The Cost of Crafting a Class: (In)Efficient Financial Aid Allocation at Two Private Colleges

by[†]

Robert E. Martin

bmart@centre.edu

Randy Campbell

rcampbell@cobilan.msstate.edu

Michael J. Rizzo

michaelr@aier.org

May 2007

ABSTRACT

In order to meet two key objectives, enrollment managers at colleges and universities make extensive use of single equation probability models. The first objective is to generate sufficient financial resources to educate the students enrolled. The more dependent the institution is on tuition revenues, the more important is this objective. The second objective is to distribute and monitor student subsidies according to need, merit, and the institution's diversity goals. This paper reviews the existing theoretical literature on the allocation of financial aid and proposes a more complete method of analyzing the matriculation process. Using proprietary data from two representative small colleges, we demonstrate that single equation estimates of enrollment probabilities can suffer from an endogeneity bias. We propose a simultaneous probit-tobit system that corrects for this bias. Our two major findings are: (1) contrary to the predictions of the theoretical model, institutions of higher education make larger financial aid awards to students with high enrollment propensities and (2) traditional single equation models therefore systematically overstate the true impact of financial aid on enrollment probabilities.

[†] Martin is the Ewing T. Boles Professor of Economics at Centre College (Danville, KY). Campbell is an Assistant Professor of Economics at Mississippi State University. Rizzo is a Senior Economist and Director of Summer Programs at the American Institute for Economic Research (Great Barrington, MA).

I. Introduction

Few private institutions have endowments sufficient to make them independent of tuition revenues. In addition, as public support declines, state colleges and universities find themselves more dependent on tuition revenues [Martin, 2005]. Consequently, extracting sufficient funds from tuition revenues to finance core activities is a primary objective for both private and public institutions. In addition, colleges and universities distribute and monitor student subsidies provided by society. These two objectives are in competition during the annual enrollment cycle, since more subsidies mean less net tuition revenue.[1]

The forgoing suggests that the representative higher education institution's (IHEs) short run objective is more complex than simple revenue maximization. Each institution's academic reputation ultimately depends on the quality of its students and the quality of their educational experience. Hence, the institution's annual objective, while allocating financial aid among individual students, is to maximize the quality of the students it enrolls, subject to a financial aid budget and an enrollment target. The dual constraints insure that sufficient tuition revenue is available for current operations. In this manner, the institution fulfills its social obligation to administer financial aid, provides funding for current operations, and advances its long run goal of maintaining or enhancing its academic reputation [Martin, 2005].

Most colleges and universities throughout the U.S. have adopted a data driven approach to fulfilling their strategic enrollment goals. Many, though not all, employ econometric analyses to aid in the determination of institutional financial aid awards to various subgroups of admitted students. The following section contains a review of the literature regarding institutional objectives, financial aid allocation, and enrollment demand, which has given rise to the application of these econometric tools. We present empirical models of enrollment probabilities and optimal financial aid allocation in Section III and demonstrate that traditional single equation approaches are subject to

[1] This is actually a function of the elasticity of enrollment demand of an admit pool. If enrollment demand at current financial aid levels is generally elastic, then increases in financial aid will result in increases in net tuition revenue. However, in the authors' limited experience, we have found that a majority of students at the schools where we have applied enrollment probability models are price inelastic.

substantial biases resulting from the dual causality of student enrollment propensities and institutional financial aid awards.

The data for this study comes from two liberal arts colleges and covers nine academic years in one case and three academic years in the other case.[2] The results are consistent with the conclusions drawn from the theoretical model, with one notable exception. The exception is that both colleges tend to award larger financial aid packages to students with high enrollment probabilities than to those with low enrollment probabilities. The theory of efficient financial aid allocation suggests that financial aid allocations should *increas*e as the probability the student will enroll *decreases*. The implication is that both colleges award more aid than is required to induce students in need, merit students, and diversity students to enroll. The implication is that this excess in financial aid comes at the expense of educational quality. Conclusions are contained in the last section, including a brief discussion of the role that enrollment managers can play in aligning the realities of the competitive enrollment market with institutional missions.

II. Extant Literature

Objective Functions for Higher Education

The "oral tradition" in economics holds that IHE's seek to maximize reputation or prestige [James, 1990] [Grossman, 1995] [Esposito and Esposito, 1995] [Brewer, Gates, and Goldman, 2002]. Casual observation motivates the oral tradition. Testimony from administrators and institutional behavior suggest reputations are paramount in the choices IHE's make. They seek to enroll the best students possible, they compete for endowment funds and grants, and they emphasize scholarship and public service as well as teaching [Cook and Frank, 1993] [Grossman, 1995] [Duffy and Goldberg, 1998].

