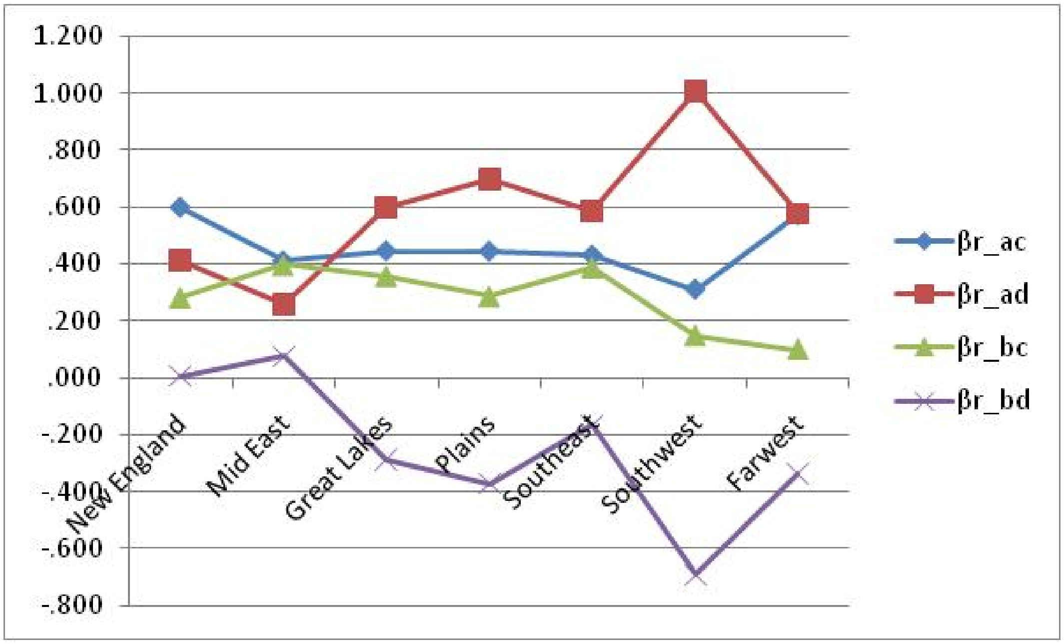

Figure 29. Comparison of direct effects by geographical regions. (*Note*. The four standardized direct effects are background to academic β_{r_ac}, background to social β_{r_ad}, finance to academic β_{r_bc} and finance to social β_{r_bd}.)

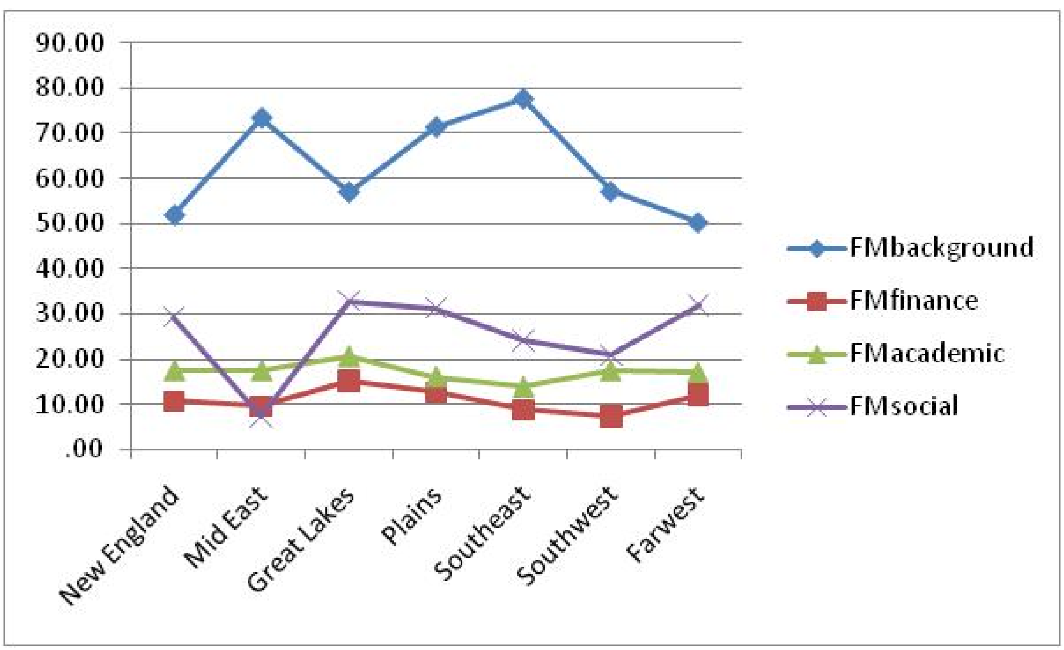

Figure 30. Comparison of factor means by geographical regions.

Table 47

Descriptive Statistics of Factor Scores by Geographical Regions

Statistics of Factor Scores	New England	Mid East	Great Lakes	Plains	South East	South West	Far West
n	141	293	245	178	376	102	140
fsgeobag							
Min	19.57	28.19	11.37	37.67	42.53	30.39	24.39
Max	80.72	116.99	86.85	111.73	120.23	90.69	89.39
M	51.99	73.47	57.02	71.43	77.70	57.13	50.28
SD	10.39	14.80	10.47	11.05	13.97	10.66	11.11
Skewness	.74	.46	-.39	.13	.23	.38	.77
Kurtosis	.76	.23	2.44	1.85	.34	.39	1.19
fsgeofin							
Min	1.08	1.11	7.07	4.76	2.64	1.35	3.69
Max	29.96	29.73	31.67	29.58	29.07	20.57	31.72
M	10.69	9.51	15.07	12.61	8.71	7.21	12.06
SD	6.95	6.61	5.29	5.37	4.48	4.39	7.06
Skewness	.79	1.00	.70	.51	1.53	1.11	.93
Kurtosis	-.15	.24	.01	-.29	2.65	.69	.07
fsgeoacd							
Min	15.12	12.91	15.70	13.78	9.67	15.45	14.55
Max	22.10	22.08	26.39	20.89	17.45	22.07	23.59
M	17.51	17.50	20.73	16.10	13.82	17.53	17.08
SD	1.47	1.33	1.49	1.09	.95	1.12	1.29
Skewness	1.01	.75	.23	.86	.40	1.01	1.81
Kurtosis	.56	.80	1.03	1.84	1.95	2.12	5.81
fsgeosoc							
Min	17.79	4.25	17.42	19.58	14.88	12.62	19.88
Max	38.84	9.84	44.65	41.91	31.53	27.76	42.17
M	29.38	7.34	32.89	31.28	24.01	20.81	32.03
SD	4.22	.93	4.88	4.58	3.18	2.93	4.79
Skewness	-.29	-.34	-.03	.01	-.02	.04	-.20
Kurtosis	-.01	.47	.37	-.08	-.09	.13	-.47

Note. The four factor scores by geographical regions are for students' background (*fsgeobag*), students' finance (*fsgeofin*), academic environment (*fsgeoacd*) and social environment (*fsgeosoc*).

Table 48

Effects on Graduation Rates in SEM Model by Geographical Regions

Effects	All	New England	Mid East	Great Lakes	Plains	South East	South West	Far West
n	1785	164	361	279	191	412	119	162
Total effects on gr4 by:								
background	.366	.446	.469	.467	.410	.368	.426	.379
finance	.171	.116	.135	.222	.162	.126	-.014	.086
social	.091	.182	.100	.068	.036	.060	-.046	.160
academic	.158	.283	-.032	.151	.364	.140	.264	.078
xret_pcf03	.786	.753	.858	.891	.862	.710	.827	.713
Total effects on xret_pcf03 by:								
background	.465	.593	.546	.524	.476	.518	.515	.531
finance	.218	.154	.157	.249	.188	.178	-.017	.121
social	.116	.242	.117	.076	.042	.084	-.055	.224
academic	.201	.376	-.038	.169	.422	.197	.319	.110
Direct effects on xret_pcf03 by:								
background	.315	.267	.532	.403	.259	.384	.471	.338
finance	.170	.046	.163	.210	.082	.115	-.103	.186
social	.116	.242	.117	.076	.042	.084	-.055	.224
academic	.201	.376	-.038	.169	.422	.197	.319	.110
Indirect effects on xret_pcf03 by:								
background	.149	.326	.015	.121	.217	.134	.044	.192
finance	.047	.108	-.006	.039	.106	.063	.086	-.065

Table 47 presents the descriptive statistics of the four factor scores, which seem to have similar variances across different geographical regions, indicating that these factor score variances are invariant across geographical regions.

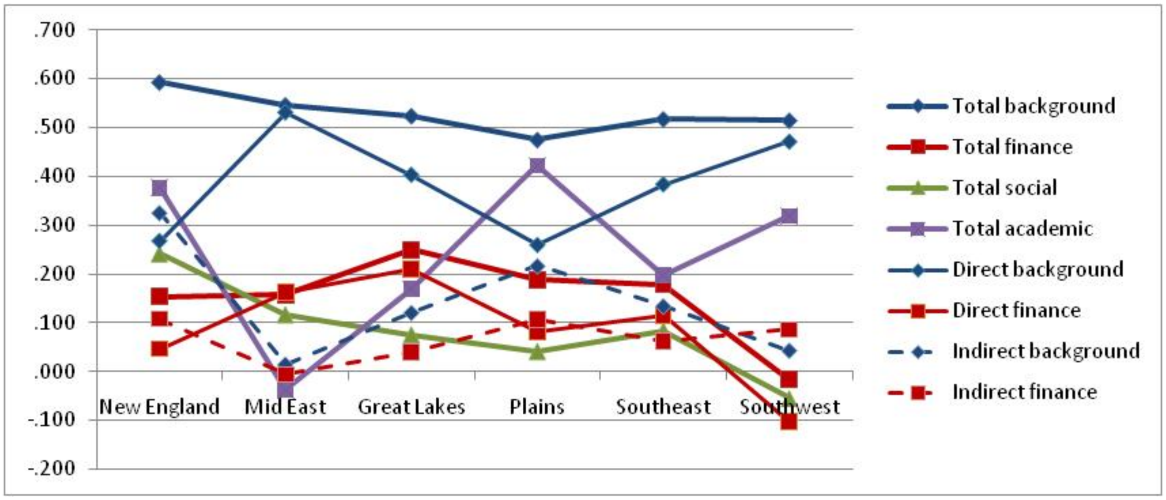

Figure 31. Comparison of direct, indirect and total effects of four factors on retention rates by geographical regions.

