MODELLING INSTITUTIONAL SIMILARITIES:
A STUDY THAT EXPLORES WHY PEERS ARE PEERS AND
THE VALIDITY OF THE US NEWS FRAMEWORK FOR ASSESSING QUALITY

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TRACK 6: THE PRACTICE OF INSTITUTIONAL RESEARCH: THEORY, TECHNIQUES, TECHNOLOGIES, TOOLS, AND ETHICS

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Abstract

This study explored institutional similarities using modelling techniques in the national university population. Measures of proximity in national datasets shed light on the dynamics of peer group construction. Factors were identified that provide the foundation for peer similarities. Structural equation modelling allowed testing of fit across competing models; researchers choose to test the fit of the factors and weightings used in national rankings. Applications for higher education are: 1) the methods provide institutions with options to determine their own peers; 2) the validity of the *US News and World Report* framework is tested; and 3) limitations are noted in the application of national datasets as they currently exist while future research should include additional data collection.

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Introduction

A few years ago, campus leaders were growing increasingly concerned with how the University compared to peers on a number of measures. Were costs inline with similar institutions? What types of outcomes could be expected given our mission? What are the influences of our region on a national university? When we looked more closely at those institutions we considered our peers we were finding more differences than similarities. Given the large number of academic programs, our three city location, and the relatively small student population, we found that we are very unique. They asked that the Planning and Research office develop a way to choose better peer groups. Our initial research found that most peer groupings were either based on institutional size, source of control, budget, or some measure of selectivity. Contacting others whose work had focused on similar problems, we found that several mathematical techniques have been applied to institutional datasets to develop measures of "*peerness*", or institutional similarities. Better peer groups were constructed on combinations of these measures. The technique is expanded on here for purposes of explanation and potential adoption by others.

When presented with the results, campus leaders were intrigued by the relationships among the institutional characteristics and questioned how we could use these patterns in planning. In particular, it became apparent that the resulting framework could be very useful in the application of strategic indicator analysis to institutional strategy. They also asked for a broader sample. Responding, we expanded the number of institutions from 40 to 248, those classified as National Universities using the Carnegie and *US News and World Report* classifications. It was at this point that we identified the value of the research to a broader audience and decided to publish the results. The research then focused more broadly on what the relationships are among the primary variables used in cross-institutional comparisons. Many competing models exist, most onerously, that contrived by *US News and World Report* to rank institutions. We chose to employ structural equation modelling techniques to explore patterns in the data and isolate the best fit model. While doing this, it required only a little more effort to test the fit of the *US News and World Report* rankings framework to the data, a form of validity testing. Finally the findings of the modelling are reviewed in detail.

Literature Review

National datasets have been used for decades in the study of higher education, but recent availability of high quality institutional data now offers rich analytic capabilities not only to higher education scholars and governments, but to institutional researchers, students, and the public. Early examples of institutional analysis include the *Yale Report* (1828) where a faculty committee commented on the future of liberal education at Yale. Today, dozens of organizations collect large sets of national data on a regular basis and the data are disseminated sometimes electronically or through publications. The *Primmer for Institutional Research* devotes a whole chapter to guidance of what is available and how to use national datasets (Milam, 2003, chap. 8). For example, the National Center for Education Statistics (NCES) collects a majority of higher education information though the Integrated Postsecondary Education Data System (IPEDS). In addition, the availability of data has created opportunities to profit considerably from remarketing summaries and rankings of generally free data.

The data can be complex however and early researchers identified the need to classify and cluster institutions to simplify their work. Astin (1962) studied statistical techniques for identifying dimensions along which higher education institutions are different. The factor analysis of 33 institutional characteristic variables yielded six factors that differentiated institutions (affluence, size, source of control, masculinity, homogeneity, and realistic orientation). The researchers suggested that others may be able to use such factors scores in future research to help simplify finding dimensions along which institutions are different. Factor scores were also plotted for individual institutions allowing for differences on the six factors to be visualized. This was one of the early studies using empirical techniques to define institutional differences.

Over the next eleven years validation research was conducted on the six factors. In 1973, an important classification system was published by the Carnegie Foundation to aid research by identifying homogenous categories of institutions. This system eliminated some of Astin's six factors and focused on affluence, size, and programs of study. The Carnegie Classification has been used for many purposes including policy making or trend analysis, for example, researchers using the classification system found that education programs were poorly funded across Carnegie groupings (Howard, Hitz, & Baker, 1998). The Carnegie Classification will change again in 2005 to allow institutions to be compared along multiple characteristics (McCormick, 2004).

Terenzini and others (1980) applied factor analytic techniques to a sample of 176 doctoral level institutions with the goal of finding an alternative to Carnegie's limited variables. The principal component identified in this sample was full-time student emphasis based on percent of full-time faculty, graduate students, and undergraduates. Faculty salaries were also isolated. The work was similar to that of Astin and both studies identified a size factor that could be used to relate institutional characteristics. More recent analysis investigated institutional prestige. A conceptual framework was offered by Volkwein & Sweitzer (2004) that showed that an institution's prestige as measured by reputation ratings may be predicted by different models. The framework overlapped prior research in using measures of size, control, and expenditures. Webster (2001) used a principal component analysis to test the accuracy of 11 ranking criteria used by *US News and World Report*. He found that four principal components explained a majority of the variance in predicting an institution's *US News and World Report* tier ranking. An important finding of the study was that the indicators were not consistent with the *US News and World Report* weighting schemes in predicating tier rankings due to multi-collinearity in the variables.

The past 20 years have witnessed the advent and growing importance of another perspective on institutional data, that of peers. The earliest peer groups were created subjectively being simple lists of other institutions that administrators thought were similar. The literature provided a variety of more objective rationale by which to construct peer groupings. For example, one typology included four comparison groups: competitor, peer, aspiration, and jurisdictional (Brinkman & Teeter, 1987). Competitors shared some overlapping markets. Peers had similar missions. Aspiration categorization included those that the institution wanted to be more like. Jurisdictional groups included other institutions based on geographic or political boundaries. Since, many methods have been used to identify comparison groups that ranged from using quantitative data and statistics to making informed decisions using a few individual's judgments (Rawson et al, 1983; Teeter & Christal, 1987; Walsh, 2000; Weeks et al, 2000). Zhao and Dean (1997) used an approach to validate a prior peer list defined by their institution that blended both a statistical analysis (cluster analysis of about 30 variables) and administrator feedback (who simply narrowed the resulting list) in the development of the peer groupings.

Taken together, all of these studies suggest that many institutional variables explain only a few factors that support institutional differentiation. Researchers have criticized national datasets used by ranking guides and focusing on factors that relate to these institutional comparisons. The popular guidebook's ranking of institutions is part of a larger debate on how to assess institutional quality. Specifically, *US News and World Report*, who suggests it ranks for quality, has been at the center of controversy. Some of the most cited criticisms of *US News and World Report* rankings were the weightings applied in the formula, validity of institutional data, and a reliance on input measures (Levin, 2002). Studies continually found that the many ranking indicators used by *US News and World Report* are highly related and only predict one construct (Clarke, 2002; Volkwein & Sweitzer, 2004). The lack of student outcome measures in popular rankings has lead to a wave of efforts into the value added by an institution. Pace introduced the idea of assessing the quality of learning at the institution by measuring student effort (Pace, 1984). Pace argued that students must put effort into college to get something out of college. Simply focusing on the characteristics of an institution like graduation rates or endowment does not speak to the quality of learning in an institution. The College Students Experience Questionnaire (CSEQ) was developed to measure what happens while students are in school. By measuring levels of engagement and effort in the many experiences of a college student's life the quality of learning can be assessed. More recently, Levin (2002) noted that other surveys like the National Survey of Student Engagement (NSSE) are alternatives to the *US News and World Report* rankings as these surveys measure more of the college experience as they relate to student outcomes.

Structural Equation Modelling (SEM) is a powerful tool that has been used by many researchers across the social sciences. More recently, it has been employed in higher education research. SEM bundles the strengths of factor and path analyses and gives researchers the ability to validate models that are composed of latent variables. The literature shows that some research has been conducted on higher education using SEM. Persistence, retention, and graduation were common foci for SEM studies (Gao et al, 2002; Knight & Arnold, 2000). Gao et al (2002) established models that explained graduation and retention for native and transfer students at one institution. Other SEM studies look at national datasets for research. Kaplan and Elliott (1997) used data from the first follow up to the National Educational Longitudinal Study to develop multilevel SEM models. Stapleton and Hancock (2000) demonstrated differences in using multilevel regression modelling and SEM with data from the National Study of Postsecondary Faculty (NSPOF). Recently, Paxton and Bollen (2003) used SEM to test perceived quality in graduate programs based on ratings by the National Research Council and *US News and World Report*. No studies were found where SEM was used to test models for institutional comparisons.

Method and Results

Building on prior research this study developed models to test factors that tie together variables of institutional similarity. This study had three primary interconnected outcomes, peer group construction, model validation, and model comparison. The methodology is presented in two parts. In Part A principal components analysis was used to find factors that relate to institutional quality. Proximity measures were also used to create peer groups. In Part B, a factor analysis was used to investigate the relationships among the factors and SEM was then employed to further explore the relationships among latent factors of institutional similarity from Part A. The model testing allowed for validation of prior research on institutional similarities and of the *US News and World Report* framework. Finally, a best fit model was sought using SEM.

The sample used in both parts consisted of 247 national universities from the 2004 *US News and World Report* rankings of undergraduate institutions. One university was excluded from the analysis due to prevalent missing data and its uniqueness as a specialized school. Institutional characteristics, enrollment, degree, finance, employee, faculty, and financial aid data were collected from the IPEDS peer analysis system and stored in an analytical environment. Additional institutional variables were collected from the Carnegie Foundation, National Association of College and University Business Officers (NACUBO), and Voluntary Support of Education. *US News and World Report* ranking variables were downloaded from the *US News and World Report* website. Indicators of academic programs present at each institution (i.e., a medical school or an arts and sciences college) were developed. Each indicator was a binary variable with 1 indicating that the program existed at that institution and 0 indicating it did not. The indicators were summed for each school to get the total number of academic units.

In developing the dataset some missing values appeared. Most statistical programs respond to a missing value by a listwise deletion of the involved case. This elimination can greatly impact a dataset with a large number of variables and modest number of cases. To correct the problem, missing values were added or estimated using data from multiple sources and regression techniques. Endowment data, for example, came from the fiscal year 2004 NACUBO report. Any missing values for endowment were filled in using data from the same fiscal year as reported to IPEDS, the Voluntary Support of Education report, and Petersons. Other missing data were filled in or calculated using IPEDS data such as percent of full time faculty. The remaining missing values were more difficult. Statistical programs offer a mean replacement function which replaces the missing value with the sample mean. This treatment often negatively impacts the results by falsely moderating relationships. Given the high correlations among variables in the data, these few remaining missing values were estimated using regression of the variable in question with its most highly correlated neighbors.

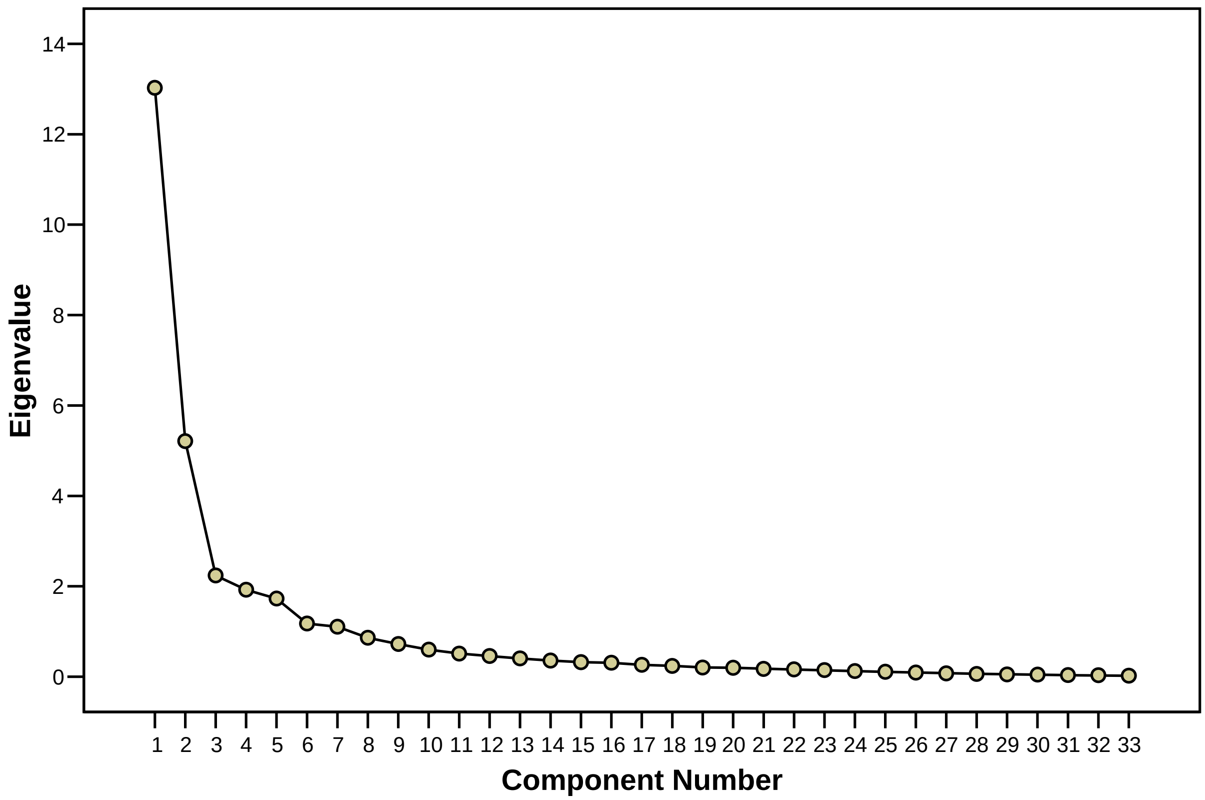
Still, with 170 variables, 247 cases, and a high degree of known collinearity, the initial factor analysis did not produce a positive-definite matrix. The dataset needed to be reduced (Ridgon, 2005). Upon further exploration multi-collinearity was found in many of the variables used in the analysis. The 170 original variables were explored in a correlation table. Variables that were highly correlated with other variables and appeared less important to the analysis were then systematically excluded. Several passes were made and the dataset was reduced to 64 variables (see Appendix A).