Recently, the competition for good students among some institutions appears to have taken a pathological turn [Duffy and Goldberg, 1998] [McPherson and Schapiro, 1999] [Redd, 2000]. Due to the disbanding of the "Overlap Group" and the importance of

[2] We are bound by confidentiality to not release the names of the institutions. However, we will make limited data available to researchers in order to preserve this confidentiality. For example, we would recreate student id numbers and remove all indications of student place of residence. However, we would be willing to provide dummies for whether the student is an in-state or an out-state student and the distance of the student's home to the campus under consideration.

3rd party rankings, an "arms race" of tuition discounting has emerged [Ehrenberg, 2000].[3] While this arms race has done little to alter the distribution of students among wealthy schools, the less wealthy schools find it more difficult to attract and retain top students and it contributes to their financial distress, particularly at less selective colleges [Redd, 2000].

Hopkins and Massy [1981] provide the seminal work on formal academic objective functions. They propose maximizing a generic value function subject to a budget constraint. From this objective function, they derive a balanced budget stationary state equilibrium. Similar models are considered by Ehrenberg and Sherman [1984], Tiffany and Ankrom [1998], and Martin [2005]. Rothschild and White [1995] take a different tack when they assume IHEs behave *as if* they are profit maximizing entities. In the end, Rothschild and White find their model leads to too many anomalies and conclude the "as if" assumption is not appropriate for higher education.[4]

Financial Aid Allocation

Hoenack [1971], Ehrenberg and Sherman [1984], and Rothschild and White [1995] consider the efficient allocation of financial aid. Hoenack [1971] proposes three different administrator objectives subject to a financial aid constraint. Ehrenberg and Sherman [E-S] assume IHEs maximize the administrator's utility function subject to a budget constraint. The administrator's utility is a function of total quality units from different student categories. Since the E-S model is not constrained by an enrollment target, enrollment scale is an implicit choice in the model. Thus, the E-S model is a long run model. Rothschild and White [R-W] assume that students are inputs in the production of human capital. Students contribute to the production of their own human capital and they have externality effects on the human capital accumulation of other students.

E-S [pp. 209-210] report a variety of interesting results. They conclude that, ceteris paribus: higher quality students should receive more financial aid, students whose enrollment is more sensitive to price should receive more financial aid, and students who are more likely to enroll should receive *less* financial aid. R-W conclude that students with higher marginal productivity should receive more financial aid. They do not model

[3] See the discussion in Chapter 5.
[4] For both the public and private sectors.

enrollment probabilities. If one considers marginal productivity a measure of student quality, R-W's result corresponds to E-S's in that respect.

E-S's quality result, confirmed by R-W, provides a theoretical foundation for merit financial aid. E-S's second result regarding price sensitivity provides a theoretical foundation for need based financial aid, since they argue that lower income students are apt to be more price sensitive than students with higher income. E-S's third result suggests we should offer students who are least likely to enroll more financial aid. Martin's model [2005, 114-121] is consistent with Ehrenberg and Sherman's results.

Enrollment Demand

Most studies of enrollment demand evaluate the impact of public policies on higher education[5]. For example, McPherson and Shapiro [1991] explore the effect of financial aid, specifically Pell Grants, on college enrollment among lower income white students. The seminal study by Manski and Wise [1983] considers industry-wide enrollment decisions by students using longitudinal data from the early 1970's. These studies are of limited use for institutional pricing, since the demand curve faced by each institution is different. Furthermore, these studies tell us little about competitive behavior in higher education because they are analogous to the study of the generic demand for toothpaste rather than the demand for a specific brand of toothpaste. The empirical analysis in Section III yields expected enrollment demand curves for two specific brands of higher education.

Recent years have shown a marked increase in the number of studies examining enrollment demand at colleges and universities. A sampling includes Moore, Studenmund and Slobko's [1991] study for Occidental College. Allen and Shen [1999] conclude that demand elasticities for students at a comprehensive religious college are higher than one, indicating that increasing institutional financial aid can improve enrollment outcomes significantly. Desjardins [2001] estimated a model of nonresident enrollment demand at a large public university to demonstrate the significance of nonresident students in a simulation model to help guide institutional policy. Singell and Stone [2002] estimate a bivariate probit model of the application and matriculation decision at a large public

[5] This point is also made by Ehrenberg and Sherman [1984, 210]. See Heller [1997] for a comprehensive review of the empirical literature on enrollment demand.

university and find that while merit aid increases enrollment propensities for all students, non-needy students are much more sensitive *ceteris paribus* than needy students.