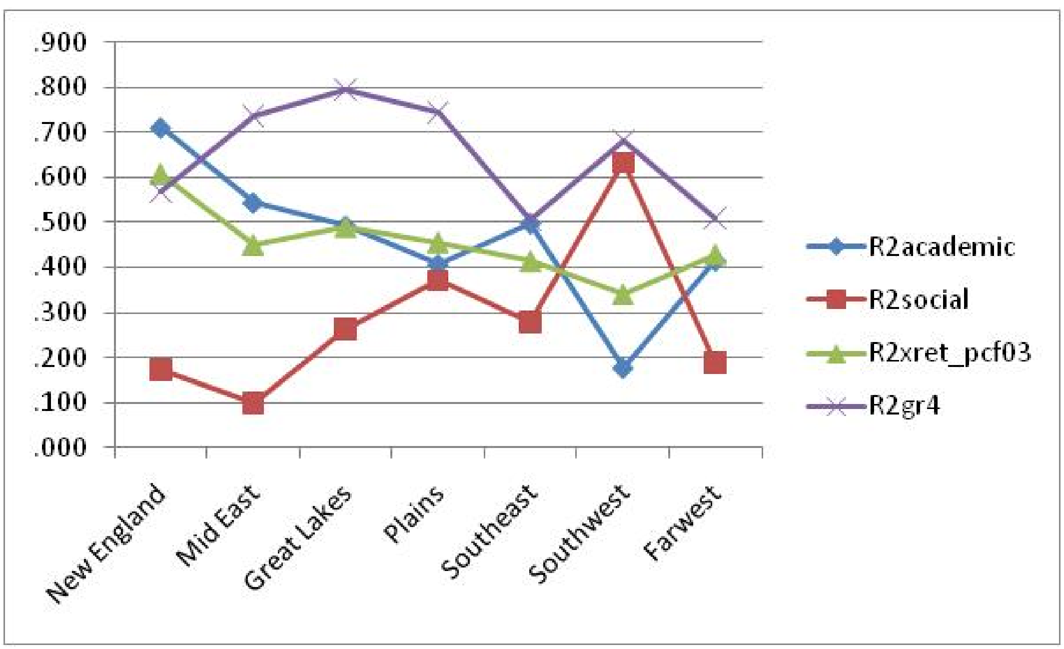

Figure 32. Comparison of multiple R^2 of four endogenous variables by geographical regions.

Groups by States

Finally, the SEM model is fit on the subgroup datasets simultaneously to compare institutions in eight states. Table 49 summarizes the SEM results, including the Beta weights of the structural paths, the multiple R^2 and the factor score means. Again the measurement portion of the model is left out here because they have been discussed earlier. The overall model fit indices are NFI = .743, CFI = .767 and RMSEA = .050, which are very close to those from other groupings of institutions previously discussed. Although NFI and CFI do not indicate good fit on the data, RMSEA indicates a good fit. The possibility for model improvement is the similar to that in previous discussion.

Figure 33 and Figure 34 present the graphical comparisons of the four direct effects of the four factors and their means between the institutions in eight states. The trend line of β_{r_ac} seems to be reflective to the trend line of β_{r_bc}, indicating that students' background may have a compensatory effect with students' finance on the academic environment across the eight states. The trend lines of β_{r_ad} and β_{r_bd} seems to be reflective at the two ends and parallel in the middle, indicating that students' background and students' finance may have compensatory effects on the social environment in CA, FL, IL, PA and TX but have proportional effects on the social environment in MA, NY and OH. The means of the four factor scores indicate the various levels at which the institutions in different states can attain in the four factor areas. Students in FL, IL, MA and NY seem to be better prepared than students in CA, OH, PA and TX. Institutions from all eight states have similar students' finance in their student bodies and similar academic environment. The social environment, however varies a lot in different states.

New York is the only state where institutions have negative social environment (-18.06). Institutions from PA have the strongest social environment (55.14), followed by institutions in CA and TX (39.11 and 36.56 respectively).

The Beta weights (β_{r_ae}, β_{r_be}, β_{r_ce} and β_{r_de}) represent, in part, the relative importance of the four factors in predicting the retention rates. However, the indirect effects should also be considered to determine the total effects of each of the four factors on the retention rates. Table 51 presents the direct, indirect and total effects of the four factors on retention rates and graduation rates. Figure 35 presents the graphical comparison of the direct, indirect and total effects of the four factors on retention rates in four states (CA, MA, OH and TX). Based on the total effects, the trend line of students' background seems to be reflective with the trend line of students' finance, indicating that students' background and students' finance may have compensatory effects on retention rates. Institutions in MA seems to have the strongest effects on retention rates from their academic environment (.978) and social environment (.224), but these large effects seem to be caused by the large indirect effects of students' background (.716) and students' finance (.301). The social environment and academic environment seem to have similar effects on retention rates among institutions in CA (.104 and .110 respectively) and in TX (.207 and .188 respectively).

Figure 36 presents the graphical comparisons of the multiple R^2 of four endogenous variables, which are the amount of variances in the variables predicted by the model. The six-year graduation rate has a higher predictability in IL and TX (80.5% and 80.1% respectively) and the lowest predictability in FL (45.7%). The predicted variances in the retention rates follow the same pattern as the graduation rates but at a lower level. The model can predict the academic environment better than it can predict the social environment. Table 50 presents the descriptive statistics of the four factor scores.

Table 49

Summary of SEM Results for Institutions Grouped by States

Parameters	All	CA	FL	IL	MA	NY	OH	PA	TX
n	1785	104	55	62	76	167	82	122	73
β_{r_ac}	.409	.645	.413	.690	.633	.482	.052	.556	.344
β_{r_ad}	.490	.575	.443	.732	.433	-.044	.497	.719	.437
β_{r_bc}	.373	.041	.355	.143	.292	.365	.534	.258	.290
β_{r_bd}	-.172	-.281	.237	-.524	.071	-.287	.038	-.395	-.372
β_{r_ae}	.290	.527	.370	1.010	-.145	.627	.440	.471	.675
β_{r_be}	.178	.075	.026	.001	-.215	.104	.180	.260	.003
β_{r_ce}	.216	.110	.121	-.365	.978	-.131	.271	.048	.188
β_{r_de}	.130	.104	.104	.143	.224	-.155	-.179	.084	.207
β_{r_ef}	.786	.845	.676	.897	.793	.843	.864	.849	.895
r_{ab}	.587	.706	.261	.642	.723	.620	.568	.762	.561
$R^2_{academic}$	.486	.455	.373	.622	.752	.583	.319	.594	.315
R^2_{social}	.171	.182	.307	.318	.237	.100	.270	.240	.147
$R^2_{xret\_pcf03}$	.412	.497	.266	.685	.680	.436	.439	.578	.732
R^2_{gr4}	.618	.714	.457	.805	.628	.711	.746	.720	.801
n_{FM}	620	86	41	53	69	115	74	116	66
$FM_{background}$	62.89	50.36	77.26	70.90	71.99	90.71	41.61	58.28	37.77
$FM_{finance}$	11.66	11.09	7.05	13.47	15.79	11.31	8.45	14.53	8.66
$FM_{academic}$	14.98	16.73	13.70	10.79	11.05	15.62	12.87	17.20	18.32
FM_{social}	23.87	39.11	20.04	19.16	18.83	-18.06	21.20	55.14	36.56

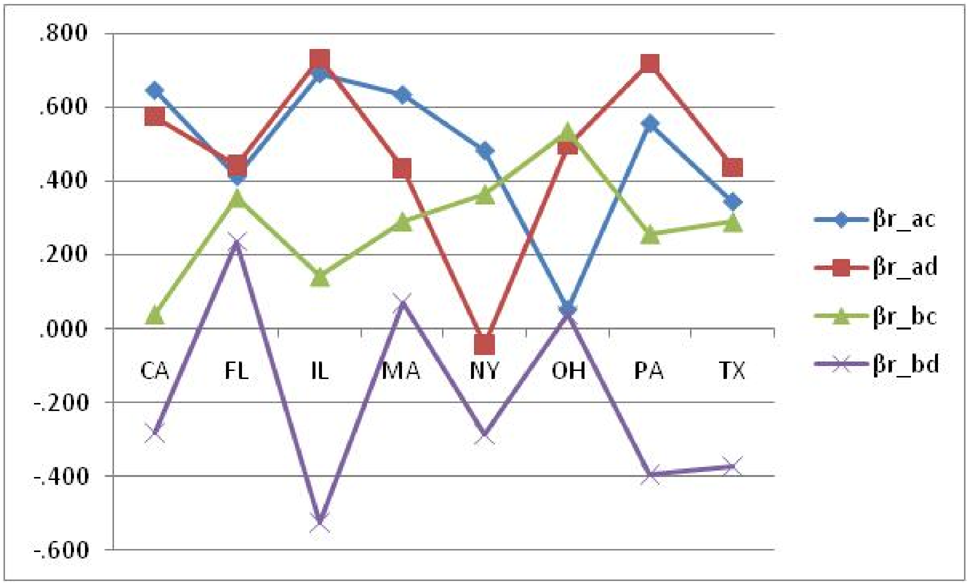

Figure 33. Comparison of direct effects for institutions grouped by states. (*Note*. The four standardized direct effects are background to academic β_{r_ac}, background to social β_{r_ad}, finance to academic β_{r_bc} and finance to social β_{r_bd}.)

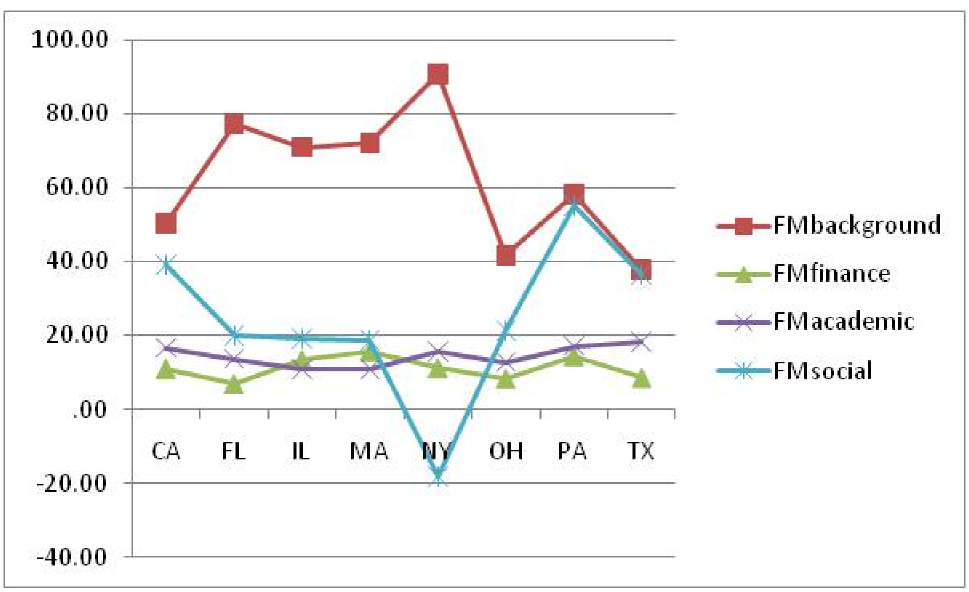

Figure 34. Comparison of factor means for institutions grouped by states.