Part A: Peer Group Construction

Several methods were identified for the development of peer groups. Rawson et al (1983) standardized all variables, developed distance measures, and summed all the variable distances to test peer groups for Kansas institutions. Teeter and Christal (1987) later described the Kansas methodology and compared it to a peer method used by the National Center for Higher Education Management Systems (NCHEMS). The method used by NCHEMS in the 1980s applied a point system awarded based on hits or misses on intervals of variable ranges; a somewhat subjective method not that different from what many colleges and universities used when they first built peer groups. Elaborating on these prior techniques, Smith (2000) employed a method of measuring distance between institutions in multi-dimensional space. Using standardized variables in a factor analysis, he generated factor scores for each institution and measured the orthogonal distances in two and three dimensional space. The differences between the home institution location and each of the other institutions in that space became the measure of "*peerness*".

This study began with a principal components factor analysis of the 59 variables (5 were nominal and not suitable for the analysis) for the 247 institutions. Certain variables were subsequently removed as they showed a high degree of collinearity and did not add to explanation of the resulting components. The final factor analysis included 33 variables. A scree plot was constructed illustrating the eigenvalue of each of the components (see Figure 1). The plot suggests that either two, five, or seven factors may be appropriate for inclusion in subsequent analyses.

Figure 1. Scree plot of principal components analysis



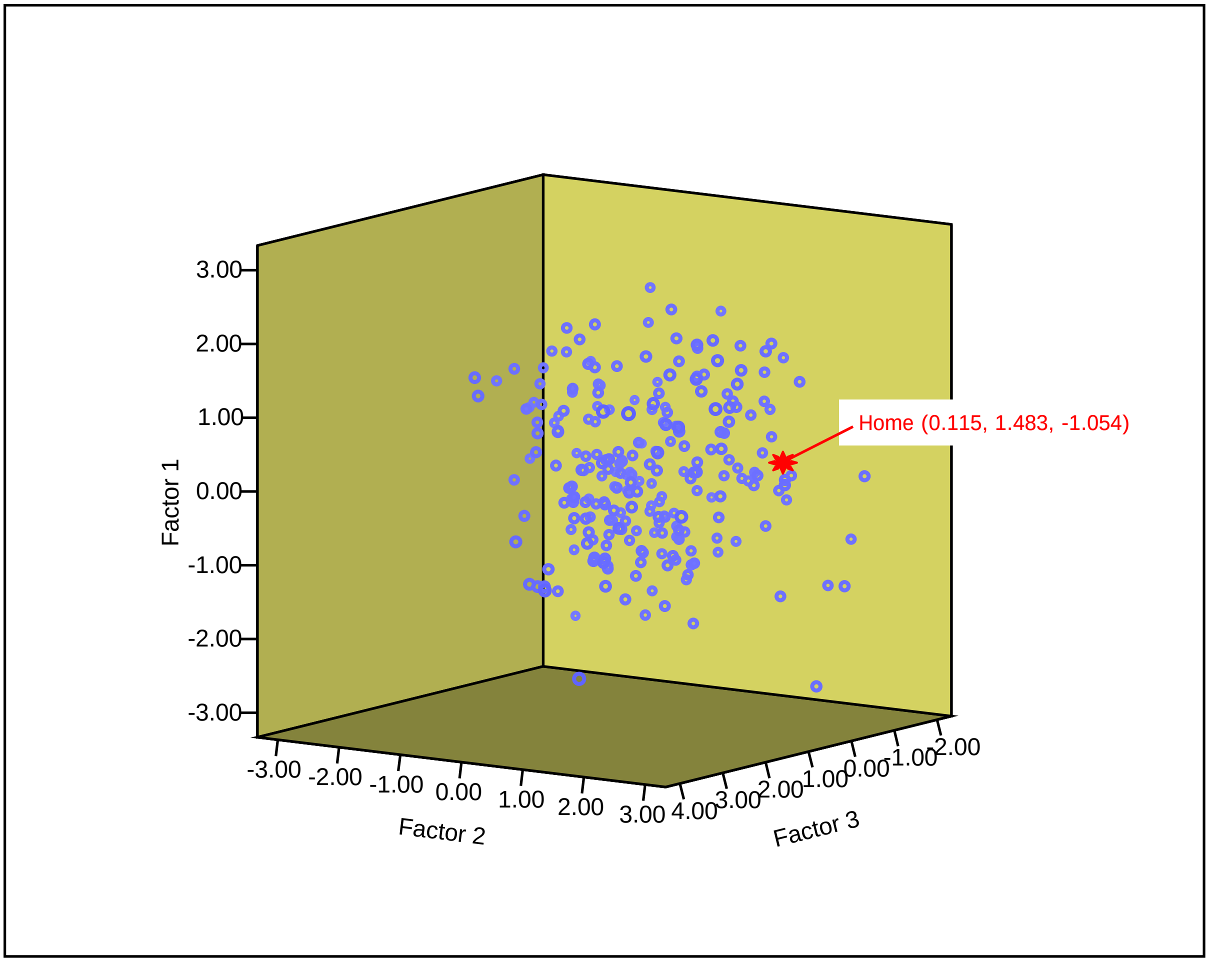
Examination of the eigenvalues suggested that the first seven components were relevant accounting for more than 80% of the variance (see Table 1, complete table in Appendix B). These seven components were isolated and the factor scores saved. This produced the rotated component matrix in Appendix C. Figure 2 shows the institutional plots of factor scores for the first three components with the home institution highlighted.

Table 1

Eigenvalues of principal components analysis

Component	Initial Eigenvalues	% of Variance	Cumulative %
1	13.026	39.473	39.473
2	5.211	15.792	55.265
3	2.240	6.787	62.051
4	1.925	5.834	67.886
5	1.729	5.240	73.126
6	1.176	3.565	76.691
7	1.105	3.349	80.040

Figure 2. Factor score plot for first three components



Since the principal components by it nature produces orthogonal factors, Euclidian distances can be calculated and are represented by the black lines connecting institutional points on Figure 3.

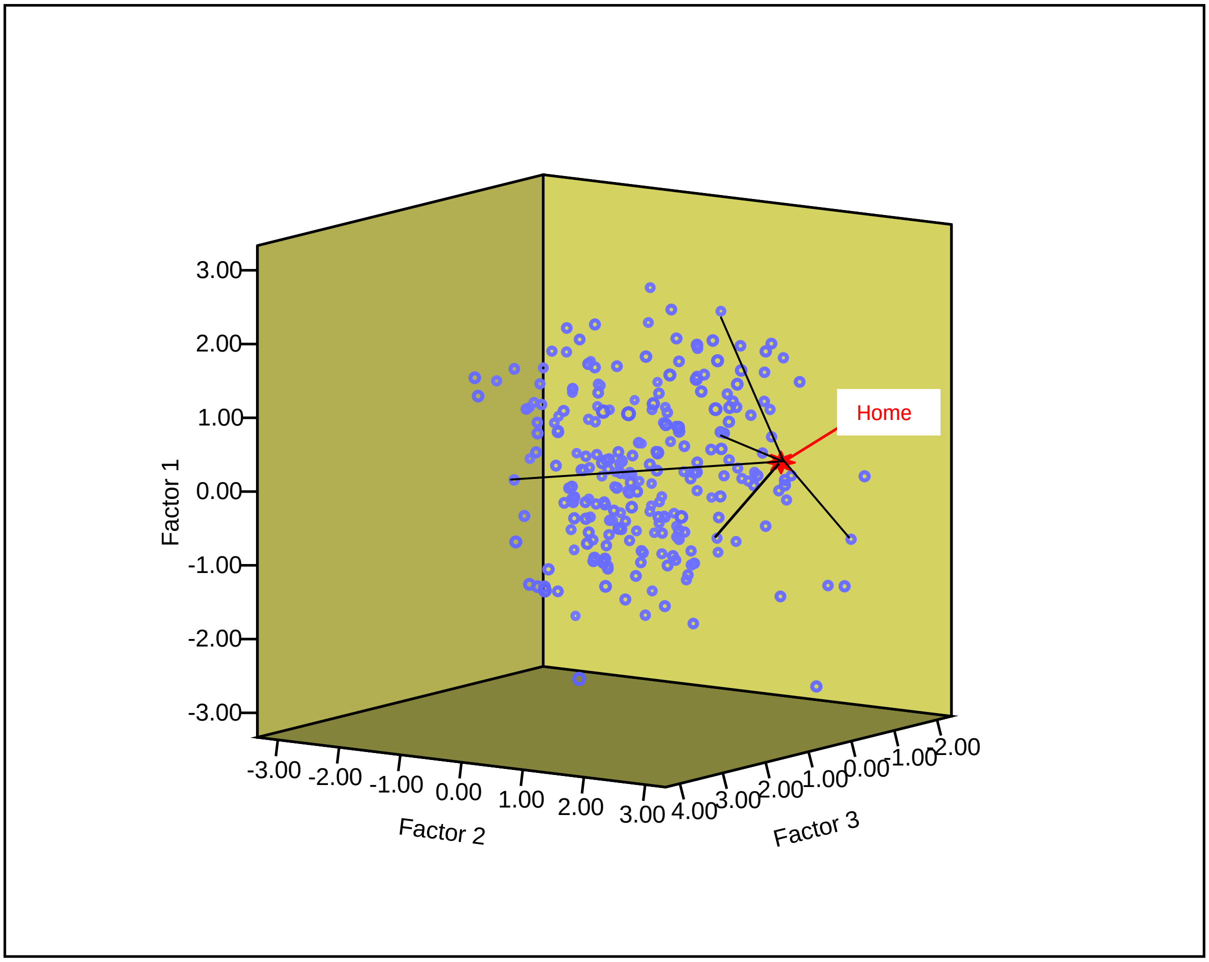
$$D = [(x_a - x_b)^2 + (y_a - y_b)^2]^{½} \tag{1}$$

Distances were calculated from the home to each peer institution in seven dimensional factor space.

$$Distance = [(f1_{Home} - f1_{Peer})^2 + (f2_{Home} - f2_{Peer})^2 + (f3_{Home} - f3_{Peer})^2 + (f4_{Home} - f4_{Peer})^2 + (f5_{Home} - f5_{Peer})^2 + (f6_{Home} - f6_{Peer})^2 + (f7_{Home} - f7_{Peer})^2]^{½} \tag{2}$$

The figure below shows an example of several distances measured in three dimensional factor space.

Figure 3. Factor score plot showing distances to home institution



Using the raw factor scores, however, to compute the distances treats each component equally. By applying weights, those components that are more important to institutional relationships can be accentuated by weighting them more heavily. Obviously, the researcher can play with weights ad infinitum, so an easily applied method for producing weights was created in this research. The eigenvalues for the first seven components were summed and proportionalized and the resulting values used as weights.

Table 2

Cumulative percent of each eigenvalue

Component	Initial Eigenvalues	Cumulative	Percent
1	13.026	13.026	49.3%
2	5.211	18.237	19.7%
3	2.240	20.477	8.5%
4	1.925	22.402	7.4%
5	1.729	24.131	6.5%
6	1.176	25.307	4.5%
7	1.105	26.412	4.2%

$$Distance = [49.3(f1_{Home} - f1_{Peer})^2 + 19.7(f2_{Home} - f2_{Peer})^2 + 8.5(f3_{Home} - f3_{Peer})^2 + 7.4(f4_{Home} - f4_{Peer})^2 + 6.5(f5_{Home} - f5_{Peer})^2 + 4.5(f6_{Home} - f6_{Peer})^2 + 4.2(f7_{Home} - f7_{Peer})^2]^{½} \quad (3)$$

The top ten resulting peers with some basic data elements are shown in Table 3 below and on the next page. Greek letters were substituted for the institution names.