These practitioners overlook a key element in estimating the effect of financial aid on matriculation: financial aid awards are not exogenously determined. The IHEs allocate aid based on the same student characteristics that influence the likelihood a given student will enroll. They also form subjective evaluations of each student based on interviews, application essays, and recommendations. The subjective and/or unobserved factors are important determinants of financial aid awards and those factors contribute to a student's matriculation probability. The omission of these factors will lead to biased estimation.

More important than this omitted factor, most researchers are not able to capture information about the alternative academic and non-academic options of admitted students (including the type, location and quality of other schools; the size and composition of financial aid awards; whether the student has seen a military recruiter; etc.). While some institutions attempt to collect limited information on their applications, most are unable to capture useful data until a student has either matriculated or turned down the offer of admission.[6] The absence of such information may lead to an over- or under-statement of the true impact of financial aid on enrollment propensities – a classic case of omitted variables bias. To the best of our knowledge, a recent paper by van der Klaauw [2002] is the only one that addresses this problem. He offers a semi-parametric solution to the problem based on a Regression Discontinuity approach commonly used in the program evaluation literature. This approach depends on exploiting idiosyncrasies in a college's financial aid awarding process. In this paper, we propose an alternative, and more traditional, solution to this problem by modeling a structural system of enrollment demand and financial aid award equations. The advantage of pursuing this strategy is the ease with which enrollment managers can execute the structural approach and communicate the importance of the exclusion restrictions to their clients as opposed to the complexities of program evaluation. Enrollment managers and their clients can also begin collecting data that will help overcome this identification problem.

---

[6] The College Board offers a service called the Admitted Student Questionnaire. See their website for more information: http://www.collegeboard.com/highered/ra/asq.html

III. The Empirical Analysis of Efficient Financial Aid

Theory suggests that financial aid offers are an increasing function of student quality (merit based aid), a decreasing function of student income (need based aid), an increasing function of tuition and fees, and a decreasing function of the likelihood an individual student may enroll. Diversity is a common objective among higher education institutions and this is certainly the case for the two colleges considered in this analysis. The dominant type of diversity sought by higher education institutions is racial and ethnic diversity; however, diversity may also include gender diversity, regional diversity and socio-economic diversity.

An unspoken service provided by colleges and universities is in the marriage market. The signal value provided by college admittance and matriculation is important in the matching of couples. Therefore, gender mix is an important component of the institution's diversity objective. Similarly, students from different geographic areas enhance cultural and experiential diversity. National and international institutions have higher prestige than regional institutions.

The strategic assumptions employed in the quality maximization model state that enrollment probability is a decreasing function of tuition and fees, a decreasing function of student quality, an increasing function of the financial aid offer, and an increasing function of the institution's quality reputation. Quality adjusted enrollment demand depends directly on the enrollment probability function, since expected enrollment is the sum of the enrollment probabilities for all admitted students.

Data

For each college, the data comes from the admitted student data file. The first college is a small private liberal arts college with a total enrollment of approximately 1,000 students. Let this be College A. The college is a national institution and maintains a reputation as a selective academic institution.[7] College B is a larger private baccalaureate college with over 5,500 students. The two panels in table 1 contain institutional characteristics for the two colleges for academic year 2003 as well as characteristics of the admitted student pool corresponding to that year. The institutional

[7] It has been consistently ranked in the Top 50 Liberal Arts Colleges by the annual U.S. News and World Report Guide to America's Colleges and recognized by a variety of independent ranking organizations.

characteristics reveal the student-faculty ratio at College A is considerably lower than is the student-faculty ratio at College B. College B is more dependent on tuition revenue than is College A.[8] The total cost of attendance at A is almost twice as high as B, more students receive aid at A than B, and the discount rate is higher at A than at B.[9] Acceptance rates and enrollment rates are lower at A than at B. While average faculty salaries are comparable, College B appears to expend a larger proportion of its total operating budget for instruction and academic support than does College A. The endowment per student is substantially higher at A than at B.

An important difference between the two institutions appears to be their respective strategies for financial stability. College A achieves financial stability through its endowment, while College B attains financial stability through returns to scale and a greater dependence on tuition revenue. This, coupled with the very significant differences we observe in their student-faculty ratios, suggests College A has chosen a higher quality of instruction than College B. However, the lower faculty salaries and smaller share of the budget for instruction and academic support at College A raise some question about this conclusion.