Table 50

Descriptive Statistics of Factor Scores by Geographical Regions

	CA	FL	IL	MA	NY	OH	PA	TX
n	86	41	53	69	115	74	116	66
fsstabag								
Min	24.58	40.30	33.68	17.86	52.57	9.26	37.76	25.79
Max	85.29	102.48	105.28	111.71	136.06	65.91	88.30	62.17
M	50.36	77.26	70.90	71.99	90.71	41.61	58.28	37.77
SD	11.78	15.29	13.80	16.56	18.51	9.13	9.43	7.36
Skewness	.65	-.37	-.20	.14	.19	-.21	.98	1.22
Kurtosis	.49	-.56	1.34	.93	-.53	1.53	.88	2.20
fsstafin								
Min	1.20	1.21	5.50	4.83	2.96	.82	6.38	2.68
Max	30.02	22.10	27.48	30.46	30.76	26.96	32.14	21.25
M	11.09	7.05	13.47	15.79	11.31	8.45	14.53	8.66
SD	7.51	5.12	4.89	6.97	7.07	5.59	6.21	4.40
Skewness	.87	1.28	.54	.26	.89	1.14	.87	.98
Kurtosis	-.26	1.06	.34	-.89	-.23	1.02	.15	.52
fsstaacd								
Min	14.23	11.42	7.43	8.23	11.35	10.36	15.43	16.07
Max	22.86	15.74	14.02	14.44	18.82	15.31	20.64	23.08
M	16.73	13.70	10.79	11.05	15.62	12.87	17.20	18.32
SD	1.38	1.01	1.09	1.23	1.47	1.21	.98	1.21
Skewness	1.73	.06	-.25	.69	.40	-.17	1.18	1.20
Kurtosis	4.73	-.43	3.23	.30	-.22	-.52	1.81	3.06
fsstasoc								
Min	24.13	13.09	12.23	12.00	-23.32	13.22	39.49	25.44
Max	50.75	26.51	25.11	24.66	-10.13	29.02	74.69	48.18
M	39.11	20.04	19.16	18.83	-18.06	21.20	55.14	36.56
SD	5.84	3.30	2.53	2.45	2.41	3.34	6.29	4.69
Skewness	-.29	-.01	.15	-.08	.77	.04	.23	.19
Kurtosis	-.24	-.46	.75	.26	1.16	-.01	.29	.23

Note. The four factor scores by states are for students' background (*fsstabag*), students' finance (*fsstafin*), academic environment (*fsstaacd*) and social environment (*fsstasoc*).

Table 51

Effects on Graduation Rates in SEM Model by States

Effects	All	CA	FL	IL	MA	NY	OH	PA	TX
n	1785	104	55	62	76	167	82	122	73
Total effects on gr4 by:									
background	.348	.556	.316	.774	.453	.481	.316	.474	.743
finance	.186	.042	.063	-.113	.068	.085	.274	.202	-.018
social	.102	.088	.070	.128	.177	-.131	-.154	.071	.186
academic	.170	.093	.082	-.327	.776	-.110	.234	.040	.168
xret_pcf03	.786	.845	.676	.897	.793	.843	.864	.849	.895
Total effects on xret_pcf03 by:									
background	.442	.658	.467	.863	.571	.571	.365	.558	.830
finance	.236	.050	.093	-.126	.086	.101	.318	.239	-.020
social	.130	.104	.104	.143	.224	-.155	-.179	.084	.207
academic	.216	.110	.121	-.365	.978	-.131	.271	.048	.188
Direct effects on xret_pcf03 by:									
background	.290	.527	.370	1.010	-.145	.627	.440	.471	.675
finance	.178	.075	.026	.001	-.215	.104	.180	.260	.003
social	.130	.104	.104	.143	.224	-.155	-.179	.084	.207
academic	.216	.110	.121	-.365	.978	-.131	.271	.048	.188
Indirect effects on xret_pcf03 by:									
background	.152	.130	.096	-.147	.716	-.056	-.075	.087	.155
finance	.058	-.025	.068	-.127	.301	-.003	.138	-.021	-.023

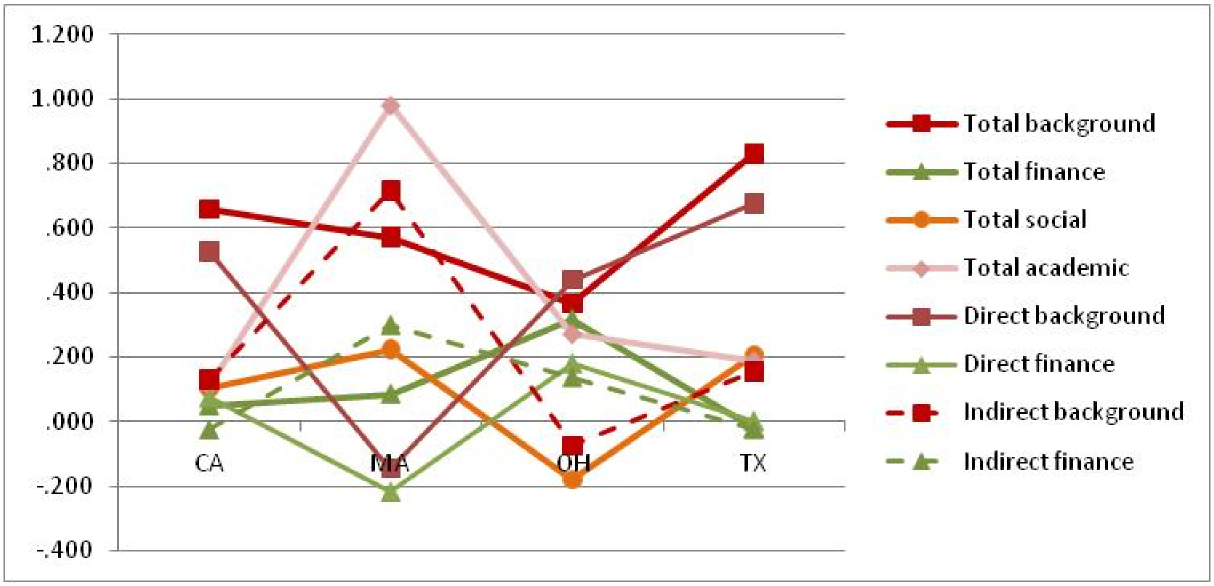

Figure 35. Comparison of direct, indirect and total effects of four factors on retention rates by states.

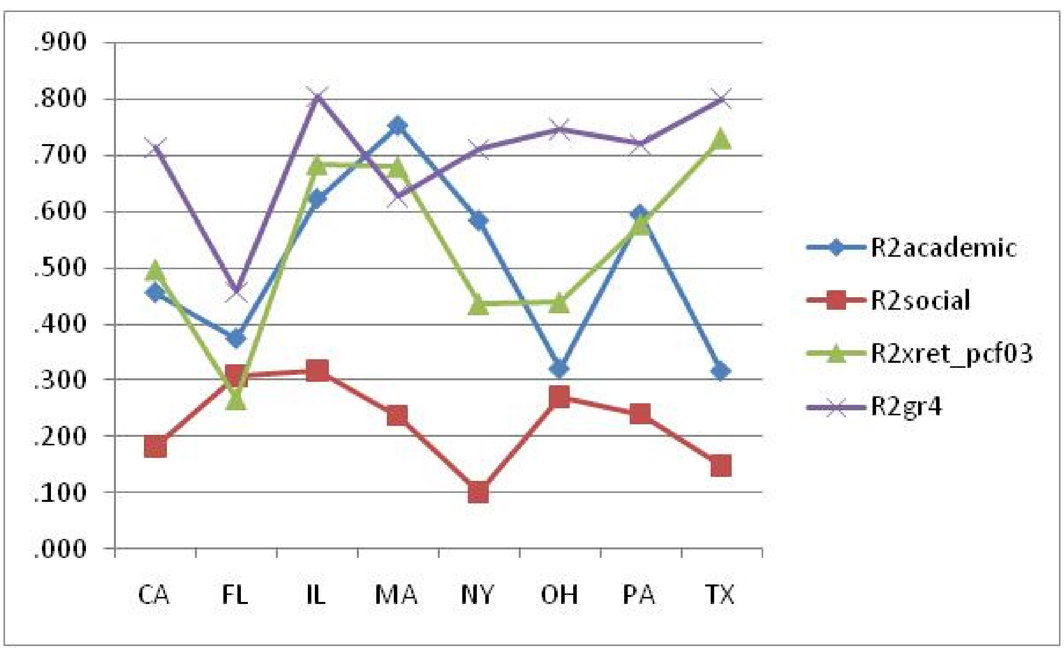

Figure 36. Comparison of multiple R^2 of four endogenous variables by state.

The SEM results above indicate that the model of institutional performance in graduation rates does not have overall model fit on the dataset and it subsets segregated by the five grouping variables. Therefore, research question 3 is answered negatively but the model fit is not hopelessly low, The RMSEA fit index which is close to .05 for groups of institutions based on state and geographical region. Although CFI and NFI show lack of model fit, practical applications of the model and its improvements are discussed in the next chapter.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

The purpose of this study is to develop a model of institutional performance in graduate rates for four-year, public and private not-for-profit, Title IV institutions in the United States. This study evaluates the institutional model based on the IPEDS dataset using the structural equation modeling (SEM) technique. This model is based on the basic structure of Tinto's (1975) theory of college dropout. This model explains the process of college persistence in terms of graduation rate and other institutional characteristics derived from the IPEDS dataset.

Discussion of Results

The findings of this study are summarized in three areas to answer the three research questions regarding the groups of institutions that have significant different graduation rates, the validity and reliability of the measurement models for the four factor areas and the overall fit of the model to the dataset and its subsets.

Groups for Significant Differences in Graduation Rates

The multiple regression model explains 21.3% of the variance in the six-year graduation rate by nine categorical predictor variables coded in orthogonal contrasts. The control of institutions and the Carnegie classification code are the most important predictors of the six-year graduation rate and they are responsible for 7.3% and 7.2% of its variance. Table 14 shows that the next better predictors are race/ethnicity (2.6%) and geographical region (1.7%). These explained variances in graduation rates, however, are not the same as the explained variances in graduation rates by the SEM model. Table 52 and Figure 37 compares the mean, minimum and maximum of the model explained variances or multiple R^2 in retention rates and graduation rates based on the set of institutions grouped by five grouping variables. Carnegie classification code is clearly the best grouping variable to yield the largest model explained variance in graduation rates (mean = 72.9%) and retention rates (mean = 60.2%). Geographical regions and states have more variation in the model explained variances in graduation rates and retention rates, but control of institutions has the least variation in the model explained variances. So, control of institutions seem to be the second best grouping variable based on the model explained variances in graduation rates and retention rates. However, the other three grouping variables can also be used to test specific hypotheses related to urbanization, geographical regions and states. Table 15 shows that public institutions have significantly lower graduation rates than private not-for-profit institutions, $t = -25.944$, $p<.001$. Doctoral or research universities–Intensive (code 15) and Doctoral or research universities–extensive (code 16) have significantly higher graduation rates than other classified groups of institutions, $t = 14.807$ and 40.142 at $p<.001$ respectively. The doctoral or research universities also have the largest model explained variances in graduation rates (83%) and retention rates (74.9%) among the Carnegie classified groups of institutions.