Table 3

Ten nearest institutions to home institution

RANK	INSTITUTION	DISTANCE	CONTROL	TUITION	DISCOUNT
	Home University	0.00	Private	23,180	24%
1	Alpha	3.31	Private	21,855	19%
2	Beta	4.06	Private	24,873	23%
3	Gamma	4.55	Private	23,250	29%
4	Delta	4.62	Private	18,750	14%
5	Epsilon	4.67	Private	20,608	21%
6	Zeta	4.70	Private	23,340	20%
7	Eta	4.76	Private	18,412	14%
8	Theta	4.76	Private	19,425	23%
9	Iota	4.94	Private	23,588	29%
10	Kappa	5.04	Private	20,544	25%

RANK	INSTITUTION	SELCTVY	SAT	UNITS	SF RATIO
	Home University	71%	1,164	9	14
1	Alpha	82%	1,100	5	15
2	Beta	79%	1,145	6	10
3	Gamma	82%	1,160	5	8
4	Delta	73%	1,085	5	17
5	Epsilon	87%	1,125	3	14
6	Zeta	82%	1,135	4	14
7	Eta	68%	1,125	5	14
8	Theta	84%	1,120	6	14
9	Iota	65%	1,205	6	11
10	Kappa	82%	1,125	5	13

RANK	INSTITUTION	CLASS <20	CLASS >50	FR PRST RATE	GRAD RATE
	Home University	58%	6%	85%	68%
1	Alpha	52%	2%	79%	59%
2	Beta	60%	3%	85%	71%
3	Gamma	60%	4%	84%	69%
4	Delta	46%	2%	84%	63%
5	Epsilon	43%	2%	86%	76%
6	Zeta	63%	3%	83%	66%
7	Eta	47%	3%	75%	56%
8	Theta	40%	7%	86%	72%
9	Iota	50%	12%	86%	71%
10	Kappa	30%	7%	84%	69%

RANK	INSTITUTION	EXPND (000s)	ENDOW (000s)	GIVING RATE	FTES
	Home University	$163,527	$136,693	12%	5,612
1	Alpha	$162,581	$162,160	17%	7,651
2	Beta	$179,581	$156,925	13%	7,825
3	Gamma	$124,372	$110,883	12%	4,535
4	Delta	$292,285	$192,276	6%	18,449
5	Epsilon	$136,029	$226,989	13%	7,430
6	Zeta	$137,323	$138,750	12%	7,554
7	Eta	$223,337	$106,978	11%	11,446
8	Theta	$143,676	$95,459	17%	8,487
9	Iota	$225,763	$810,071	16%	9,020
10	Kappa	$293,987	$192,100	7%	11,296

Part B: Data Reduction and Modelling

Since principal components analysis produced orthogonal components, it had to be used to determine the institutional distances but was of little use when exploring the relationships among the underlying latent variables. To do that, principal axis factoring was employed, which by nature produced oblique, or correlated, factors. Since the underlying variables affecting institutional character are indeed related, this made sense. The analysis extracted seven factors that looked very much the same as the first seven principal components, although in a different order (see Appendix D).

Factor one was named *IO* as it appeared to contain the majority of input and output measures traditional used. Positive factor scores on *IO* were related to higher retention rates, higher SAT scores, and lower selectivity (meaning selecting fewer applicants). Factor two, named *Control*, had the highest loading on tuition (negative) and very high loadings on percent of classes under 20 (negative), student faculty ratio (positive), and freshman aid amount (negative). It appeared related to the degree to which an institution was publicly funded, however, the sign of this factor tended to switch from model to model. Factor three had few strong loadings; with one primary variable, the percent of the undergraduate population that was white, it was best described as *Diversity* (or lack in ethnic diversity). Factor four most highly loaded on the percent of the overall expenditures that were spent on research and the research dollars to graduate and professional FTES enrollment; the factor was named *Research*.

Factor five loaded on the four financial aid variables and was named *Aid*. Institutions with higher factor scores on *Aid* had a greater percent of freshmen receiving aid and a larger percent of aid that came from institutional grants. Factor six appeared to be the *Affluence* variable from the principal components analysis and shared a number of overlapping loadings with *IO*. *Affluence* was driven by high endowment to FTES ratios, endowment, and student service expenditure dollars per FTES enrollment. The final factor, *Size*, was composed of total FTES enrollment, total expenditures, the number of academic units, and the percent of classes over 50. *Size* was inverted and the larger institutions had lower factor scores. The table below shows the relationships among the seven factors.

Table 4

Factor correlation matrix

Factor	IO	Control	Diversity	Research	Aid	Affluence	Size
IO	1.000	-0.349	-0.113	0.333	-0.162	0.501	-0.194
Control	-0.349	1.000	-0.061	0.100	-0.077	-0.341	-0.264
Diversity	-0.113	-0.061	1.000	-0.026	0.058	0.101	-0.027
Research	0.333	0.100	-0.026	1.000	-0.189	0.315	-0.239
Aid	-0.162	-0.077	0.058	-0.189	1.000	-0.252	0.202
Affluence	0.501	-0.341	0.101	0.315	-0.252	1.000	-0.059
Size	-0.194	-0.264	-0.027	-0.239	0.202	-0.059	1.000

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

In order to adequately model the latent variable structures, the researchers switched from SPSS to AMOS, a SEM program. Three fit indices were chosen for model comparison the GFI, goodness of fit index (Jöreskog & Sörbom, 1984), the AGFI, adjusted goodness of fit index, and the CFI, comparative fit index (Bentler, 1990). In each case, the higher the fit statistic the better the fit and values near 1.000 show a perfect fit to the data. The root mean square error of approximation (RMSEA) was also used to judge model complexity in relation to model fit. Lower RMSEA values suggest lower error in approximation. Complete diagrams for all models are shown in Appendices E through I and a summary of model fit is found in Table 5.

The initial principal components results from the rotated component matrix (named *Orthogonal*) was modeled in AMOS with seven factors each loading uniquely on each of the 33 variables. The model showed a poor fit to the data with GFI = 0.438, AGFI = 0.365, CFI = 0.556, and RSMEA = 0.185 (see Appendix E). This fit represented a straightforward model with orthogonal factors and therefore had no covariances among the factors. Since the model had correlated factors, covariances were added to better represent the model. The resulting fit (*First Order Model Using Orthogonal Loadings*) improved to GFI = 0.489, AGFI = 0.397, CFI = 0.611, and RSMEA = 0.177. Other models with two and five factors were also constructed as suggested by the scree plot and these models showed significantly decreased fit indicating that a seven factor model was preferable.

Indices below 0.500 suggest that the models did not fit the data at all. Given the high degree of collinearity in the dataset, it was necessary to employ the factor structure matrix which represented an oblique solution. All factor loadings found in the factor analysis with a value of 0.400 were added (see Appendix F). The model, named *First Order Using Full Loadings*, showed much better fit with GFI = 0.665, AGFI = 0.570, CFI = 0.800, and RSMEA = 0.132. At this point SEM is confirming that an oblique solution fits the data better than an orthogonal one. Seeking higher fit, a similar model was constructed using all factor loadings with a value of 0.300 or greater. The model, named *First Order Using All Loadings > 0.3*, showed slightly better fit with GFI = 0.690, AGFI = 0.580, CFI = 0.827, and RSMEA = 0.126. While additional models were tested, incorporating more loadings only complicated the model and showed little to no improvement in fit.

First order factors have loadings on the observed variables and covariances to other factors. Often the model of best fit to the data has second order factors that can both load on other factors as well as observed variables. These are called second order models. Using the literature as a guide, a number of potential second order models were constructed and fit tested. One example was the *Affluence Second Order* model (see Appendix G). The resulting fit was relatively low with GFI = 0.436, AGFI = 0.356, CFI = 0.566, and RSMEA = 0.184. Similar results were found with other variants suggesting that second order models were not inherent in the dataset.

To this point, both the literature and the results suggested overlapping factors leaving the researchers perplexed at the variables selected by *US News and World Report* for their ranking system. Having a clean and well prepared dataset, the *US News and World Report* model was tested using the same methods as above. An initial model, *USN Orthogonal Comparison*, was built as a baseline model (see Appendix H) with the fit values as GFI = 0.414, AGFI = 0.342, CFI = 0.493, and RSMEA = 0.200. When the factors suggested by *US News and World Report* were loaded on the observed variables, the model (*USN Only*) produced no fit to the data (GFI = 0.000, AGFI = 0.000, CFI = 0.000) and an extreme RSMEA of 0.402. The initial models suggested that two factors, *IO* and *Size*, should be apparent from the observed variables selected by *US News and World Report*. When this model was constructed (*USN Corrected* in Appendix G) the fit improved over both the *USN Orthogonal Comparison* and the *USN Only* model to GFI = 0.606, AGFI = 0.486, CFI = 0.718, and RSMEA = 0.228.

Finally, the researchers sought the model of best fit to the data through a series of variations where observed and latent variables were added and deleted, loadings were manipulated, and covariances added and removed. Also, other second order variables were built. The final model (see *Best Fit* in Appendix I) had 11 observed variables, one factor, and several factor loadings removed. All covariances were maintained. The fit was GFI = 0.774, AGFI = 0.661, CFI = 0.876, and RSMEA = 0.131. A summary of all models is shown in Table 5.

Table 5

Summary of model fit

Model	Appendix	GFI	AGFI	CFI	RMSEA
Orthogonal	E	0.438	0.365	0.556	0.185
First Order Using Orthogonal Loadings (7fac)	E	0.489	0.397	0.611	0.177
First Order Using Orthogonal Loadings (5fac)	E	0.366	0.269	0.543	0.189
First Order Using Orthogonal Loadings (2fac)	E	0.362	0.277	0.504	0.195
First Order Using Full Loadings	F	0.665	0.570	0.800	0.132
First Order Using All Loadings > 0.3	F	0.690	0.580	0.827	0.126
Affluence Second Order	G	0.436	0.356	0.566	0.184
USN Orthogonal Comparison	H	0.414	0.342	0.493	0.200
USN Only	H	0.000	0.000	0.000	0.402
USN Corrected	H	0.606	0.486	0.718	0.228
Best Fit	I	0.774	0.661	0.876	0.131

Discussion

Within the variables that higher education has collected about itself, several factors have been repeatedly isolated over the last forty years (Astin, 1962; Terenzini et al, 1980; Webster, 2001; Volkwein & Sweitzer, 2004). This study found them again and enhanced the literature in three new directions; first, by extending methods for applying the factors to peer construction; second, SEM was used to further assess the fit of competing models to the data; and third, the relationships among the factors and the *US News and World Report* ranking system were explored.

The method for peer construction included a principal components analysis of typical national data (Smith, 2000). This followed with the computation of institutional distances with the assumption that the closer the peer to the home institution the greater the similarity. Weighting the results allows an institution to emphasize certain characteristics more than others as they construct peer groups. The results seemed to fit the assumptions and many of the computed peer institutions were known peers of the home institution. In addition, many of the variables showed consistency across the top rated peers (from Table 3).

In order to meet the multiple demands placed on peer group analysis, schools may wish to develop a large core peer group and small specialized peer groups for comparisons such as tuition setting, outcomes assessment, or marketing and admissions. They may then use a smaller list of factors or indicators that are more pertinent than the larger list for specific peer group construction. One example is considering institutions that have a large number of coapplicants. These institutions compete for students and design costs, services, and programs to increase yield rates on admitted students. In the end, each institution is unique and while peer comparison can inform decision making, institution specific analyses must augment comparisons and benchmarking.

Results for model fit were somewhat disappointing. With fit indices ranging from 0.414 to a high of 0.876, the models achieved only marginal fit. Multicolinearity in the variables was obvious and substantially limited the research (again, consistent with the literature). While many variables were used, they were so strongly related that they did not add to the discrimination across institutions and likely failed to capture institutional differences that surely exist. The first principal component, *IO* for input-output, was difficult to name and appeared to contain institutional characteristics at either end of the college experience. It contained no measures that differentiate the process of higher education. Still it was a strong factor and dominated the models. *Affluence* was another important factor dependent on the financial resources of an institution and, in turn, its expenditures on students. It was highly related to *IO* reinforcing the notion that the best students go to the wealthiest schools and achieve the highest outcomes. They tend to show increased income levels later in life and are contributors to their institutions in what is known as a self-reinforcing positive feedback loop.

Other factors such as *Control*, *Size*, and *Research* are mission dependent yet showed moderate relationships to *IO* and *Affluence*. Institutions with private characteristics such as small class sizes and student-faculty ratios and fewer FTES tended to show higher levels of *IO* characteristics such as SAT scores and retention rates. *Affluence* influenced these variables as well and appeared to offset the effects of larger sized institutions when large endowments were present. Beyond the endowment, revenue associated with *Research* also appeared to influence *IO* measures. Finally *Aid* and *Diversity* were the two least integrated factors in the model. In fact, the *Best Fit* model was achieved by removing the *Diversity* factor and its associated observed variables altogether. *Aid* appeared to relate to *Size* and *Affluence* with smaller, wealthier institutions using more institutional grants to more freshmen.

The model suggested by *US News and World Report* was tested and did not fit the data. As was found in prior research, their chosen variables appear to all be measuring the same thing as they are pervasively multicolinearity. This was validated as the best fit model for the *US News and World Report* dataset (see *US News Corrected*) was composed of only the *IO* and *Size* factors with *IO* loading on most of the variables. Based on this research, the researchers could not be sure of what the rankings measure in the institutional comparative context. Given the likelihood of the positive feedback loop at play among the institutional measures, *US News and World Report's* effect on the higher education industry is only a reinforcement of a system that has already been in place, not necessarily to the benefit of students who seek to find the institution that best fits their special needs (Levin, 2002). This is the major assumptional flaw in *US News and World Report* approach as it is marketed as a decision tool for selecting colleges.

All that being said, the researchers were left with an empty feeling at the end of this research. The essence of college was not captured. What remains to be discussed are the variables that should be part of this entire line of research yet are not. Students succeed in environments that match their needs to support their learning and development. National rankings are meaningless in determining this fit. It is very likely that within those additional variables lie the information that students need to select the right university or college. Currently, modelling of the higher education enterprise is only partial at best. Measures for differentiation based on mission are yet undeveloped. Learning is still a nebulous concept and little agreement has been reached in the higher education community regarding the "value-added" versus "pure outcome" debate. Good measures of student development can be elusive and are highly dependent on students' entering character and the dynamic social environment.