Panel B in table 1 reveals that the representative student at College A receives more total grant aid and need based aid than does the representative student at College B. The expected family contribution is twice the amount at College A than at College B, reflecting differences in the cost of attendance at each institution. A substantially larger percentage of the students at College A are in the top 10% of their high school class than in College B. SAT scores are higher at College A than at College B, the proportion of female students is similar at each institution, and the proportion of minority students at College A is double the proportion at College B.

---

[8] We mean this in a purely statistical sense in that at College B a larger share of revenues come from tuition and fees than at College A. This should be distinguished from the economic question of whether one institution is more dependent on tuition than another.

[9] The discount rate is calculated as: $\frac{\sum_{i=1}^{N} institutional\ \ grant\ aid_{\ i}}{\sum_{i=1}^{N} tuition\ \ and\ \ fees_i}$. It might be the case that College A's discount rate is higher than College B's because College A is more guilty of "overpaying" for its students than College B – and this will be empirically checked later in the paper – because College A's "endowment cushion" puts less pressure on it to keep costs down as opposed to College B.

The data used in the subsequent analyses covers a period before the 2003-4 academic year. The admitted students file for College A contains 7,599 usable observations and covers the years from 1995 through 2003, suggesting an average admittance of 1,000 students each year. The number of students admitted was 8,550. From that total, 2,599 students enrolled for an average class size of 289 students and average yield of 30.4%. Female students made up 52% of the enrollment, 34.9% of those enrolling came from out of state, 3.4% were National Merit finalists or semifinalists, and 5.4% were minority students.

The admitted students file for College B contains 11, 304 usable observations and covers the period from academic year 2000 through academic year 2002. From this total, 3,468 students enrolled for an average class size of 1,156 students and an average yield of 26.4%. Of those who enrolled, 58% were female, 47.6% were from out of state, 19.9% were in the top 20% of their high school classes, and 2.9% were minority students.

Empirical Models- Single Equation Model[10]

The literature suggests that student enrollment probabilities and institutional scholarship offers are simultaneously determined. However, the standard practice among enrollment professionals is to use probability estimates from single equation logit or probit models in their formulation of financial aid offers. Thus, the college estimates an enrollment equation of the form:

$$y^* = \gamma_1 aid + X_1\beta_1 + u_1 \qquad \textbf{[1]}$$

where y^*, the student's enrollment utility, is only observed as a dichotomous variable equal to one if the student enrolls and zero otherwise, *aid* is the total amount of grant aid offered, and X_1 is a matrix of explanatory variables which includes measures of student access to financial resources, quality, high school characteristics, demographic characteristics, year dummy variables and other factors that are believed to impact enrollment propensities (such as whether the student is a legacy). The year dummies are included to control for unobserved student invariant factors which change over time, such as changes to federal student aid regulations or macroeconomic conditions.

[10] In both the single equation models in this section and the simultaneous model that follows, note that we are necessarily estimating partial equilibrium models. This is because we do not have information on the other schools admitted students have applied to or have been accepted to, and therefore cannot control for relative price or quality measures, as well as the dynamic effects of competing aid offers.

In order to provide a benchmark for the simultaneous model that we propose below, we estimate the enrollment probability equation for each school in single equation probit models. We specify the *aid* variable to include all institutional grant aid (merit awards, need-based aid, talent based aid, entitlements, etc.) plus external grant aid from federal (e.g. Pell and SEOG) and state (e.g. Georgia's HOPE scholarship) sources.[11] We also exclude from this and the subsequent analyses any student groups with 100% yields or those with non-existent or unusual eligibility for institutional aid programs.[12] Complete descriptions of the variables used in this paper are included in appendix table 1.[13]

The results for the enrollment probability models are contained in Table 2. Most of the variables are significant at least at the .01 level. In each case, the larger the financial aid offer the more likely the student is to enroll and the higher the student's financial need the less likely the student is to enroll. Similarly, black students are less likely to enroll at both institutions. The coefficient for Hispanic students is also negative, but it is not significant.

The *peers* variable in each equation represents the number of students accepted from the student's high school in the case of College A and the number of students accepted from the student's home county for College B. The coefficient is positive in each model, but is significant only in the equation for College B. For College A, legacy status and campus visits are positive indicators for enrollment.

The distance variable used in the model for College A represents the linear distance from the college's zip code to the student's home zip code measured in miles. The distance function is a quadratic since driving distance would influence the decision to enroll up to distances that represent one day's drive. Beyond that, students are most likely to take public transportation to attend college. For both colleges the higher the objective

---

[11] We do not include funds that show up in financial aid records only once a student matriculates. We call these awards "outside aid." Examples of this aid include Knights of Columbus scholarships, which the institutions in question have no knowledge of at the time aid packages are being put together. This aid typically travels with the student as well and its magnitude is invariant to the tuition charges at other schools.