The above results answered research question 1 positively. While most groups based on the seven grouping variables have statistical significant different graduation rates than other groups, the groups by control (public vs. private not-for-profit) and the groups by Carnegie classification (Baccalaureate college–Liberal Arts and Research universities–Extensive) account for the biggest differences.

Table 52

Comparison of Multiple R^2 of Retention Rates and Graduation Rates

Parameters	control	Carnegie	locale	region	state
No. of groups	2	3	3	7	8
Max_{R2gr4}	.688	.830	.743	.794	.801
Min_{R2gr4}	.600	.658	.602	.504	.457
$Mean_{\mathrm{R2gr4}}$	.644	.729	.673	.648	.698
$Max_{\mathrm{R2retention}}$	.495	.749	.451	.609	.732
$Min_{\mathrm{R2retention}}$	.415	.508	.298	.340	.266
$Mean_{\mathrm{R2retention}}$	.455	.602	.415	.456	.539

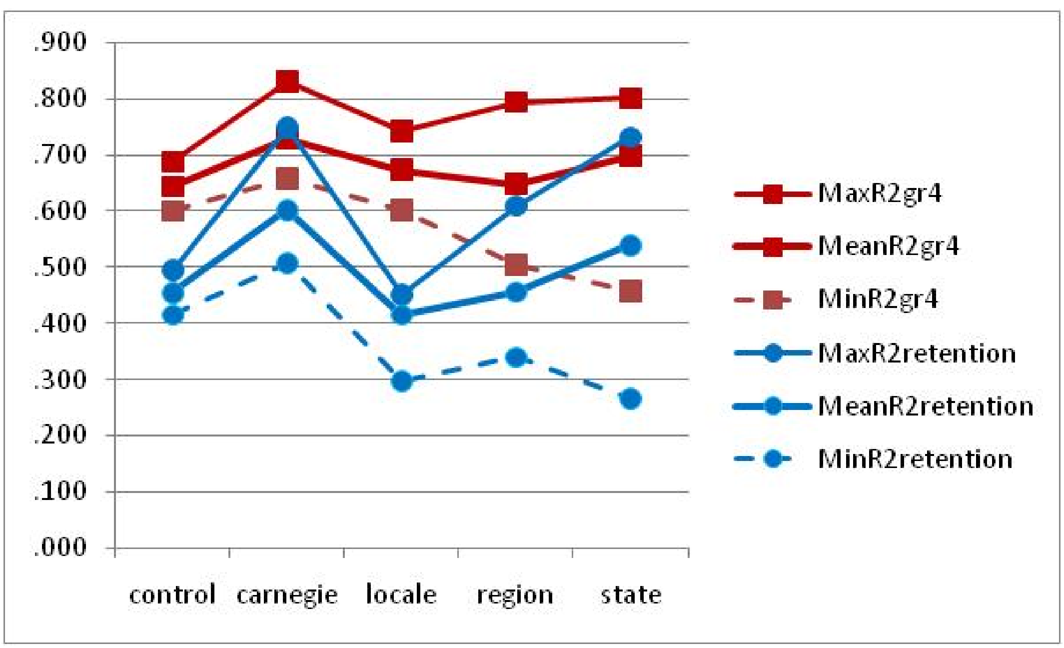

Figure 37. Comparison of multiple R^2 of retention rates and graduation rates.

Measurement Models for Selected Group Comparisons

The four measurement models are for measuring the four latent factors (*background*, *finance*, *academic* and *social*) by their respective observed indicators. These latent factors are used to build the structural model to predict retention rates and graduation rates. So, they must be evaluated before the structural model can be evaluated. The measurement models are evaluated by confirmatory factor analysis (CFA). Table 53 summaries the χ^2 statistics and the fit indices (CFI, NFI and RMSEA) of the four measurement models in five groupings of institutions. All the χ^2 are statistically significant at the .001 level, indicating that the models fit the data. Figure 38 compares the CFI and RMSEA of the four measurement models in five groupings. The student finance measurement model has the largest CFIs (close to .95), indicating good fit to the data. The student background measurement model also has large CFIs (close to .95), except in the groups by geographical regions (.917). The academic environment measurement model has better fit to the data in groups by degree of urbanization and by geographical regions, but less fit in groups by control, Carnegie classification code and by state. The social environment measurement model is least fit to the data in all groups. The social environment factor has three indicators: percentages of full-time enrollment, full-time enrollment and student services expenditures. Better indicators are needed to improve the measurement model of social environment. Degree of urbanization seems to yield the highest CFIs for the three measurement models other than social environment, followed by state. Control and Carnegie classification code both have large CFIs for student background and student finance lacking the academic environment.

Table 53

Comparison of Model Fit Indices for Four Factor Models

Fit Indices	control	Carnegie	locale	region	state
background					
χ^2	152.33	79.75	138.92	259.28	131.17
df	3	4	4	8	9
CFI	.953	.972	.948	.917	.946
NFI	.953	.971	.947	.916	.944
RMSEA	.118	.078	.107	.095	.073
finance					
χ^2	218.08	211.68	231.70	323.39	277.27
df	6	8	8	17	21
CFI	.954	.962	.950	.947	.937
NFI	.953	.960	.948	.944	.933
RMSEA	.100	.090	.098	.069	.070
academic					
χ^2	294.08	267.80	174.29	189.83	191.73
df	6	9	8	16	19
CFI	.922	.927	.943	.949	.931
NFI	.921	.925	.941	.945	.926
RMSEA	.116	.096	.084	.056	.060
social					
χ^2	370.89	371.54	430.88	490.25	354.67
df	3	4	4	8	9
CFI	.926	.902	.902	.909	.909
NFI	.926	.902	.902	.909	.908
RMSEA	.185	.172	.191	.132	.124

Note. CFI and NFI > .95 indicate good fit. RMSEA < .05 indicates good fit.
All χ^2 are statistically significant at the .001 level.

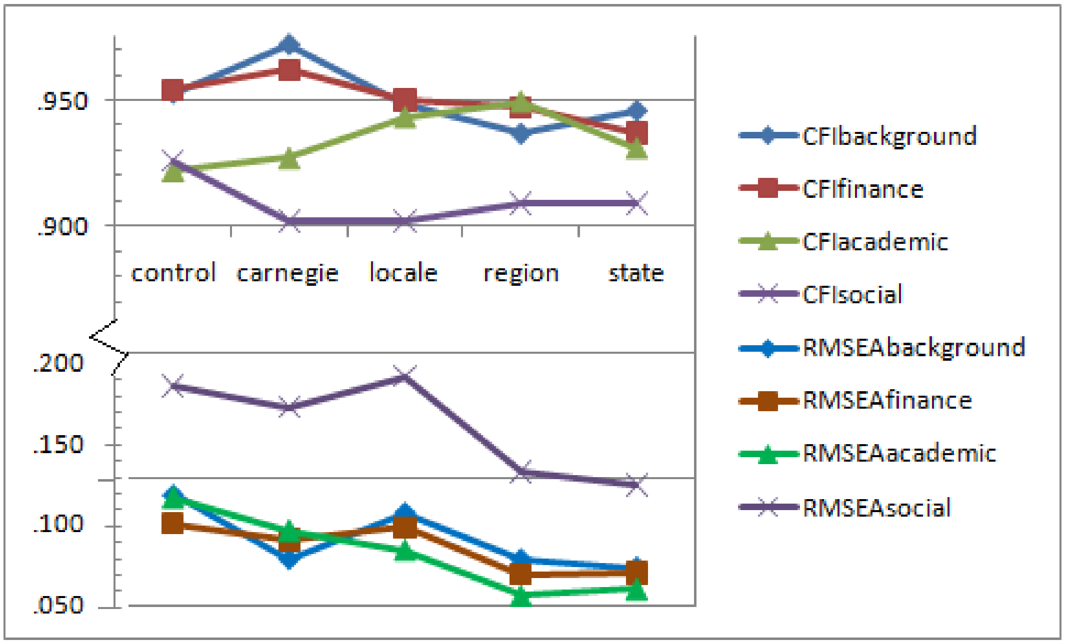

Figure 38. Comparison of the CFI and RMESA of four measurement models.

The above results show that three of the four measurement models, except for the social environment factor, fit the data well based on the model fit indices (CFI, NFI and RMSEA). Hence the second research question is answered positively.

The factor scores of an institutions are based on the set of regression weights computed from a group of data to which the institution belongs. Different groups will have different sets of regression weights. For this reason, researchers should be cautious about comparing the factor scores of institutions across groups. These factor scores from different groups may or may not reflect the true scores of the institutions in the factor scales on which they are being measured. Factor scale invariance should be established before these cross-group factor scores should be compared. Widaman, Reise, Windle and West (1997) have distinguished five levels of measurement invariance—equality in number of factors, configural invariance, weak factorial invariance, strong factorial invariance and strict factorial invariance. Vandenberg and Lance (2000) used the terms "metric invariance" and "scalar invariance" to describe the weak and strong invariance. Table 54 summarizes the results of weak and strong invariance for the four factors in five groupings. Most groups displayed at least weak factorial invariance, except for the groups by state, supporting the multi-group SEM analysis in the next step.

Table 54

Comparison of Measurement Invariance for Four Factor Models

Factor Models	control	Carnegie	locale	region	state
background					
Metric invariance	Yes	No	Yes	No	No
Scalar invariance	No	No	Yes	No	No
Finance					
Metric invariance	No	Yes	Yes	No	No
Scalar invariance	No	No	Yes	No	No
Academic					
Metric invariance	Yes	Yes	Yes	Yes	No
Scalar invariance	No	No	Yes	No	No
Social					
Metric invariance	Yes	Yes	Yes	Yes	No
Scalar invariance	No	No	Yes	No	No

Note. The metric invariance has equal factor loadings across the groups. The scalar invariance has both equal factor loadings and equal intercepts across the groups.

Structural Models for Selected Group Comparisons

The structural model is built from the four factors—student background, student finance, academic environment and social environment—to predict retention rates and six-year graduation rates. Table 55 summarizes the fit indices of the model in five different groupings of institutions. All the χ^2 are statistically significant at the .001 level, indicating that the model fit the data. However, χ^2 is not an accurate model index because it is heavily influenced by the sample size. Both CFI and NFI are lower than the .95 level required for good fit. The RMSEA looks better and is closer to the .05 level in two cases. Figure 39 compares these fit indices graphically. The CFI and NFI gradually decline from grouping by control toward grouping by state. The RMSEA is the reverse.

These results answer the third research question negatively. The model of institutional performance in graduation rates does not fit the dataset as a whole nor does it fit the subsets based on the five grouping variables.