What is quality? It is unlikely that there could ever be a single metric for all of higher education. Quality is so mission dependent that ranking systems are not possible at the institutional level. Quality is likely a highly fluid concept related to student success and experiences (Pascarella, 2001), but not only those simple measures of degree attainment and satisfaction. It is more about the fundamental goals and needs of students. Included in the mission of higher education is also the support of the multiple communities in which universities and colleges are placed. Quality should be defined as well by the degree to which universities, for example, support the research and development needed by society, or by the degree to which citizen leaders are developed. How does higher education as an industry engage in systemic assessment along these lines?

Approaches assessing program quality make more sense. Certain students have expectations for a specific social environment while others are searching for a specific academic program. Some universities have ample activities in their local regions while others are like cultural islands. If peer selection and ranking systems became much more highly focused on specific qualities of institutions rather than on a single measure of institutional quality, all would be better served. In the end, while peer set construction and broad rankings may be hot topics *du jour*, it is likely that both more fundamental data collection and context development need to occur before institutional comparison can become more useful and less of a hoax. Focusing on educational outcomes, program level assessment, the social environment, and student fit would be valuable additions to the current body of knowledge surrounding institutional comparison, peer selection, and national rankings.

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Appendix A

Variables in the Study

INSTITUTION	Name of institution (IPEDS)
CITY	City of institution (IPEDS)
STATE	State of institution (IPEDS)
CONTRL	Public or private control (IPEDS)
TUITION	Yearly tuition and fees (IPEDS)
DISCOUNT_RATE	Institutional discount rate (IPEDS)
SUM_UNIT	Number of academic units similar to home university
USN_RANK	2004 rank determined by US News formula (US News)
USN_REP_SCORE	2004 reputation score based on US New survey (US News)
USN_GRAD_RATE_DIFF	2004 variable computed by US News formula (US News)
USN_PCNT_FT_FAC	Percent of full-time faculty (CDS)
STUD_FAC_RATIO	Student faculty ratio (1ft + 1/3pt formula) (CDS)
SELECTIVITY	Percent of freshman applicants that were accepted (CDS)
SAT_MEDIAN	Median SAT score of incoming freshmen (CDS)
TOP_10_HS	Percent of freshmen in top 10 percent of high school class (CDS)
CLASS_UNDER_20	Percent of undergraduate classes with enrollment < 20 (CDS)
CLASS_OVER_50	Percent of undergraduate classes with enrollment > 50 (CDS)
FR_PERST_RATE	Percent of freshmen that returned for sophomore year (CDS)
FR_GRAD_RATE_AVG	Six year graduation rate (CDS)
GIVING_RATE	Percent of undergraduate alumni that donated (CAE)
ENR_PCT_UG_FEMALE	Percent of undergraduate enrollment that is female (IPEDS)
ENR_PCT_UG_NON_WHITE	Percent of undergraduate enrollment that is non-white (IPEDS)
ENR_PCT_UG_TOTAL	Percent of total enrollment that is undergraduate (IPEDS)
ENR_PCT_GR_TOTAL	Percent of total enrollment that is graduate (IPEDS)
ENR_PCT_PR_TOTAL	Percent of total enrollment that is first-professional (IPEDS)
FTES_UG	Undergraduate full-time equivalent enrollment (1+1/3) (IPEDS)
FTES_GR	Graduate full-time equivalent enrollment (1+1/3) (IPEDS)
FTES_PR	First-professional full-time equiv. enrollment (1+1/3) (IPEDS)
FTES_GR_PR	Graduate and first-professional FTE enrollment (1+1/3) (IPEDS)
FTES_TOTAL	Total full-time equivalent enrollment (1+1/3) (IPEDS)

BACH_DEG_AWD	Number of Bachelor’s degrees awarded (IPEDS)
MAST_DEG_AWD	Number of Master’s degrees awarded (IPEDS)
DOCT_DEG_AWD	Number of Doctoral degrees awarded (IPEDS)
PROF_DEG_AWD	Number of First-Professional degrees awarded (IPEDS)
FTEF	Full-time equivalent faculty (1+1/3) (IPEDS)
FAC_FT_PCT	Percent of faculty that are full-time (IPEDS)
FAC_PT_PCT	Percent of faculty that are part-time (IPEDS)
FTEE	Full-time equivalent employees minus faculty (1+1/3) (IPEDS)
FTES_FTEE_RATIO	FTE student to employee ratio (IPEDS)
FTES_FTEF_RATIO	FTE student to faculty ratio (IPEDS)
AAUP_SALARY	Average salary of full-time instructional faculty (IPEDS)
AID_FR_AMT	Average dollar amount of freshman aid package (IPEDS)
AID_FR_AID_PCT	Percent of freshman class that received aid (IPEDS)
AID_FR_FED_GRANT_PCT	Percent of freshman class that received grant aid (IPEDS)
AID_FR_STATE_GRANT_PCT	Percent of freshman class that received state grant aid (IPEDS)
AID_FR_INST_GRANT_PCT	Percent of freshman class that received institutnl. grants (IPEDS)
AID_FR_LOAN_PCT	Percent of freshman class that received loans (IPEDS)
EXP_TOTAL	Total expenditures in dollars (IPEDS)
EXP_INST_PCT	Percent of total expenditures spent on instruction (IPEDS)
EXP_RSCH_PCT	Percent of total expenditures spent on research (IPEDS)
EXP_PBSV_PCT	Percent of total expenditures spent on public service (IPEDS)
EXP_ACSP_PCT	Percent of total expenditures spent on academic support (IPEDS)
EXP_STSV_PCT	Percent of total expenditures spent on student services (IPEDS)
EXP_SPPT_PCT	Percent of total expenditures spent on support services (IPEDS)
EXP_FTES_RATIO	Total expenditures per full-time equivalent student (IPEDS)
EXP_RSCH_FTES_GR_PR	Research exp. per FTE graduate and first-prof. student (IPEDS)
EXP_INST_FTES_RATIO	Total instructional exp. per full-time equivalent student (IPEDS)
EXP_STSVC_FTES_RATIO	Total student services exp. per FTE student (IPEDS)
ENDOWMENT	Dollar value of endowment (NACUBO)
END_FTES_RATIO	Endowment per full-time equivalent student

Appendix B

Eigenvalues of Principal Component Analysis

Component	Initial Eigenvalues	% of Variance	Cumulative %
1	13.026	39.473	39.473
2	5.211	15.792	55.265
3	2.240	6.787	62.051
4	1.925	5.834	67.886
5	1.729	5.240	73.126
6	1.176	3.565	76.691
7	1.105	3.349	80.040
8	0.862	2.611	82.651
9	0.724	2.194	84.845
10	0.599	1.814	86.659
11	0.513	1.555	88.214
12	0.459	1.391	89.605
13	0.406	1.231	90.836
14	0.357	1.083	91.919
15	0.321	0.973	92.892
16	0.309	0.936	93.828
17	0.263	0.797	94.625
18	0.238	0.722	95.347
19	0.204	0.619	95.967
20	0.198	0.599	96.566
21	0.173	0.523	97.089
22	0.163	0.495	97.584
23	0.146	0.443	98.026
24	0.125	0.378	98.404
25	0.110	0.333	98.737
26	0.092	0.280	99.017
27	0.074	0.223	99.240
28	0.060	0.181	99.421
29	0.051	0.154	99.575
30	0.048	0.144	99.719
31	0.037	0.112	99.831
32	0.033	0.101	99.932
33	0.022	0.068	100.000

Appendix C

Rotated Component Matrix

	Component						
	IO	Control	Research	Affluence	Aid	Size	Diversity
FR_PERST_RATE	**0.935**	0.024	0.138	0.073	0.002	0.088	-0.076
FR_GRAD_RATE_AVG	**0.917**	0.121	0.086	0.111	0.036	0.057	-0.181
USN_RANK	**-0.887**	-0.124	-0.220	-0.095	0.020	-0.164	0.135
SAT_MEDIAN	**0.885**	0.175	0.196	0.224	-0.063	0.037	-0.086
TOP_10_HS	**0.851**	0.087	0.213	0.209	-0.101	0.066	0.114
AAUP_SALARY	**0.813**	0.130	0.120	0.274	-0.083	0.205	0.141
USN_REP_SCORE	**0.811**	0.031	0.272	0.266	-0.197	0.280	-0.028
SELECTIVITY	**-0.672**	-0.178	-0.004	-0.297	0.218	0.024	-0.388
GIVING_RATE	**0.664**	0.139	0.186	0.447	-0.005	-0.139	-0.223
AID_FR_AMT	**0.653**	0.595	-0.062	0.214	0.142	-0.064	-0.013
EXP_INST_FTES_RATIO	**0.546**	0.462	0.209	0.451	-0.152	0.126	0.040
EXP_FTES_RATIO	**0.517**	0.428	0.411	0.465	-0.131	0.094	0.056
CLASS_UNDER_20	0.194	**0.770**	0.026	0.199	-0.038	-0.134	0.119
ENR_PCT_UG_TOTAL	-0.314	**-0.738**	0.074	-0.117	-0.068	-0.197	-0.223
CLASS_OVER_50	0.251	**-0.717**	0.251	-0.030	-0.144	0.260	0.046
STUD_FAC_RATIO	-0.499	**-0.682**	-0.105	-0.199	-0.012	0.074	0.007
TUITION	0.602	**0.639**	-0.124	0.195	0.213	-0.116	-0.013
EXP_RSCH_PCT	0.252	-0.130	**0.878**	0.029	-0.101	0.172	-0.003
EXP_RSCH_FTES_GR_PR	0.303	0.040	**0.845**	0.218	-0.161	0.021	-0.027
EXP_INST_PCT	-0.065	0.038	**-0.834**	0.017	-0.077	-0.011	-0.031
USN_PCNT_FT_FAC	0.186	-0.454	**0.487**	0.162	-0.110	0.003	-0.258
END_FTES_RATIO	0.323	0.180	0.112	**0.860**	-0.101	-0.066	0.021
ENDOWMENT	0.297	0.089	0.061	**0.852**	-0.078	0.172	0.036
EXP_STSVC_FTES_RATIO	0.372	0.376	0.026	**0.533**	-0.011	-0.166	0.060
AID_FR_AID_PCT	-0.223	0.043	-0.005	-0.018	**0.892**	-0.035	0.078
AID_FR_INST_GRANT_PCT	0.239	0.441	-0.039	-0.062	**0.650**	-0.110	-0.199
AID_FR_LOAN_PCT	-0.035	0.161	-0.238	-0.186	**0.548**	-0.293	-0.065
AID_FR_STATE_GRANT_PCT	-0.149	-0.354	-0.001	-0.068	**0.534**	0.127	0.431
SUM_UNIT	0.081	-0.047	0.032	-0.022	-0.047	**0.860**	-0.118
FTES_TOTAL	0.178	-0.542	0.054	-0.086	-0.144	**0.709**	-0.004
EXP_TOTAL	0.513	0.029	0.311	0.289	-0.166	**0.626**	0.094
ENR_PCT_UG_NON_WHITE	0.008	0.219	-0.021	0.047	-0.069	-0.076	**0.880**
AID_FR_FED_GRANT_PCT	-0.589	0.019	-0.015	0.036	0.250	-0.128	**0.585**

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 8 iterations.

Bolded values indicate the primary loadings for each variable.

Appendix D

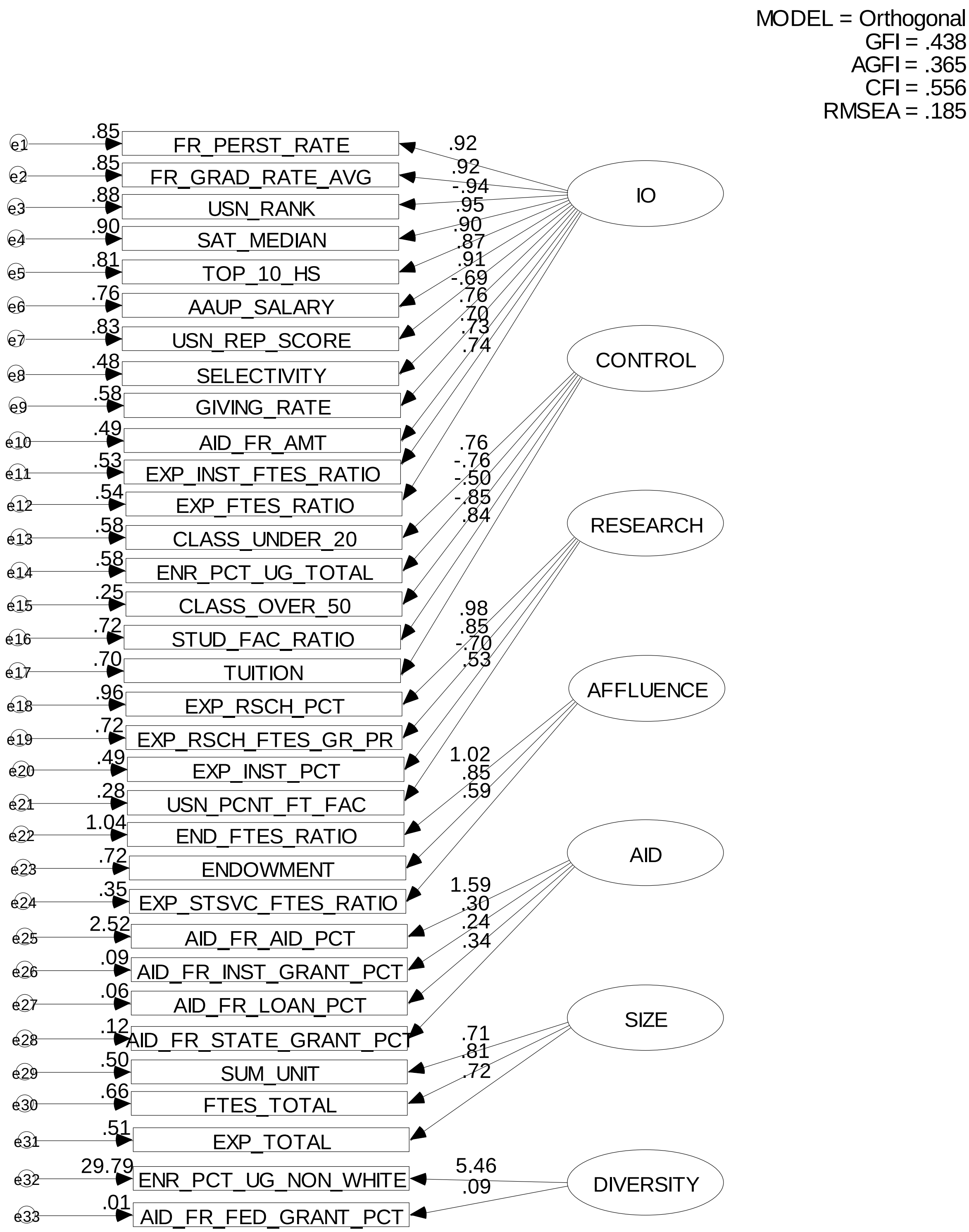
Factor Structure Matrix

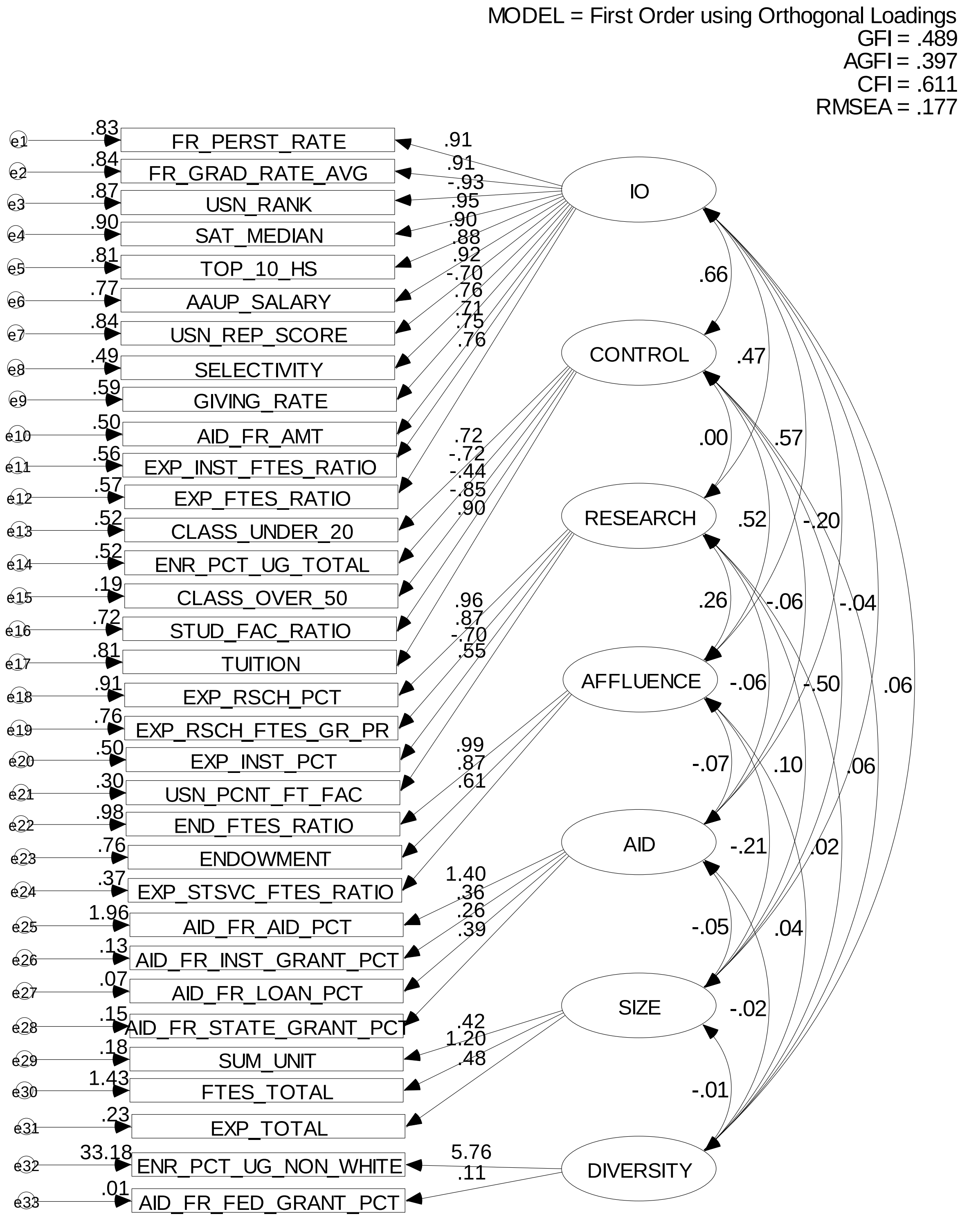
	Factor						
	IO	Control	Diversity	Research	Aid	Affluence	Size
FR_PERST_RATE	**0.949**	-0.233	-0.134	0.371	-0.154	**0.439**	-0.251
FR_GRAD_RATE_AVG	**0.947**	-0.333	-0.236	0.309	-0.129	**0.465**	-0.181
USN_RANK	**-0.928**	0.310	0.182	**-0.438**	0.180	**-0.468**	0.296
SAT_MEDIAN	**0.935**	-0.381	-0.130	**0.425**	-0.226	**0.594**	-0.166
TOP_10_HS	**0.873**	-0.288	0.071	**0.442**	-0.239	**0.566**	-0.224
AAUP_SALARY	**0.843**	-0.333	0.107	0.356	-0.222	**0.609**	-0.323
USN_REP_SCORE	**0.867**	-0.207	-0.050	**0.525**	-0.363	**0.609**	**-0.455**
SELECTIVITY	**-0.669**	0.368	-0.338	-0.211	0.274	**-0.583**	0.101
GIVING_RATE	**0.732**	-0.332	-0.215	0.372	-0.176	**0.657**	0.028
AID_FR_AMT	**0.720**	**-0.772**	-0.024	0.053	0.046	**0.509**	0.130
EXP_INST_FTES_RATIO	**0.654**	**-0.608**	0.054	0.374	-0.272	**0.710**	-0.133
EXP_FTES_RATIO	**0.642**	**-0.559**	0.068	**0.555**	-0.260	**0.739**	-0.126
CLASS_UNDER_20	0.302	**-0.758**	0.144	0.005	-0.019	0.396	0.282
ENR_PCT_UG_TOTAL	-0.394	**0.771**	-0.213	0.043	-0.054	-0.357	0.005
CLASS_OVER_50	0.169	**0.621**	-0.013	0.392	-0.226	-0.005	**-0.516**
STUD_FAC_RATIO	**-0.593**	**0.769**	-0.001	-0.167	0.052	**-0.497**	-0.156
TUITION	**0.668**	**-0.815**	-0.023	-0.037	0.135	**0.468**	0.214
EXP_RSCH_PCT	0.322	0.149	-0.026	**0.939**	-0.194	0.220	-0.330
EXP_RSCH_FTES_GR_PR	**0.402**	-0.060	-0.036	**0.928**	-0.271	**0.433**	-0.162
EXP_INST_PCT	-0.149	-0.101	-0.011	**-0.676**	0.000	-0.123	0.105
USN_PCNT_FT_FAC	0.200	0.363	-0.219	**0.529**	-0.225	0.154	-0.236
END_FTES_RATIO	**0.447**	-0.321	0.076	0.282	-0.229	**0.969**	0.049
ENDOWMENT	**0.423**	-0.235	0.101	0.251	-0.210	**0.872**	-0.193
EXP_STSVC_FTES_RATIO	**0.462**	**-0.508**	0.085	0.140	-0.099	**0.614**	0.158
AID_FR_AID_PCT	-0.219	-0.053	0.056	-0.137	**0.961**	-0.196	0.198
AID_FR_INST_GRANT_PCT	0.270	**-0.491**	-0.188	-0.096	**0.539**	0.036	0.271
AID_FR_LOAN_PCT	-0.093	-0.191	-0.058	-0.316	**0.475**	-0.230	0.358
AID_FR_STATE_GRANT_PCT	-0.229	0.270	0.265	-0.051	**0.419**	-0.231	-0.091
SUM_UNIT	0.141	0.105	-0.067	0.129	-0.122	0.026	**-0.662**
FTES_TOTAL	0.133	**0.523**	-0.027	0.198	-0.206	-0.066	**-0.883**
EXP_TOTAL	**0.582**	-0.143	0.099	**0.514**	-0.294	**0.524**	**-0.748**
ENR_PCT_UG_NON_WHITE	-0.014	-0.231	**0.857**	-0.047	0.046	0.135	0.096
AID_FR_FED_GRANT_PCT	**-0.589**	0.077	**0.574**	-0.201	0.367	-0.208	0.241

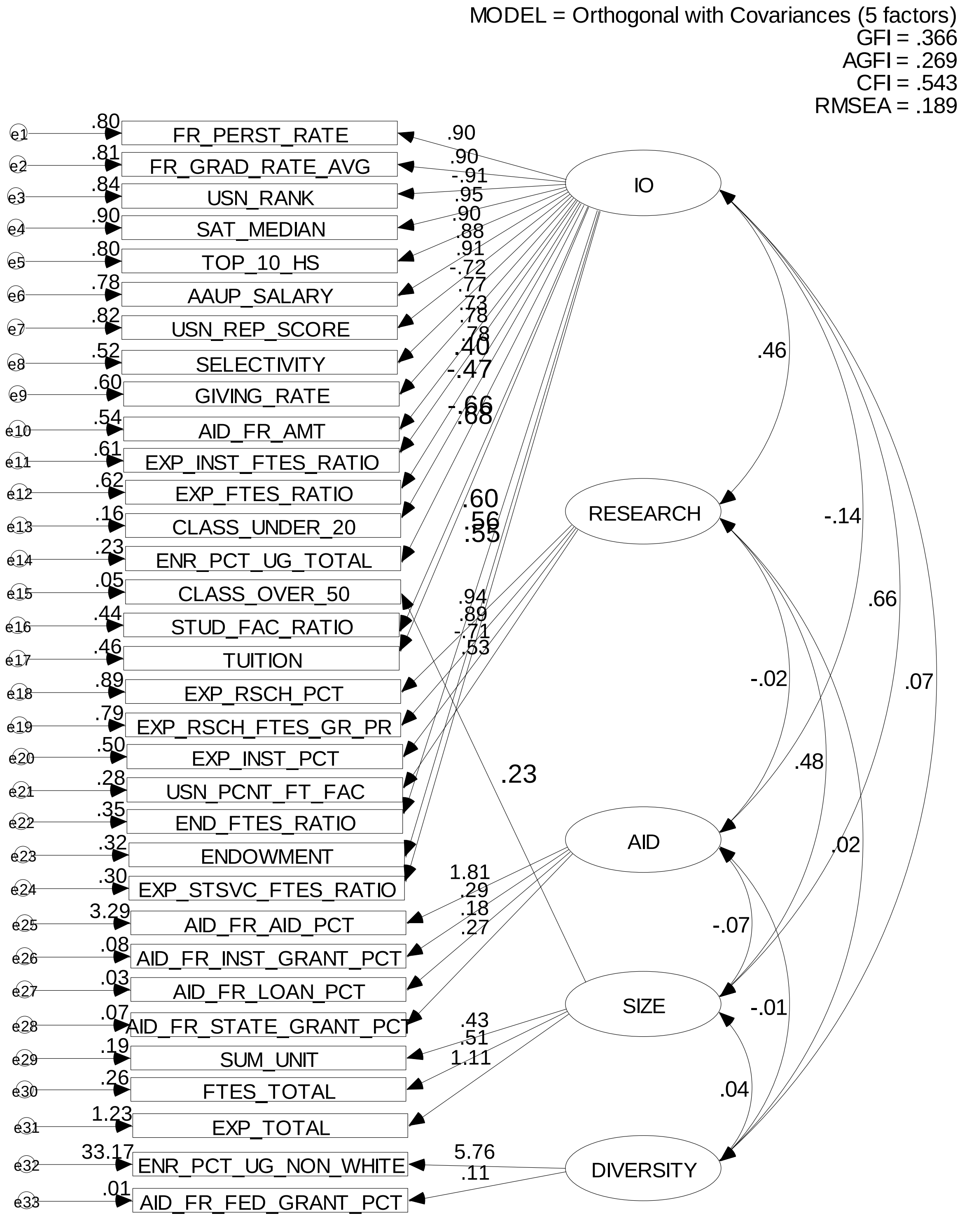
Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