Table 55

Comparison of Fit Indices for the SEM Model by Five Groupings

	control	carnegie	locale	region	state
χ^2	6778.81	6465.21	6021.49	7880.65	6449.39
df	291	388	390	782	886
CFI	.794	.794	.787	.778	.767
NFI	.787	.785	.777	.761	.743
RMSEA	.079	.071	.070	.051	.050

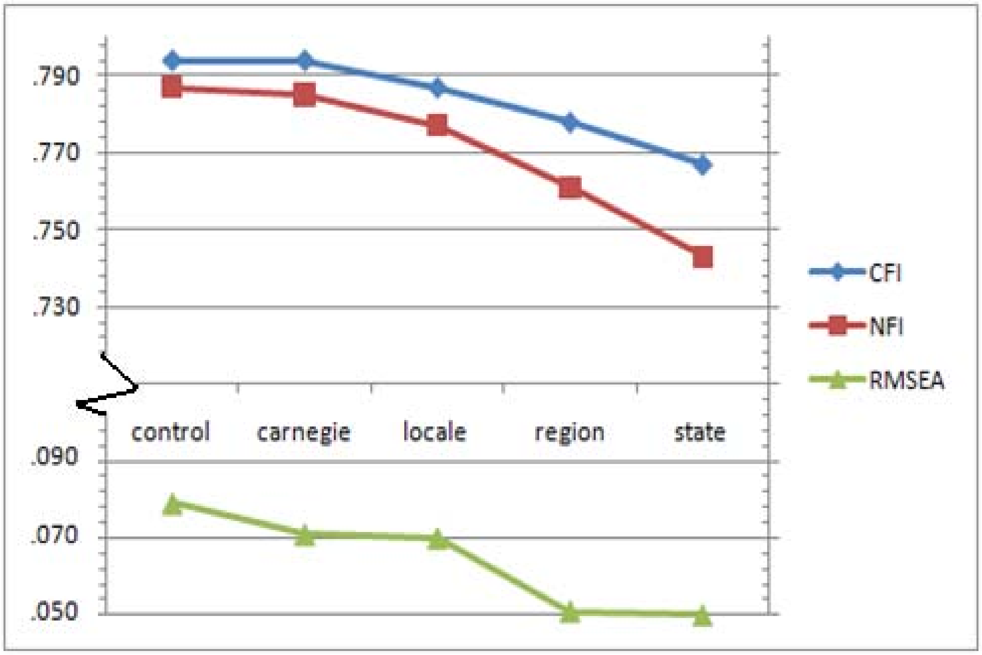

Figure 39. Comparison of fit indices for the SEM model by five groupings.

Now, we see that the model of institutional performance in graduation rates does not fit the current dataset well based on the low CFI and NFI. The RMSEA may indicate marginal fit of the model. What should we do next? Should we throw the model away and start it all over again? Far from it! The model of institutional performance in graduation rates is a pioneer model of its kind to synthesize piecemeal results from previous studies. It should not be surprising to find problems with it at its first formulation and validation. Moreover, the SEM model explains more variances in retention rates and graduation rates than previous studies based on multiple regression. Figure 40 shows that the SEM model in this study explains about 70% of the variances in six-year graduation rates and 50% of the variance in retention rates in average. Table 56 summarizes the explained variances from previous studies. SEM is a much more rigorous method than multiple regression method to test theory based models.

Instead of throwing the model, several things can be done, such as modifying the model to improve its fit. Table 57 presents the fit indices of three alternative SEM models for public and private not-for-profit institutions. Model 2 is created from Model 1 by deleting the percentage of full-time enrollment. Likewise, Model 3 is created from Model 2 by deleting the percentage of full-time faculty. All χ^2 are statistically significant at the .001 level. The fit indices CFI, NFI and RMSEA are all improved in the alternative models. The parsimony-adjusted ratios are also improved because the alternative models are simpler than the baseline model. The Akaike information criterion (AIC) and Browne-Cudeck criterion (BCC) are criteria for selecting alternative models. A 10 or more lower in AIC and BCC indicates that the alternative model is much stronger than the baseline model. Both Model 1 and Model 2 show significant improvement. However, such improvement should be guided by theory rather than purely driven by statistics of the data. The percentage of full-time enrollment variable may be partly redundant with the full-time enrollment variable (*lgenrolft*). So, its deletion may be justified. The percentage of full-time faculty variable may be partly redundant with the faculty-student ratio variable (*rofac2stu*) because the latter also depends on the number of full-time faculty members. The deletion of the percentage of full-time enrollment leaves the social environment a two-indicator factor, which is generally undesirable because of identification problems. The social environment factor is the most problematic factor, which has the lowest model fit in its measurement, the lowest explained variance and the weakest relationship with other factors and variables in the model. It must be improved before the overall model can be improved.

Table 56

Summary of Explained Variances in the Literatures

Literatures	Explained Variances
1. Bean's (1979) model to predict dropout rates using path modeling	21% for female and 12% for male groups
2. Bean's (1985) model to predict dropout syndrome	27% to 47%
3. Cabrera, Nora and Castaneda's (1992) study of the influences of finances on persistence and intent to persist	47% for persistence and 25.5% for intent to persist
4. Pascarella and Terenzini's (1980) prediction of persister and non-persister using discriminant analysis	21.46%
5. Pascarella and Terenzini's (1983) validation of Tinto's model using path modeling	18% of the variance in persistence
6. Pascarella, Duby and Iverson's (1983) testing of Tinto's model in nonresidential institutions using path modeling	19% to 28% of the variance in persistence
7. Beekhoven, De Jong and Van Hout's (2002) testing of Tinto's model using SEM technique	18% to 33% of the variance in academic progress
8. Bernard and Amundsen's (1989) testing of Tinto's model in distance learning context	50% to 58% of variances in course dropout rate
9. Astin's (1997) study of retention rates using multiple regression method	12% of variance in retention rates
10. Goenner and Snaith's (2003) prediction of graduation rates using institutional characteristics as predictors in multiple regression model	79%, 77% and 78% in four-, five- and six-year graduation rates
11. Gansemer-Topf and Schuh's (2006) prediction of retention rates using IPEDS data and regression method	63% of variance in retention rates
12. Ryan's (2004) prediction of graduation rates by institutional expenditures in IPEDS data using OLS regression method	75% of six-year graduation rates

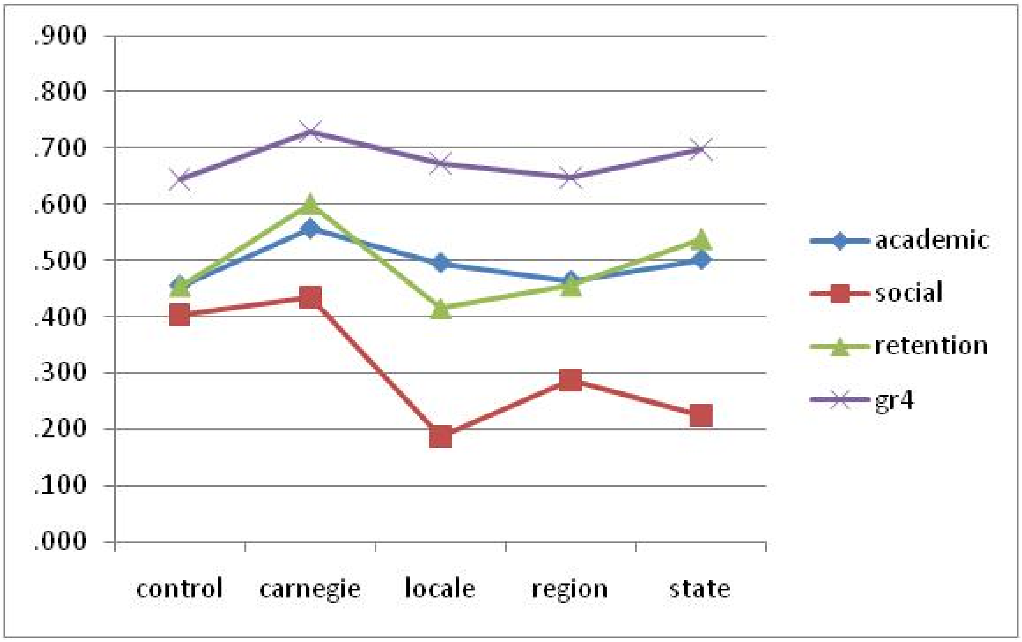

Figure 40. Comparison of model explained variances in four endogenous variables. (*Note*. The *academic* and *social* are the latent factors for academic environment and social environment. The *retention* and *gr4* are the retention rates and the six-year graduation rates which are the outcome variables in the model.)

Table 57

Comparison of Alternative SEM Models

Fit Indices	Model 1	Model 2	Model 3
χ^2	6778.813	5108.675	3889.145
df	291	249	207
CFI	.794	.835	.869
NFI	.787	.829	.863
RMSEA	.079	.074	.071
Parsimony-Adjusted Ratio	.713	.692	.657
AIC	7108.813	5420.675	4189.145
BCC	7114.857	5426.05	4193.987

Note. Model is the baseline mode as depicted in Figure 7. Model 2 is the same as Model 1 without the percentage full-time enrollment (*enrolftpct*) variable. Model 3 is the same as Model 2 without the percentage full-time faculty (*rofacftpct*) variable.

Practical Implications

Two practical implications of the institutional model of graduation rates are discussed here. Specific examples are used to illustrate how the model can be used to inform policy- and decision-makers in higher education to improve institutional performance in graduation rates.

Benchmarking Analysis

One application of the model of institutional performance in graduation rate is benchmarking analysis. A benchmarking analysis is a kind of performance evaluation by comparing an entity with its peers. Table 58 presents the peer institutions of University of North Texas (UNT). These institutions are compared based on their scores at the four factor areas—student background, student finance, academic environment and social environment. The student background factor measures the preparedness of the student body. High means well prepared and low means unprepared for college education. This factor is an input factor and is affected by the institution's selectivity and admission policy. The student finance factor measures the costs of going to college. High means that the students are financially resourceful either by their ability to afford high tuitions or their ability to access financial aid. Low means that the students are financially depraved. The academic environment factor measures the overall level of academic support the institution can provide to help its students succeed academically. High means supportive. Low means unsupportive. The social environment factor measures the overall opportunities the institution can provide to help its students establish meaningful personal and communal relationship within the institution. Table 59 presents the four factor scores of UNT and its peer institutions. Table 60 presents the formulae to compute these factor scores. Figure 41 and Figure 42 display the graphical comparisons of the four factor scores between UNT and its peer institutions. Researchers should be cautious about cross-group comparison of factor scores because only metric invariance is established in the factor models. Because UNT and its peers are all public institutions, their factor scores are comparable within the same group. This peer group has a higher factor score means and a smaller standard deviation in all four factors than the group of all public institutions. UNT's peers are better than average and are a more homogenous group in terms of student background, student finance, academic environment and social environment. The student background factor score of UNT is 66.16, about half standard deviation higher than the group mean (60.83) and half standard deviation lower than the peer mean (68.37). In fact, all of UNT's peer institutions have their student background factor scores within 1.96 standard deviation of the group mean, indicating that their students' preparedness are statistically neither better nor worse than the group average. The student finance factor score of UNT is 1.79, right at the group mean and about half standard deviation lower than the peer mean (1.91). The academic environment factor score of UNT is 12.93, very close to the group mean (12.99) and about one standard deviation lower than the peer mean (13.13). The social environment factor score of UNT is 67.96, about one standard deviation higher than the group mean (60.25) and about half standard deviation higher than the peer mean (66.94). The overall picture of UNT in the four factor areas is above average compared with all other public institutions by less than one standard deviation but is below average compared with its peer institutions by less than one standard deviation. A difference less than 1.96 standard deviation from the mean is not statistically significant at the .05 level. Compared with its peers, UNT's relative strength is in its social environment and its weakness is in its academic environment.