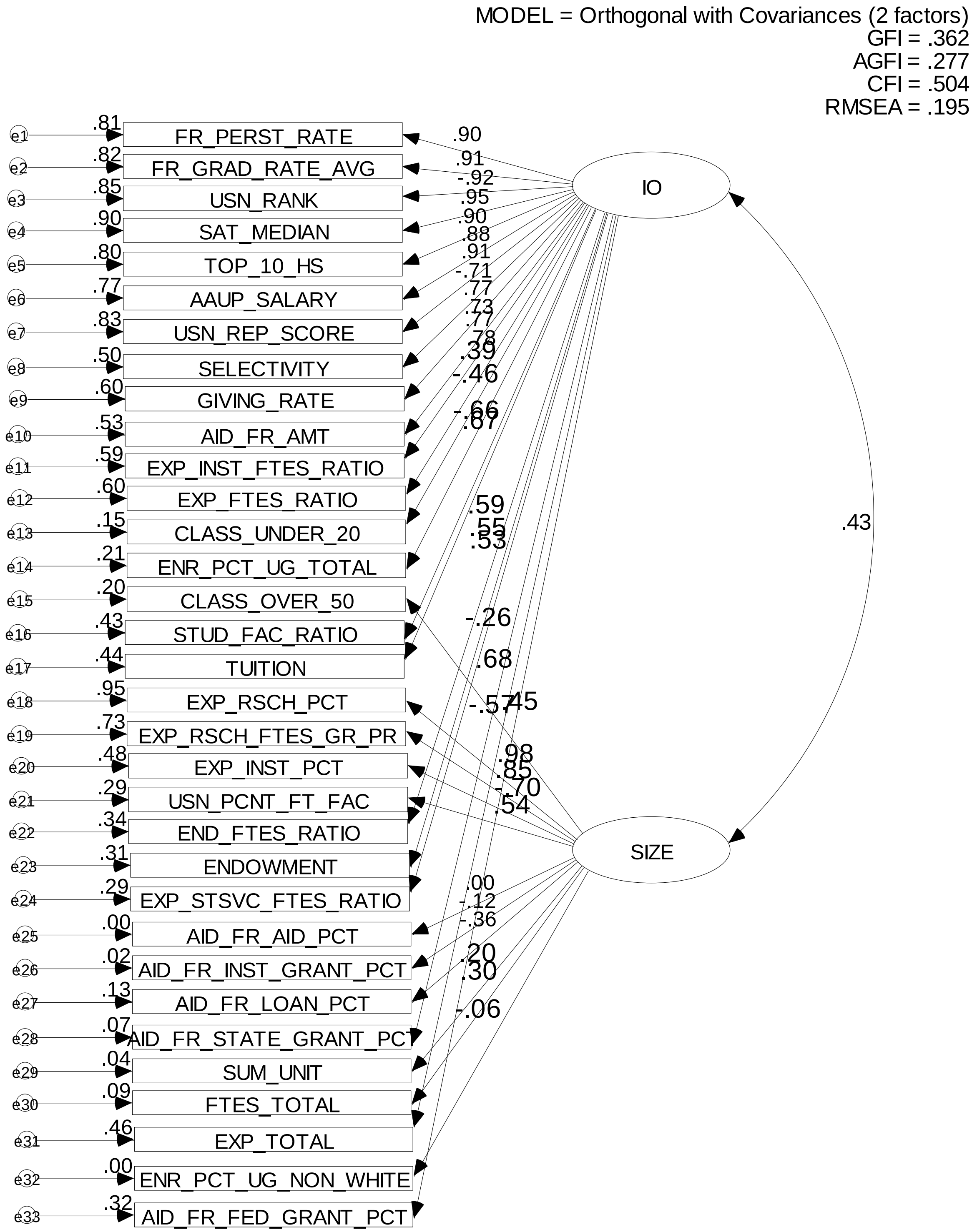
Bolded values indicate all loadings greater than 0.4.

Appendix E

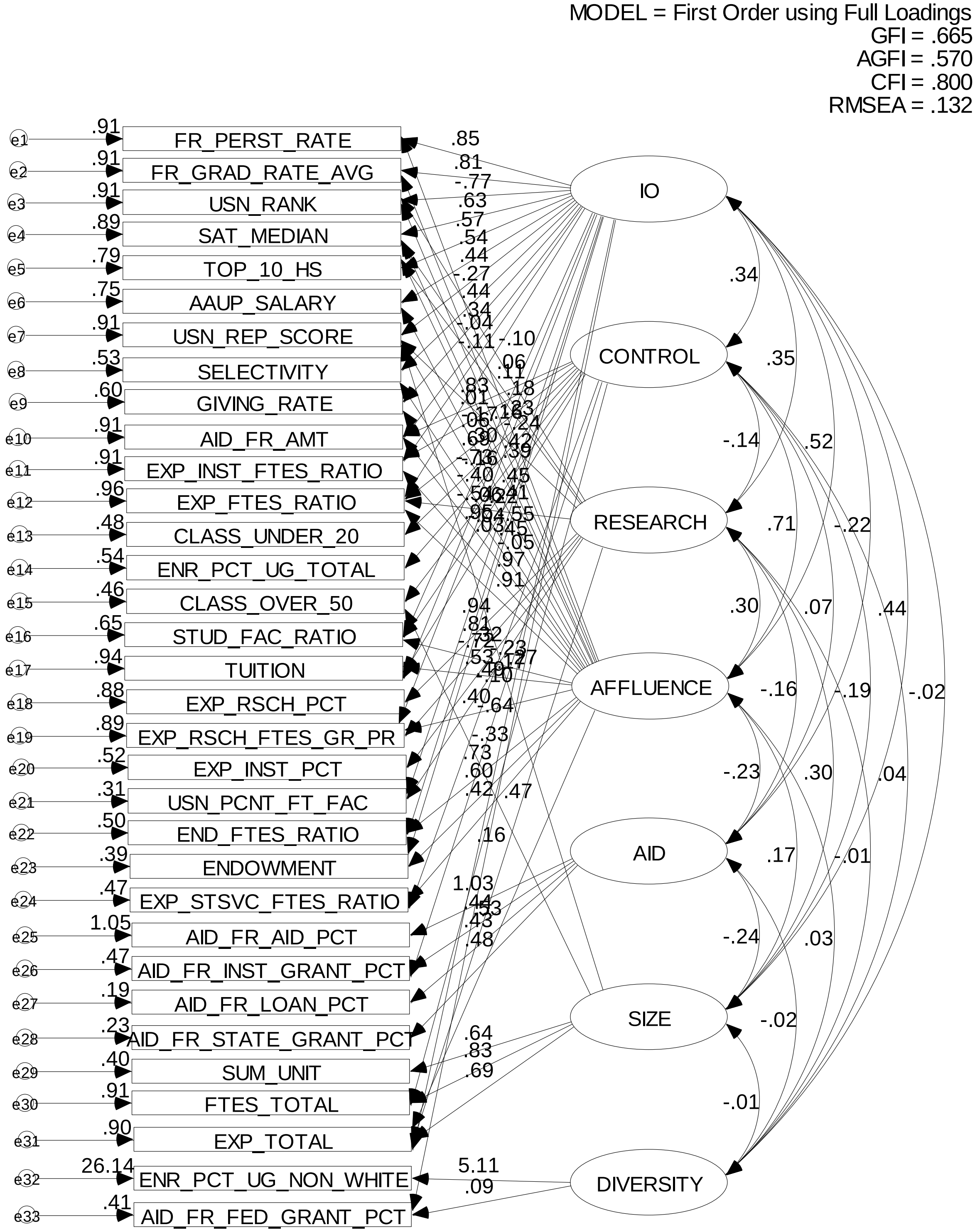

MODEL = Orthogonal
GFI = .438
AGFI = .365
CFI = .556
RMSEA = .185
IO
CONTROL
RESEARCH
AFFLUENCE
AID
SIZE
DIVERSITY
FR_PERST_RATE
FR_GRAD_RATE_AVG
USN_RANK
SAT_MEDIAN
TOP_10_HS
AAUP_SALARY
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_RSCH_FTES_GR_PR
EXP_INST_PCT
USN_PCNT_FT_FAC
END_FTES_RATIO
ENDOWMENT
EXP_STSVC_FTES_RATIO
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
AID_FR_LOAN_PCT
AID_FR_STATE_GRANT_PCT
SUM_UNIT
FTES_TOTAL
EXP_TOTAL
ENR_PCT_UG_NON_WHITE
AID_FR_FED_GRANT_PCT
e1 .85
e2 .85
e3 .88
e4 .90
e5 .81
e6 .76
e7 .83
e8 .48
e9 .58
e10 .49
e11 .53
e12 .54
e13 .58
e14 .58
e15 .25
e16 .72
e17 .70
e18 .96
e19 .72
e20 .49
e21 .28
e22 1.04
e23 .72
e24 .35
e25 2.52
e26 .09
e27 .06
e28 .12
e29 .50
e30 .66
e31 .51
e32 29.79
e33 .01
.92 .92 -.94 .95 .90 .87 .91 -.69 .76 .70 .73 .74
.76 -.76 -.50 -.85 .84
.98 .85 -.70 .53
1.02 .85 .59
1.59 .30 .24 .34
.71 .81 .72
5.46 .09

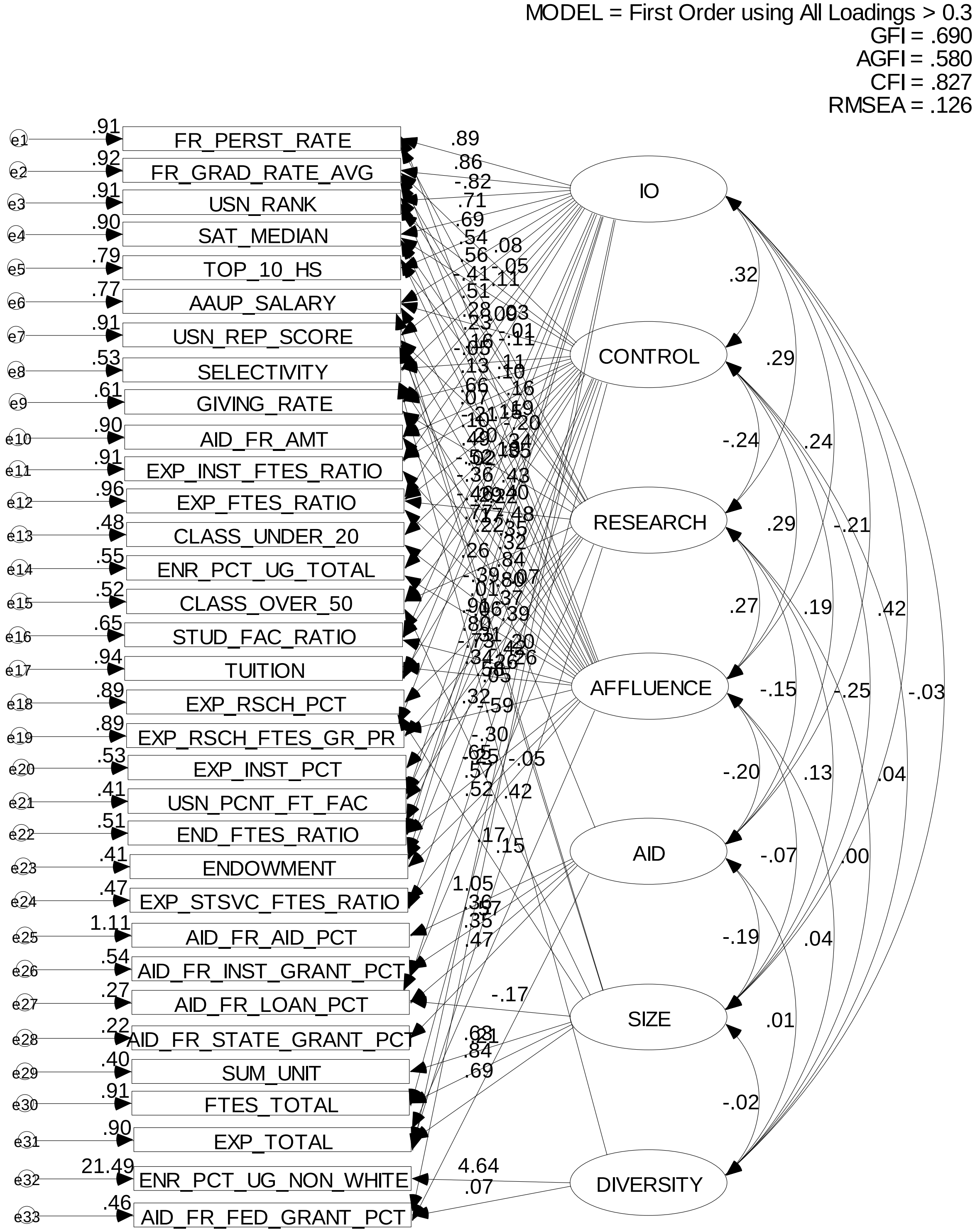

MODEL = First Order using Orthogonal Loadings
GFI = .489
AGFI = .397
CFI = .611
RMSEA = .177
FR_PERST_RATE
FR_GRAD_RATE_AVG
USN_RANK
SAT_MEDIAN
TOP_10_HS
AAUP_SALARY
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_RSCH_FTES_GR_PR
EXP_INST_PCT
USN_PCNT_FT_FAC
END_FTES_RATIO
ENDOWMENT
EXP_STSVC_FTES_RATIO
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
AID_FR_LOAN_PCT
AID_FR_STATE_GRANT_PCT
SUM_UNIT
FTES_TOTAL
EXP_TOTAL
ENR_PCT_UG_NON_WHITE
AID_FR_FED_GRANT_PCT
IO
CONTROL
RESEARCH
AFFLUENCE
AID
SIZE
DIVERSITY


MODEL = Orthogonal with Covariances (5 factors)
GFI = .366
AGFI = .269
CFI = .543
RMSEA = .189
IO
RESEARCH
AID
SIZE
DIVERSITY
FR_PERST_RATE
FR_GRAD_RATE_AVG
USN_RANK
SAT_MEDIAN
TOP_10_HS
AAUP_SALARY
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_RSCH_FTES_GR_PR
EXP_INST_PCT
USN_PCNT_FT_FAC
END_FTES_RATIO
ENDOWMENT
EXP_STSVC_FTES_RATIO
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
AID_FR_LOAN_PCT
AID_FR_STATE_GRANT_PCT
SUM_UNIT
FTES_TOTAL
EXP_TOTAL
ENR_PCT_UG_NON_WHITE
AID_FR_FED_GRANT_PCT
e1 .80
e2 .81
e3 .84
e4 .90
e5 .80
e6 .78
e7 .82
e8 .52
e9 .60
e10 .54
e11 .61
e12 .62
e13 .16
e14 .23
e15 .05
e16 .44
e17 .46
e18 .89
e19 .79
e20 .50
e21 .28
e22 .35
e23 .32
e24 .30
e25 3.29
e26 .08
e27 .03
e28 .07
e29 .19
e30 .26
e31 1.23
e32 33.17
e33 .01
.90
.90
-.91
.95
.90
.88
.91
-.72
.77
.73
.78
.78
.40
-.47
-.66
.68
.60
.56
.55
.94
.89
-.71
.53
.23
1.81
.29
.18
.27
.43
.51
1.11
5.76
.11
.46
-.14
.66
.07
-.02
.48
.02
-.07
-.01
.04

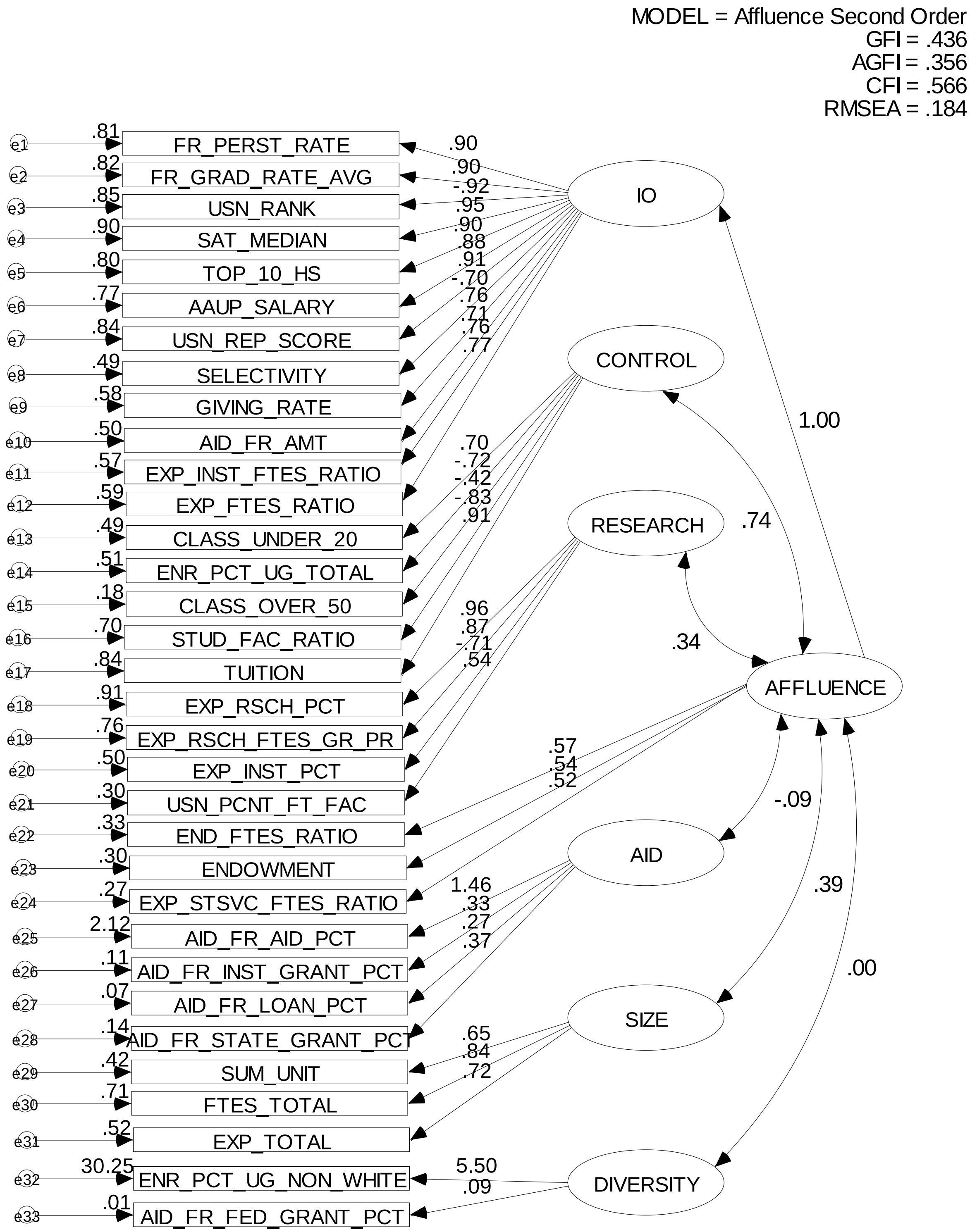

MODEL = Orthogonal with Covariances (2 factors)
GFI = .362
AGFI = .277
CFI = .504
RMSEA = .195
IO
SIZE
.43
FR_PERST_RATE
FR_GRAD_RATE_AVG
USN_RANK
SAT_MEDIAN
TOP_10_HS
AAUP_SALARY
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_RSCH_FTES_GR_PR
EXP_INST_PCT
USN_PCNT_FT_FAC
END_FTES_RATIO
ENDOWMENT
EXP_STSVC_FTES_RATIO
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
AID_FR_LOAN_PCT
AID_FR_STATE_GRANT_PCT
SUM_UNIT
FTES_TOTAL
EXP_TOTAL
ENR_PCT_UG_NON_WHITE
AID_FR_FED_GRANT_PCT

Appendix F

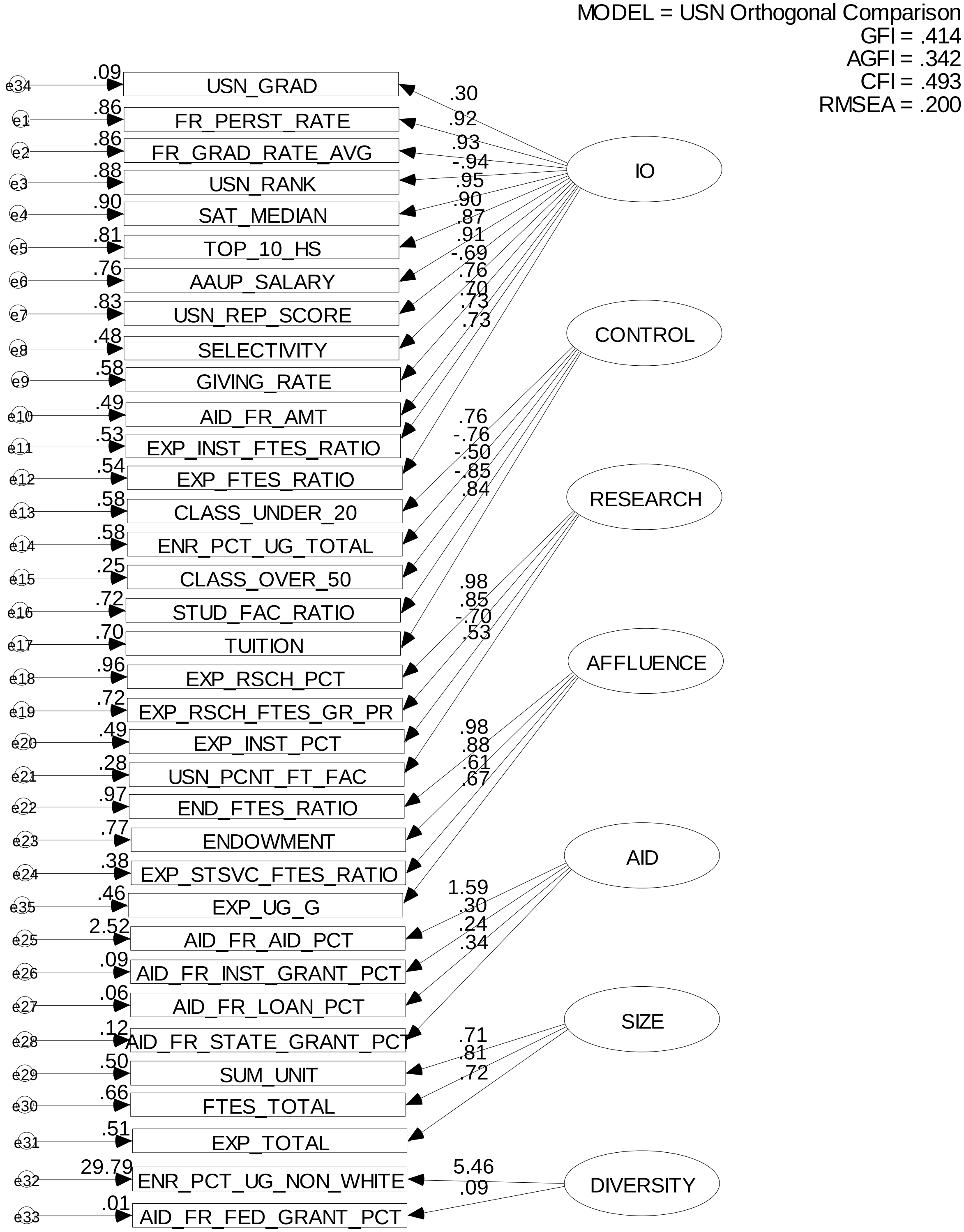

MODEL = First Order using Full Loadings
GFI = .665
AGFI = .570
CFI = .800
RMSEA = .132
FR_PERST_RATE
FR_GRAD_RATE_AVG
USN_RANK
SAT_MEDIAN
TOP_10_HS
AAUP_SALARY
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_RSCH_FTES_GR_PR
EXP_INST_PCT
USN_PCNT_FT_FAC
END_FTES_RATIO
ENDOWMENT
EXP_STSVC_FTES_RATIO
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
AID_FR_LOAN_PCT
AID_FR_STATE_GRANT_PCT
SUM_UNIT
FTES_TOTAL
EXP_TOTAL
ENR_PCT_UG_NON_WHITE
AID_FR_FED_GRANT_PCT
IO
CONTROL
RESEARCH
AFFLUENCE
AID
SIZE
DIVERSITY

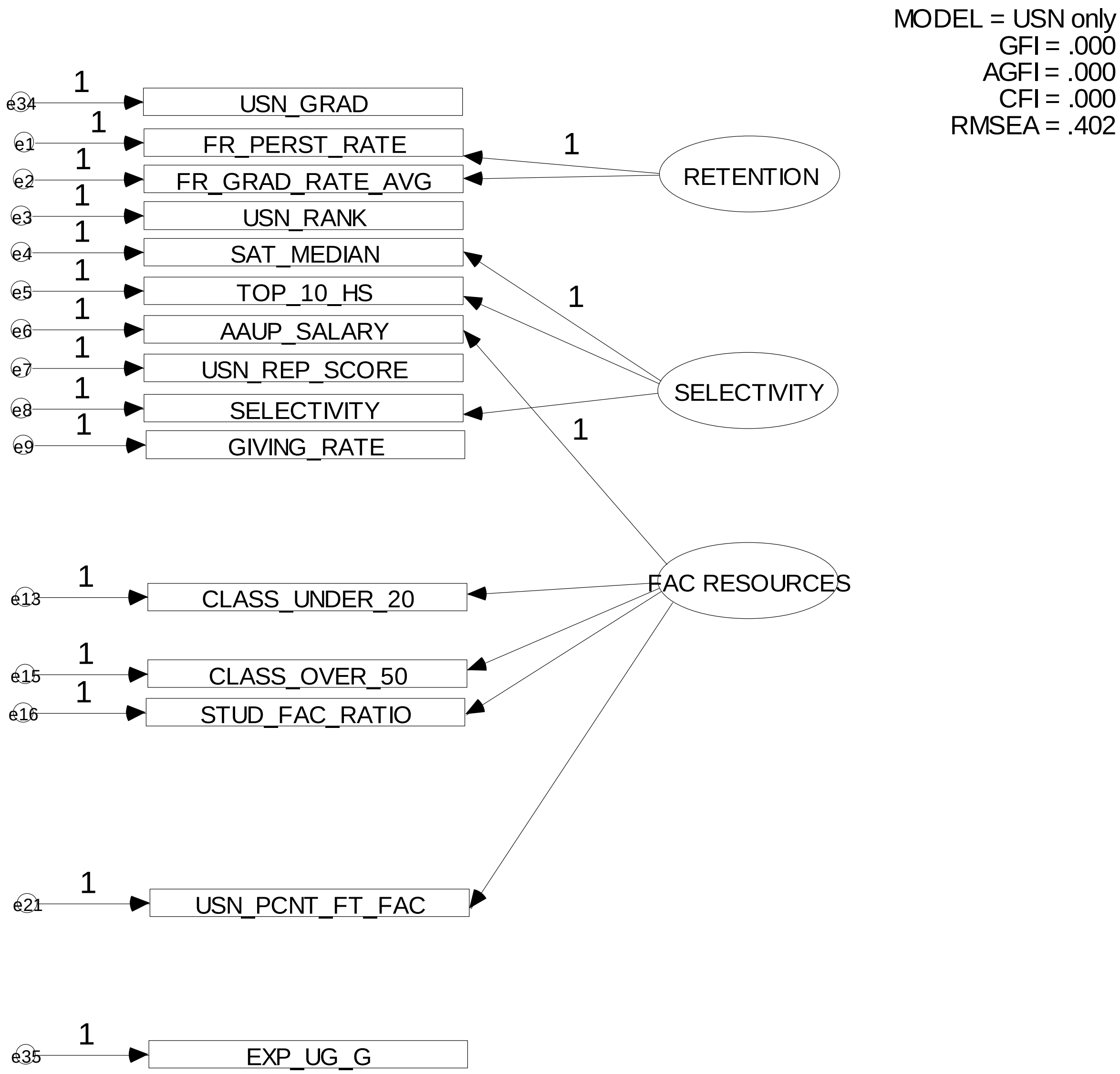

MODEL = First Order using All Loadings > 0.3
GFI = .690
AGFI = .580
CFI = .827
RMSEA = .126
FR_PERST_RATE
FR_GRAD_RATE_AVG
USN_RANK
SAT_MEDIAN
TOP_10_HS
AAUP_SALARY
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_RSCH_FTES_GR_PR
EXP_INST_PCT
USN_PCNT_FT_FAC
END_FTES_RATIO
ENDOWMENT
EXP_STSVC_FTES_RATIO
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
AID_FR_LOAN_PCT
AID_FR_STATE_GRANT_PCT
SUM_UNIT
FTES_TOTAL
EXP_TOTAL
ENR_PCT_UG_NON_WHITE
AID_FR_FED_GRANT_PCT
IO
CONTROL
RESEARCH
AFFLUENCE
AID
SIZE
DIVERSITY