Table 58

Peer Institutions of University of North Texas (UNT)

Institutions	abbrev.	state	carnegie	locale	obereg
University of Alabama	UA	AL	Doctoral[a]	Mid-size city	Southeast
Northern Arizona University	NAU	AZ	Doctoral[b]	Large town	Southwest
University of Central Florida	UCF	FL	Doctoral[b]	Urban fringe[f]	Southeast
Florida Atlantic University	FAU	FL	Doctoral[b]	Mid-size city	Southeast
Florida International University	FIU	FL	Doctoral[a]	Large city	Southeast
Georgia State University	GSU	GA	Doctoral[a]	Large city	Southeast
Northern Illinois University	NIU	IL	Doctoral[a]	Mid-size city	Great Lakes
Western Michigan University	WMU	MI	Doctoral[a]	Mid-size city	Great Lakes
University of New Mexico	UNM	NM	Doctoral[a]	Large city	Southwest
New Mexico State University	NMSU	NM	Doctoral[a]	Mid-size city	Southwest
Bowling Green State University	BGSU	OH	Doctoral[b]	Mid-size city	Great Lakes
Kent State University	KSU	OH	Doctoral[a]	Mid-size city	Great Lakes
University of Memphis	UM	TN	Doctoral[a]	Large city	Southeast
University of Houston	UH	TX	Baccal.[c]	Large city	Southwest
The University of Texas at Arlington	UTA	TX	Doctoral[a]	Large city	Southwest
The University of Texas at Dallas	UTD	TX	Doctoral[b]	Urban fringe[e]	Southwest
The University of Texas at El Paso	UTEP	TX	Doctoral[b]	Large city	Southwest
The University of Texas at San Antonio	UTSA	TX	Masters[d]	Large city	Southwest
Texas Tech University	TTU	TX	Doctoral[a]	Mid-size city	Southwest
George Mason University	GMU	VA	Doctoral[b]	Urban fringe	Southeast
University of Wisconsin-Milwaukee	UWM	WI	Doctoral[a]	Large city	Great Lakes

Note. a. Doctoral or research universities–extensive; b. Doctoral or research universities–intensive; c. Baccalaureate colleges–general; d. Masters colleges and universities I;
e. Urban fringe of large city; f. Urban fringe of mid-size city

Table 59

Comparison of Factor Scores with Peer Institutions Based on Control

Institutions	background	finance	academic	social
UNT	66.16	1.79	12.93	67.96
BGSU	75.84	2.16	13.17	70.20
FAU	58.35	1.74	13.18	62.16
FIU	69.40	1.72	12.90	63.82
GMU	68.84	2.39	13.49	66.32
GSU	62.98	1.67	13.33	63.24
KSU	72.28	2.01	12.99	69.14
NMSU	61.11	1.74	13.02	64.48
NAU	68.96	1.71	13.05	67.85
NIU	67.67	2.23	13.19	69.51
UA	75.45	2.17	13.65	69.02
UCF	72.30	1.74	12.68	70.41
UM	66.87	1.88	13.11	64.46
UWM	66.86	1.82	13.29	65.42
WMU	72.54	1.84	13.03	70.11
Group *Mean*	60.83	1.79	12.99	60.25
Group *SD*	11.49	.25	.66	6.63
Peer *Mean*	68.37	1.91	13.13	66.94
Peer *SD*	4.98	.23	.24	2.82

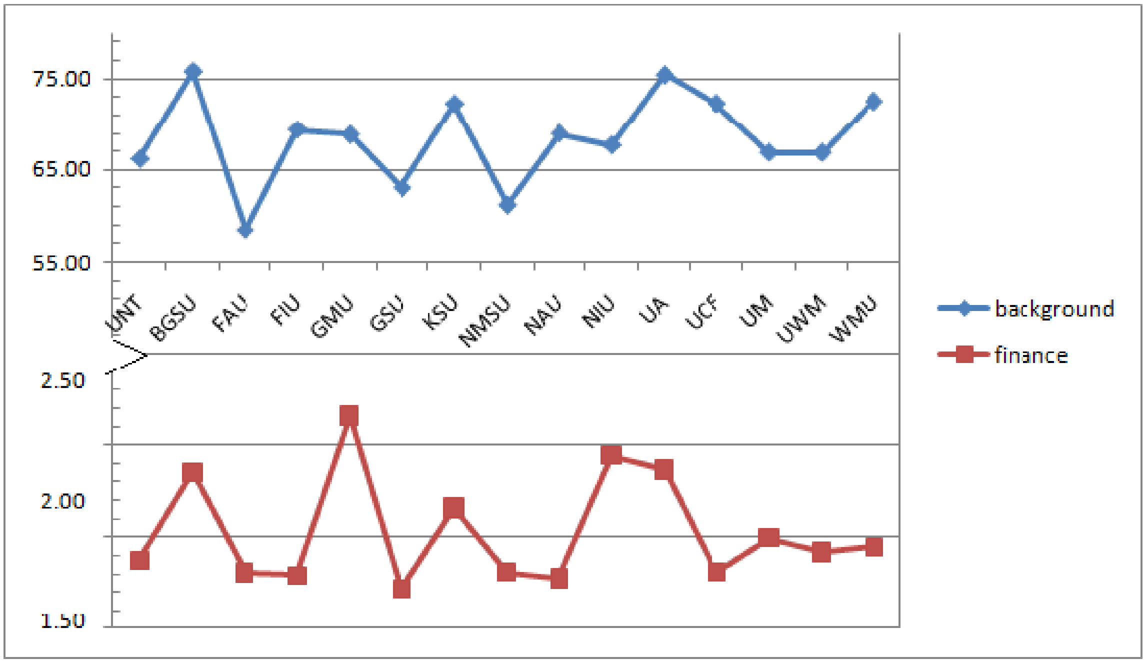

Figure 41. Comparison of student background and student finance factor scores with peer institutions.

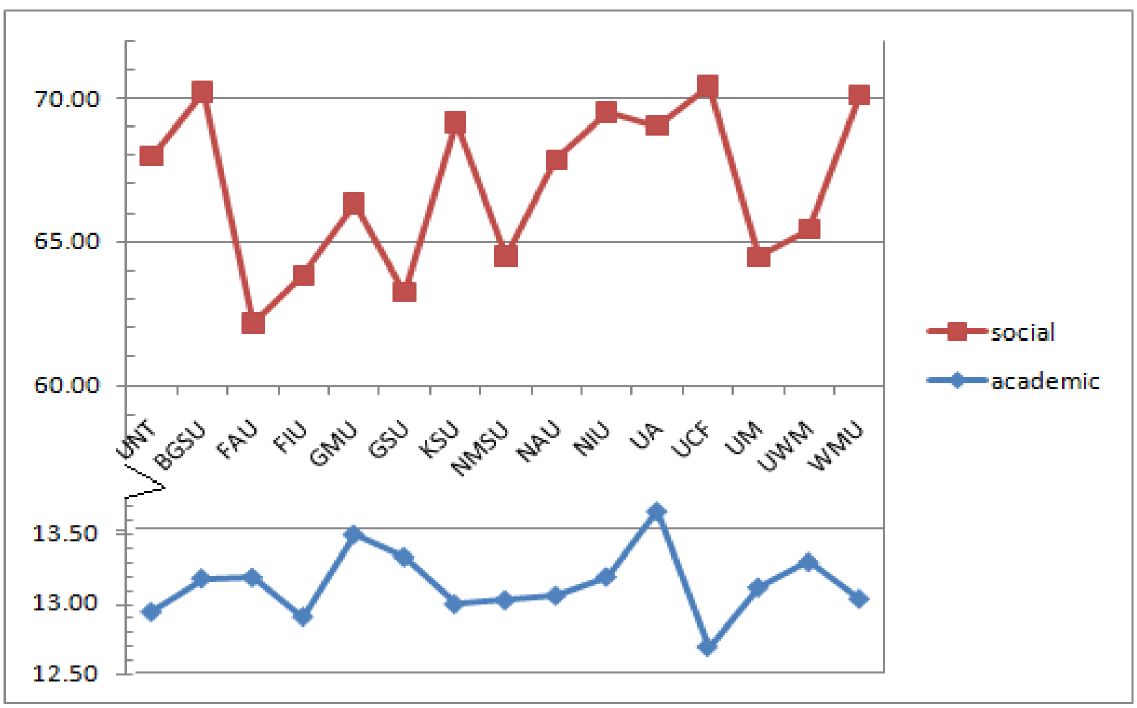

Figure 42. Comparison of academic and social environment factor scores with peer institutions.

Table 60

SPSS Syntax for Computing Factor Scores for Institutions Grouped by Control

```
COMMENT four factor scores for institutions by control.
do if (control = 1). /* for public institutions.
compute fsctlbag=xret_pcf03*.094752+stuition2*.009345+sxrofgrnt_a*.005868
        +sxrosgrnt_a*.004828+sxroigrnt_a*.014659+xact25*1.371287+instses*.141210
        +efage*-.870536+xlgdormcap*.557345+lgenrolft*.539383+enrolftpct*.007483
        +rofac2stu*.030175+rofacftpct*.001472+lginsexpfte*.586831+xlgacsexpfte*.227036.
compute fsctlfin=xret_pcf03*.002470+stuition2*.010156+sxrofgrnt_a*.006377
        +sxrosgrnt_a*.005247+sxroigrnt_a*.015931+xact25*.001343+instses*.000138
        +efage*-.000853+xlgdormcap*.012080+lgenrolft*.011691+enrolftpct*.000162
        +rofac2stu*.003302+rofacftpct*.000161+lginsexpfte*.064210+xlgacsexpfte*.024842.
compute fsctlsoc=xret_pcf03*.064619+stuition2*.009990+sxrofgrnt_a*.006273
        +sxrosgrnt_a*.005161+sxroigrnt_a*.015672+xact25*.066257+instses*.00683
        +efage*-.042062+xlgdormcap*3.079436+lgenrolft*2.980192+enrolftpct*.041348
        +rofac2stu*-.003820+rofacftpct*-.000186+lginsexpfte*-.074288+xlgacsexpfte*-.028741.
compute fsctlacd=xret_pcf03*.006043+stuition2*.002388+sxrofgrnt_a*.001499
        +sxrosgrnt_a*.001234+sxroigrnt_a*.003746+xact25*.003137+instses*.000323
        +efage*-.001991+xlgdormcap*-.003341+lgenrolft*-.003233+enrolftpct*-.000045
        +rofac2stu*.054338+rofacftpct*.002651+lginsexpfte*1.056742+xlgacsexpfte*.408837.
else if (control = 2). /* for private not-for-profit institutions
compute fsctlbag=xret_pcf03*.027158+stuition2*.041541+sxrofgrnt_a*.002995
        +sxrosgrnt_a*.001026+sxroigrnt_a*.006050+xact25*1.718366+instses*.035788
        +efage*-.123335+xlgdormcap*.017657+lgenrolft*.018754+enrolftpct*.000073
        +rofac2stu*.015032+rofacftpct*.000746+lginsexpfte*.357578+xlgacsexpfte*.064263.
compute fsctlfin=xret_pcf03*.012818+stuition2*.386397+sxrofgrnt_a*.027862
        +sxrosgrnt_a*.009544+sxroigrnt_a*.056271+xact25*.045427+instses*.000946
        +efage*-.003260+xlgdormcap*.140759+lgenrolft*.149505+enrolftpct*.000580
        +rofac2stu*.017208+rofacftpct*.000854+lginsexpfte*.409346+xlgacsexpfte*.073567.
compute fsctlsoc=xret_pcf03*.003415+stuition2*.026877+sxrofgrnt_a*.001938
        +sxrosgrnt_a*.000664+sxroigrnt_a*.003914+xact25*.003687+instses*.000077
        +efage*-.000265+xlgdormcap*2.053771+lgenrolft*2.181377+enrolftpct*.008461
        +rofac2stu*.000983+rofacftpct*.000049+lginsexpfte*.023374+xlgacsexpfte*.004201.
compute fsctlacd=xret_pcf03*.004745+stuition2*.012233+sxrofgrnt_a*.000882
        +sxrosgrnt_a*.000302+sxroigrnt_a*.001782+xact25*.011686+instses*.000243
        +efage*-.000839+xlgdormcap*.003658+lgenrolft*.003886+enrolftpct*.000015
        +rofac2stu*.062258+rofacftpct*.003089+lginsexpfte*1.481022+xlgacsexpfte*.266166.
end if.
execute.
```

Note. The if-else if clauses distinguish the public and private not-for-profit institutions. Each factor score is a linear combination of the observed variables multiplied by the factor score weights generated by the Amos software.

Institutional Performance Evaluation

The model of institutional performance in graduation rates can be used to evaluate an institution’s performance by comparing its actual graduation rate with its predicted graduation rate based on the model parameters generated from a group of institutions. If an institution’s graduation rate is higher than its predicted graduation rate, the institution performs better than what is expected based on the model. If the actual rate is lower than the predicted rate, the institution performs worse than expected. The comparison between an institution’s actual and expected graduation rates is a more accurate comparison based on the group norms. Table 61 summaries the model parameters generated for two groups—public and private not-for-profit institutions. Table 62 presents the actual and predicted retention rates and graduation rates of UNT’s peer institutions. Figure 43 and Figure 44 presents the graphical comparison of the retention and graduation rates. UNT’s actual retention rate is 75%, which is about one fourth standard deviation lower than the group mean (71.62%), slightly higher than the peer mean (74.46%) and about half standard deviation lower than its model predicted retention rate (81.19%). UNT’s actual graduation rate is 44.35%, which is slightly lower than the group mean (45.86%), about half standard deviation lower than the peer mean (49.45%) and about one third standard deviation lower than its model predicted graduation rate (50.29%). So, UNT does not meet the performance expectation both in terms of retention rates and graduation rates. What can UNT do to improve its retention rates and graduation rates?

Administrators can use sensitivity analysis to assess the impacts of a set of institutional parameters on graduation rates. For example, what is the impact of raising admission test scores by 10% on graduation rates? Table 63 summaries the impacts of a 10% increases in 14 institutional parameters on the four factor scores and the graduation rate of UNT based on the model. As discussed earlier, student background is the most important factor to predict graduation rates. The impacts of a 10% increase in admission test scores are 7.2% increase in the student background factor score and 3.9% increase in graduation rate in UNT. For student finance, the biggest impact comes from institutional grant (1.6%) followed by federal grant (.9%). For social environment, percentage of full-time enrollment and dormitory capacity have the greatest impacts, .47% and .43% respectively. Instructional expenditures have the greatest impacts on the academic environment (.78%). This kind of impact assessment analysis helps administrators focus on the areas where they can make policy changes to effectively affect the bottom lines. For example, the administrators can raise the admission standard and increase the institutional grant to attract more talented students. They can also improve the academic environment by hiring more qualified faculty and supporting a campus-wide mentoring program for entering freshmen students. The social environment can be improved by expanding the student dormitory capacity and building more user friendly student centers in convenient locations. Of course, the ultimate success of the institution's admission policy depends on its marketing strategy and its reputation. The reputation also depends on the social environment and the academic environment of the institution. The above benchmarking analysis is based on the grouping by control of institutions. When other groupings, such as Carnegie classification, are used to compare UNT with its peer institutions, the same analytical strategy established above still holds.

Table 61

Parameters for Predicting Retention Rates and Graduation Rates Based on Control

Parameters	All	Public	Private
n	1785	577	1208
B_{r_ac}	.040	.015	.030
B_{r_ad}	.129	.288	.008
B_{r_bc}	.088	1.269	.142
B_{r_bd}	-.109	5.955	.597
B_{r_ae}	.221	.158	.233
B_{r_be}	.327	3.422	.410
B_{r_ce}	1.681	2.663	1.400
B_{r_de}	.375	.444	.095
B_{r_ef}	1.355	1.398	1.310
$FM_{background}$	65.27	60.83	67.68
$FM_{finance}$	12.89	1.79	18.92
$FM_{academic}$	15.24	12.99	16.47
FM_{social}	42.51	60.25	32.88
Int_{xret_pcf03}	73.41	71.85	74.16
Int_{gr4}	-47.62	-54.56	-42.47
xret_pcf03	73.44	71.85	74.21
gr4	51.87	45.86	54.77
Pred_{xret_pcf03}	60.21	77.09	49.71
Pred_{gr4}	51.89	45.88	54.75

Note. The parameters in this table are from the SEM model fit on the institutions grouped by control. Institutions should use the parameters in the appropriate column (public or private not-for-profit) to predicted their retention rates and graduation rates. The bottom two row are the predicted retention and graduation rates based on the means of the groups.

Table 62

Comparison of Actual and Predicted Performance Based on Control

	Retention rates		Graduation rates	
Institutions	Actual	Predicted	Actual	Predicted
UNT	75.00	81.19	44.35	50.29
BGSU	74.00	85.61	56.82	48.89
FAU	69.00	77.85	37.89	41.90
FIU	72.25*	79.55	49.21	46.44
GMU	82.00	84.41	58.27	60.07
GSU	71.33*	79.21	47.19	45.15
KSU	72.17*	83.58	49.08	46.33
NMSU	72.00	78.89	45.10	46.09
NAU	69.00	81.63	48.18	41.90
NIU	73.63*	84.28	52.29	48.38
UA	84.00	86.33	65.10	62.87
UCF	83.00	82.41	59.15	61.47
UM	75.00	80.54	34.43	50.29
UWM	68.57*	81.24	41.19	41.29
WMU	76.00	83.59	53.57	51.69
Group *Mean*	71.62	-	45.86	-
Group *SD*	13.64	-	16.16	-
Peer *Mean*	74.46	82.02	49.45	49.54
Peer *SD*	4.96	2.57	8.35	6.94

Note. * indicates imputed values for missing data. All the institutions are public institutions. So, the parameters for the public group are used to predict the retention rates and graduation rates.

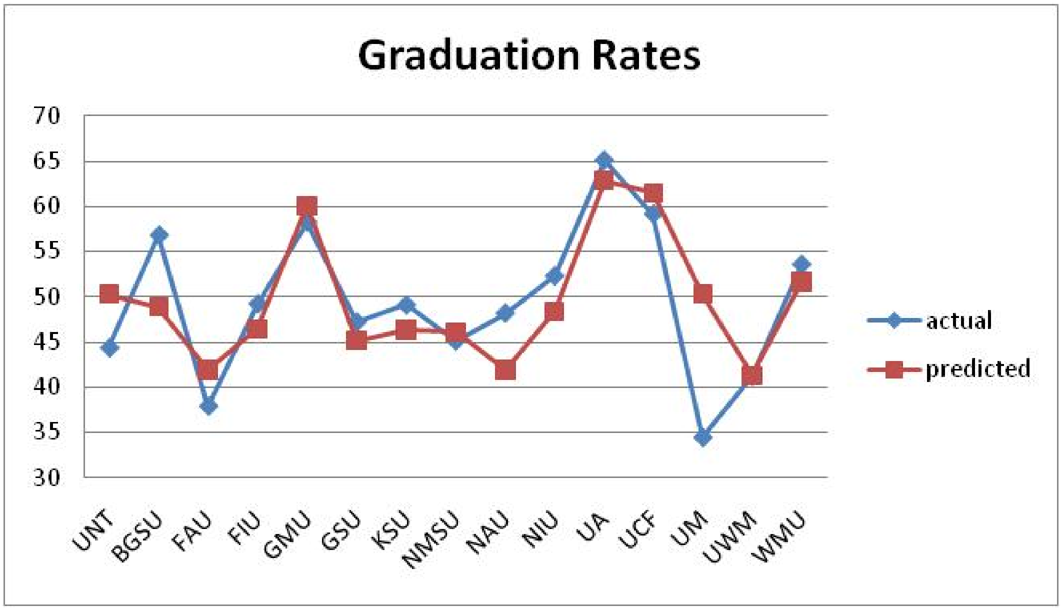

Figure 43. Comparison of actual and predicted graduation rates by control.

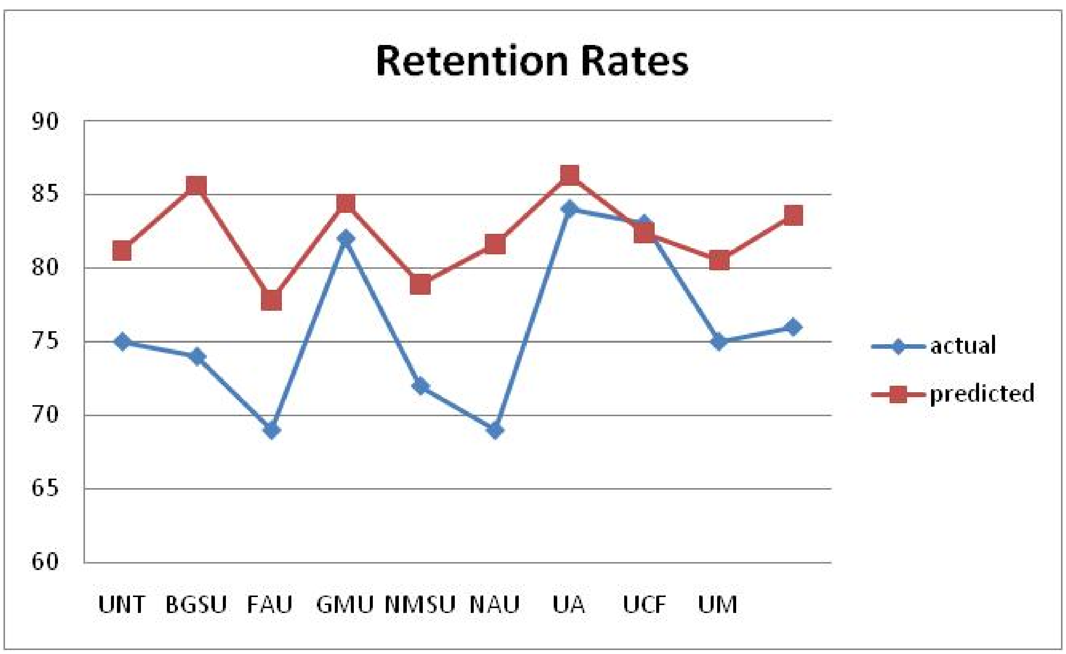

Figure 44. Comparison of actual and predicted retention rates by control.