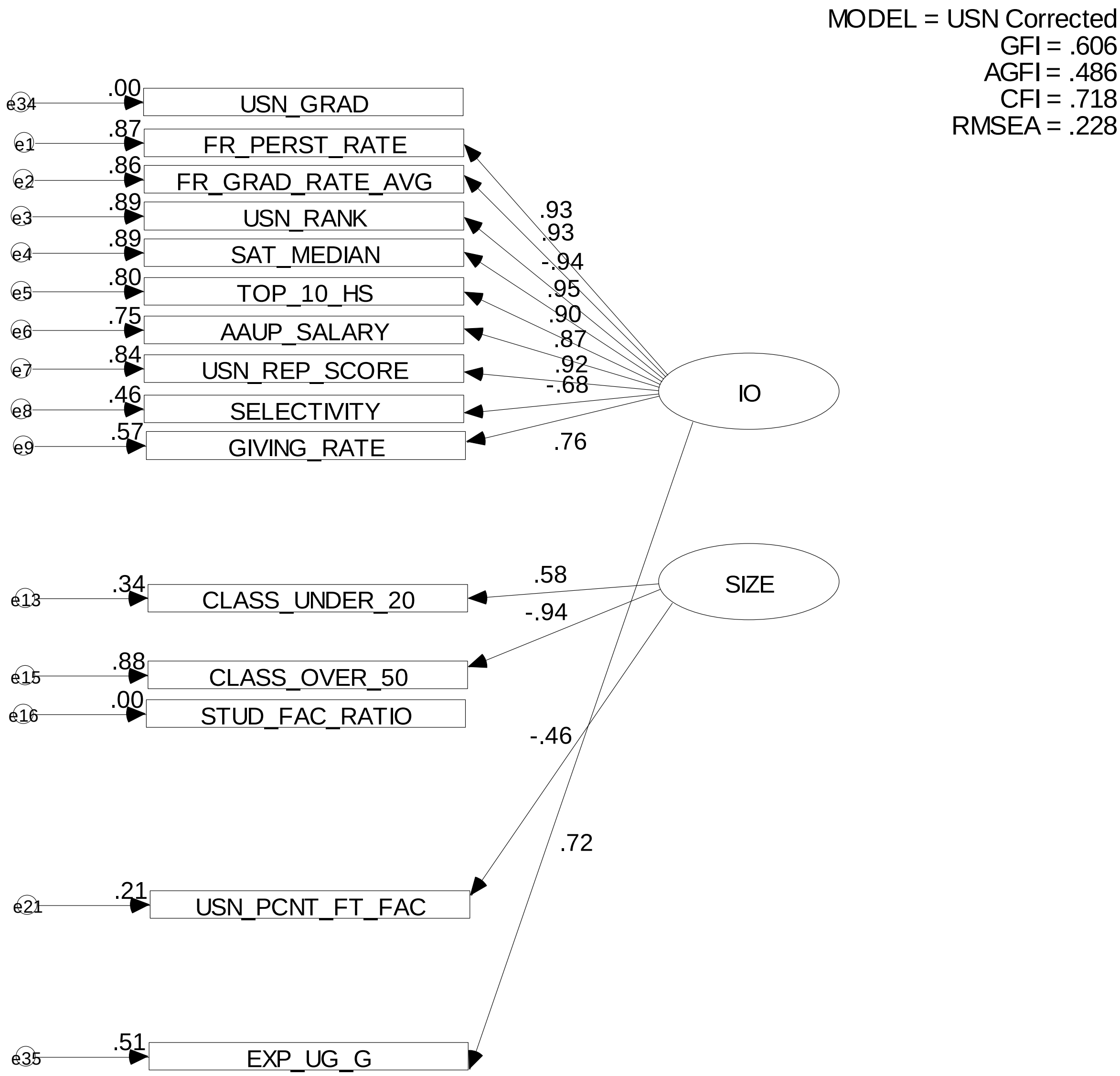
Appendix G


MODEL = Affluence Second Order
GFI = .436
AGFI = .356
CFI = .566
RMSEA = .184
FR_PERST_RATE
FR_GRAD_RATE_AVG
USN_RANK
SAT_MEDIAN
TOP_10_HS
AAUP_SALARY
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_RSCH_FTES_GR_PR
EXP_INST_PCT
USN_PCNT_FT_FAC
END_FTES_RATIO
ENDOWMENT
EXP_STSVC_FTES_RATIO
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
AID_FR_LOAN_PCT
AID_FR_STATE_GRANT_PCT
SUM_UNIT
FTES_TOTAL
EXP_TOTAL
ENR_PCT_UG_NON_WHITE
AID_FR_FED_GRANT_PCT
IO
CONTROL
RESEARCH
AFFLUENCE
AID
SIZE
DIVERSITY
1.00
.74
.34
-.09
.39
.00

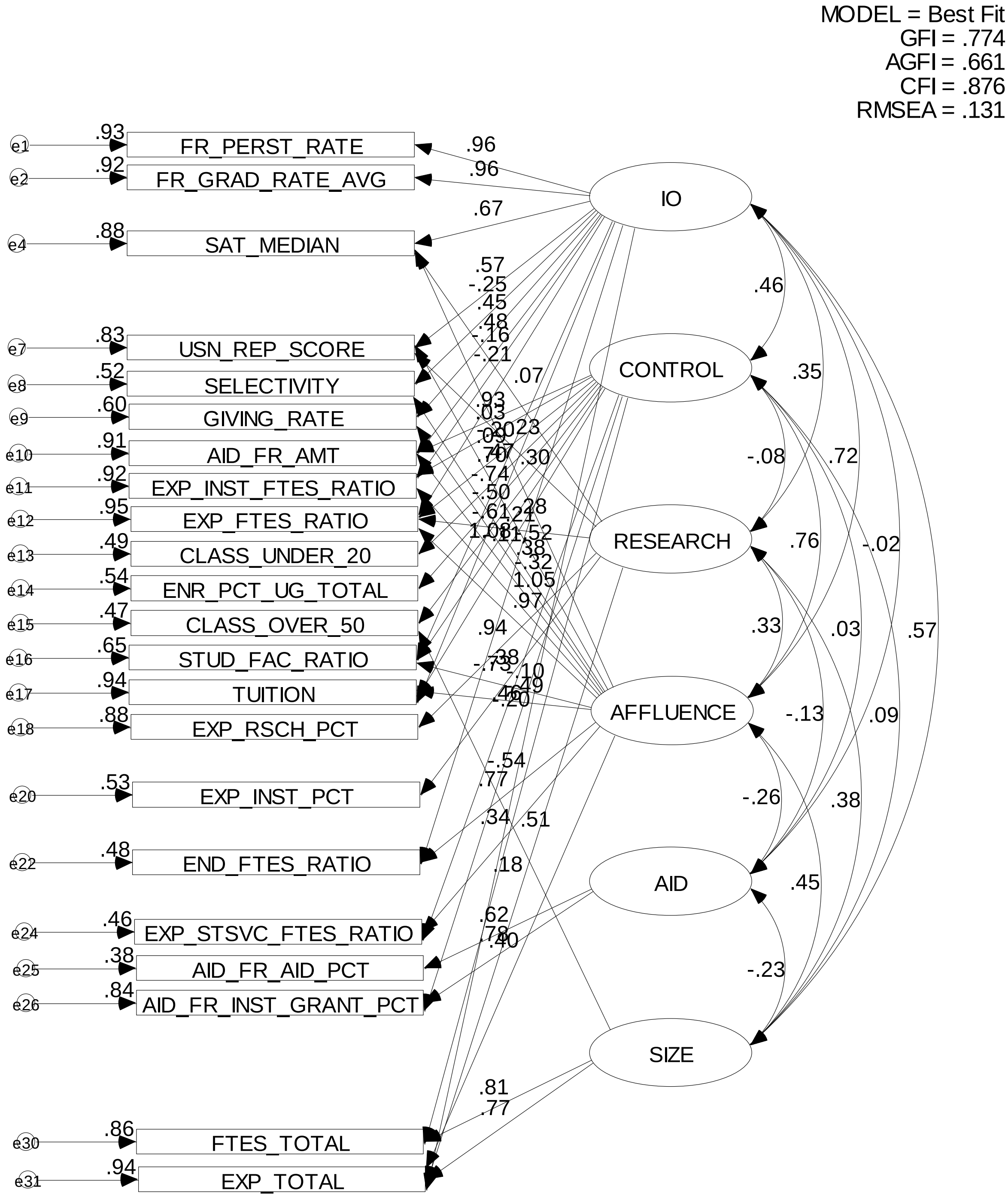
Appendix H


MODEL = USN Orthogonal Comparison
GFI = .414
AGFI = .342
CFI = .493
RMSEA = .200
USN_GRAD
FR_PERST_RATE
FR_GRAD_RATE_AVG
USN_RANK
SAT_MEDIAN
TOP_10_HS
AAUP_SALARY
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_RSCH_FTES_GR_PR
EXP_INST_PCT
USN_PCNT_FT_FAC
END_FTES_RATIO
ENDOWMENT
EXP_STSVC_FTES_RATIO
EXP_UG_G
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
AID_FR_LOAN_PCT
AID_FR_STATE_GRANT_PCT
SUM_UNIT
FTES_TOTAL
EXP_TOTAL
ENR_PCT_UG_NON_WHITE
AID_FR_FED_GRANT_PCT
IO
CONTROL
RESEARCH
AFFLUENCE
AID
SIZE
DIVERSITY


MODEL = USN only
GFI = .000
AGFI = .000
CFI = .000
RMSEA = .402
e34
USN_GRAD
e1
FR_PERST_RATE
e2
FR_GRAD_RATE_AVG
e3
USN_RANK
e4
SAT_MEDIAN
e5
TOP_10_HS
e6
AAUP_SALARY
e7
USN_REP_SCORE
e8
SELECTIVITY
e9
GIVING_RATE
RETENTION
SELECTIVITY
FAC RESOURCES
e13
CLASS_UNDER_20
e15
CLASS_OVER_50
e16
STUD_FAC_RATIO
e21
USN_PCNT_FT_FAC
e35
EXP_UG_G
1


MODEL = USN Corrected
GFI = .606
AGFI = .486
CFI = .718
RMSEA = .228
e34
.00
USN_GRAD
e1
.87
FR_PERST_RATE
e2
.86
FR_GRAD_RATE_AVG
e3
.89
USN_RANK
e4
.89
SAT_MEDIAN
e5
.80
TOP_10_HS
e6
.75
AAUP_SALARY
e7
.84
USN_REP_SCORE
e8
.46
SELECTIVITY
e9
.57
GIVING_RATE
.93
.93
-.94
.95
.90
.87
.92
-.68
.76
IO
e13
.34
CLASS_UNDER_20
e15
.88
CLASS_OVER_50
e16
.00
STUD_FAC_RATIO
.58
-.94
SIZE
-.46
.72
e21
.21
USN_PCNT_FT_FAC
e35
.51
EXP_UG_G

Appendix I


MODEL = Best Fit
GFI = .774
AGFI = .661
CFI = .876
RMSEA = .131
FR_PERST_RATE
FR_GRAD_RATE_AVG
SAT_MEDIAN
USN_REP_SCORE
SELECTIVITY
GIVING_RATE
AID_FR_AMT
EXP_INST_FTES_RATIO
EXP_FTES_RATIO
CLASS_UNDER_20
ENR_PCT_UG_TOTAL
CLASS_OVER_50
STUD_FAC_RATIO
TUITION
EXP_RSCH_PCT
EXP_INST_PCT
END_FTES_RATIO
EXP_STSVC_FTES_RATIO
AID_FR_AID_PCT
AID_FR_INST_GRANT_PCT
FTES_TOTAL
EXP_TOTAL
IO
CONTROL
RESEARCH
AFFLUENCE
AID
SIZE