Table 63

Sensitivity Analysis of Factor Scores and Graduation Rates of UNT

	background		*finance*		*social*		*academic*		Pred.
10% increase	FS	%Δ	FS	%Δ	FS	%Δ	FS	%Δ	*gr4*
Tuition	66.159	.003	1.790	.115	67.965	.003	12.934	.004	46.274
Federal grant amount	66.171	.022	1.804	.900	67.979	.023	12.937	.029	46.287
State grant amount	66.166	.014	1.798	.564	67.973	.015	12.935	.018	46.282
Institutional grant amount	66.183	.040	1.817	1.626	67.991	.042	12.940	.053	46.299
ACT score	70.910	7.186	1.792	.260	68.192	.338	12.944	.084	48.076
Institutional SES	67.329	1.772	1.789	.064	68.019	.083	12.936	.021	46.717
Average age of students	64.287	-2.827	1.786	-.103	67.872	-.133	12.929	-.033	45.563
Dormitory capacity	66.210	.080	1.789	.064	68.256	.432	12.933	-.002	46.375
Enrollment	66.208	.078	1.789	.062	68.247	.418	12.933	-.002	46.372
% FT enrollment	66.215	.088	1.789	.071	68.286	.475	12.933	-.003	46.385
Faculty-student ratio	66.167	.016	1.789	.064	67.961	-.002	12.952	.145	46.280
% FT faculty	66.167	.016	1.789	.063	67.961	-.002	12.952	.143	46.280
Instructional expenditures	66.213	.085	1.794	.342	67.956	-.010	13.034	.779	46.312
Academic support exp.	66.178	.033	1.790	.132	67.960	-.004	12.972	.301	46.288

Note. The four factor scores (*FS*) and the predicted six-year graduation rates are computed each time based on the 10% increase in the 14 institutional variables separately. The baseline graduation rate of UNT is 46.273. The percentage changes are calculated for the factor scores.

Recommendations for Future Studies

In this study, an institutional model of performance in graduation rates is created to synthesize the results from previous studies regarding the effects of institutional characteristics on graduation rates. This model is derived from Tinto's model and Astin's model, which have been tested by many researchers. The current model, however, does not have good fit based on the IPEDS dataset and the SEM technique. Several areas should be pursued in future studies to improve the current model.

Replication Studies

Science is strengthened by repetitions and the collaboration of results. Likewise, this study should be replicated in the future using different IPEDS datasets in different years. The results may produce better model fit or worse. New issues may also arise. But different researchers should take a fresh look at the model and evaluate it in a different set of data. Hopefully, future researchers will have better ideas to improve the model. IPEDS is a living data system. New data are collected and added into the system each year. Other data may become available and can be used to improve the model in the future. This study is better viewed as a beginning of a new line of research, rather than a finished project.

Time Effects of Predictors on Graduation Rates

In this study, most data are drawn from the cohort year to predict the six-year graduation rates. In future studies, several years of data can be used together to predict the graduation rates. This should yield more accurate prediction and explanation. One way of doing this is by explicitly modeling the factors in time series, but that will increase the structural complexity of the model. Another way is by treating different years of data as different group. This will allow the current model to be simultaneously evaluated in several years of data. But the disadvantage is the difficulty in specifying cross-year relationship in the model.

Multilevel Models of Student Persistence

The current model is an institutional model. The student information, such as age, gender and race/ethnicity, are aggregated at the institutional level and lose their capability to identify individual students. Multilevel models can accurately partition the effects for each level of predictors. Multilevel SEM should be used to expand the current model by incorporating student level variables and state level variables into the model. However, Amos does not provide the capability to create multilevel SEM models. Other software, such as Mplus, provides the multilevel SEM feature.

APPENDIX

DEFINITIONS OF SELECTED IPEDS VARIABLES

Variable	Description	Data File
grrace<nn>	Number of students by gender and race/ethnicity in cohort, where 01 = Nonresident alien men, 02 = Nonresident alien women, 03 = Black non-Hispanic men, 04 = Black non-Hispanic women, 05 = American Indian or Alaska Native men, 06 = American Indian or Alaska Native women, 07 = Asian or Pacific Islander men, 08 = Asian or Pacific Islander women, 09 = Hispanic men, 10 = Hispanic women, 11 = White non-Hispanic men, 12 = White non-Hispanic women, 13 = Race/ethnicity unknown men and 14 = Race/ethnicity unknown women.	gr2007
grtype	Cohort data is a categorical variable range from 2 to 40, indicating 2 = Adjusted cohort in 4-year institutions, 3 = completers within 150% of normal time for the degree/certificate in 4-year institutions, etc.	gr2007
satvr25	SAT Verbal 25th percentile score is a continuous variable with range from 200 to 800.	ic2001
satmt25	SAT Math 25th percentile score is a continuous variable with range from 200 to 800.	ic2001
acten25	ACT English 25th percentile score is a continuous variable with range from 1 to 36	ic2001
actmt25	ACT Math 25th percentile score is a continuous variable with range from 1 to 36	ic2001
fgrnt_p	Percentage of full-time, first-time degree/certificate-seeking students who received Federal grant aid is a continuous variable with range from 0 to 100%.	sfa2001s

Variable	Description	Data File
fgrnt_a	Average amount of Federal grant aid received by full-time, first-time degree/certificate-seeking students is a continuous non-negative variable.	sfa2001s
sgrnt_a	Average amount of state/local grant aid received by full-time, first-time degree/certificate-seeking students is a continuous non-negative variable.	sfa2001s
igrnt_a	Average amount of institutional grant aid received by full-time, first-time degree/certificate-seeking students is a continuous non-negative variable.	sfa2001s
openadmp	Open admission policy is an admission policy that the school will accept any student who applies. This is a dichotomous variable with 1 = With open admission policy and 2 = Without open admission policy.	ic2001
efag01 efag02	The number of male (01) and female (02) full-time students in an age group specified by the *line* variable, in which 1 = less than 18, 2 = 18 to 19, 3 = 20 to 21, 4 = 22 to 24, 5 = 25 to 29, 6 = 30 to 34, 7 = 35 to 39, 8 = 40 to 49, 9 = 50 to 64 and 10 = 65 and more.	ef2001b
ref_pcf	Percent of first-time full-time degree/certificate-seeking undergraduate students in fall 2002 returning in fall 2003 is a continuous variable with range 0 to 100%.	ef2003d
tuition2	In-state average tuition for full-time undergraduate students is a continuous non-negative variable.	ic2001ay
tuition3	Out-of-state average tuition for full-time undergraduate students is a continuous non-negative variable.	ic2001ay

Variable	Description	Data File
empcount	Number of full-time instructional faculty is a continuous non-negative variable. Instructional faculty are Instruction/research staff employed full time (as defined by the institution) whose major regular assignment is instruction, including those with released time for research.	sal2001_a_s
fte	Full-time equivalent enrollment is a continuous non-negative variable. The full-time equivalent of the institution's part-time enrollment is estimated and then added to the full-time enrollment of the institution. The full-time equivalent of part-time enrollment is estimated by multiplying the part-time enrollment by factors that vary by control and level of institution and level of student.	fa2001hd
staff15 staff16	The total number of male (15) and female (16) faculty members engaged in services specified by the *line* variable in which 18 = full-time faculty (instructional/research/public service) and 68 = part-time faculty (instructional/research/public service).	s2001_abd
b013	Expenditures of the colleges, schools, departments, and other instructional divisions of the institution and expenditures for departmental research and public service that are not separately budgeted. This is a continuous non-negative variable.	f2001_f1

Variable	Description	Data File
b043	Expenditures for the support services that are integral part of the institution's primary mission of instruction, research, or public service. Includes expenditures for libraries, museums, galleries, audiovisual services, academic computing support, ancillary support, academic administration, personnel development, and course and curriculum development. This is a continuous non-negative variable.	f2001_f1
b063	Expenditures for student services are funds expended for admissions, registrar activities, and activities whose primary purpose is to contribute to students' emotional and physical well-being and to their intellectual, cultural, and social development outside the context of the formal instructional program.	f2001_f1
efrace15	Total enrollment of male students in the fall semester is a continuous non-negative variable.	ef2001a
efrace16	Total enrollment of female students in the fall semester is a continuous non-negative variable.	ef2001a
section	Attendance status a categorical variable with three levels: 1 = Full-time, 2 = Part-time and 3 = All student.	ef2001a
lstudy	Level of study is a categorical variable with four levels: 1 = Undergraduate, 2 = First-professional, 3 = Graduate and 4 = All students.	ef2001a

Variable	Description	Data File
roomcap	Total dormitory capacity is the maximum number of students that the institution can provide residential facilities for, whether on or off campus. This is a continuous non-negative variable.	ic2001
locale	Degree of urbanization is a categorical variable with a eight-level scale: 1 = Large city, 2 = Mid-size city, 3 = Urban fringe of large city, 4 = Urban fringe of mid-size city, 5 = Large town, 6 = Small town, 7 = Rural, 9 = Not assigned.	fa2001hd
control	Control of institution (1 = Public, 2 = Private, not-for-profit, etc.)	fa2001hd
fips	FIPS State code (e.g., 1 = Alabama, 48 = Texas, etc.)	fa2001hd
carnegie	Carnegie classification code (15 = Doctoral or Research universities–Extensive, 16 = Doctoral or Research universities–Intensive, 21= Masters colleges and universities I, 22 = Masters colleges and universities II, 31 = Baccalaureate colleges–liberal arts, 32 = Baccalaureate colleges–general)	fa2001hd
obereg	Bureau of Economic Analysis Code (OBE) Region (1 = New England, 2 = Mid East, 3 = Great Lakes, 4 = Plains, 5 = Southeast, 6 = Southwest, 7 = Rock Mountains, 8 = Far West)	fa2001hd

Source. Integrated Postsecondary Education Data System (IPEDS) 2001–03 datasets.

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