[12] These include students that receive faculty-staff benefits, students participating in tuition-exchange programs, recruited athletes, part-time students, international students and certain ROTC students.

[13] Many schools collect the high school code assigned by the college board and hence are able to control for high school characteristics in these regressions. The two schools in our sample did not collect this CEEB code and we are therefore unable to include these controls.

measures of student quality, the less likely the student is to enroll which reflects the intense competition for merit students across all colleges and universities.

Simultaneous Equations Models

The theory of enrollment management suggests that if colleges are economizing on their use of financial aid funds, they should be using financial aid to induce attractive students who are at the margin by offering them more financial aid. Other things equal, if the student is more likely to enroll, she should receive less financial aid. Since financial aid offers and enrollment probabilities are simultaneously determined, the single equation approach used in the previous subsection may suffer from simultaneous equation bias.[14] Hence, in order to test the two hypotheses stated above, we estimate enrollment probability and financial aid offers in a simultaneous equations model. The equations are

$$y^* = \gamma_1 aid^* + X_1\beta_1 + u_1 \qquad [2]$$

$$aid^* = \gamma_2 y^* + X_2\beta_2 + u_2 \qquad [3]$$

where y^*, the student's enrollment utility, is only observed as a dichotomous variable equal to one if the student enrolls and zero otherwise. In addition, the actual financial aid offer, *aid*, is observed only when the latent variable aid^* is positive. Therefore,

$$y = \begin{cases} 1 & if \;\; y > 0 \\ 0 & otherwise \end{cases} \qquad [4]$$

$$aid = \begin{cases} aid^* & if \; aid^* > 0 \\ 0 & otherwise \end{cases} \qquad [5]$$

Our model has one dichotomous and one censored variable.

Nelson and Olson (1978) develop a two-stage estimator for a simultaneous equations model with one censored and one continuous dependent variable. Amemiya (1979) derives the asymptotic covariance matrix and suggests a more efficient GLS

[14] In other words, in equation 1 *aid* is theorized to have a negative correlation with u_1. If this were the case, then $\hat{\gamma}_1$ will be a downwardly biased estimate of γ_1 . If *aid* has a positive correlation with u_1 then our estimate of the impact of aid on enrollment probabilities will be too high. For example, suppose the unobservable in equation 1 is that the student had a bad campus visit. If this is the case, then a student is unlikely to enroll. In equation 2, students with low enrollment probabilities should receive larger aid packages, and then looking to equation 1 we see that every time a student has a poor visit, she receives more financial aid – and that researchers will attribute the negative effect of a bad campus visit to higher aid rather than the true unobservable factor.

estimator for this model. Amemiya (1978) develops a similar estimator and derives the asymptotic covariance matrix for a model with one dichotomous and one continuous dependent variable. Deis and Hill (1998) estimate a simultaneous equations model of this type and use the bootstrap method to show that the GLS *t*-statistics and *p*-values are overstated. Mallar (1977) considers a model in which both dependent variables are dichotomous. Zimmer (2001) uses the two-step procedure to estimate a simultaneous probit model of this type. We will follow a two-step procedure to properly estimate the system characterized by equations (2) and (3) from above.

The reduced form equations for the system of equations given by (2) and (3) are

$$y^* = X\pi_1 + v_1 \qquad [6]$$

$$aid^* = X\pi_2 + v_2 \qquad [7]$$

where $\boldsymbol{X}$ is a $T \times K$ matrix consisting of all variables in (X_1, X_2). To obtain two-stage estimates for the structural equations (2) and (3), we first estimate equation (6) by probit and equation (7) by tobit. We replace aid^* in equation (2) by $aid^* = X\hat{\pi}_2$ and estimate the resulting equation by probit. We replace y^* in equation (3) by $y^* = X\hat{\pi}_1$ and estimate the resulting equation by tobit. This two-stage estimator gives consistent estimates for the structural parameters in equations (2) and (3).

The success of the two-stage procedure depends on both the proper specification of the structural equations and on the empirical availability of relevant exclusion restrictions.[15] Identification of structural equation (2) requires the existence of a factor (or factors) that affects the financial aid award made by the IHE, but not enrollment propensities. Identification of structural equation (3) requires the existence of a factor (or factors) that affects a student's enrollment propensity, but that should not be a major determinant of the financial aid award. For College A, our financial aid equation is over-identified by the distance measures, the amount of need-based loans offered, *peers* and legacy variables and for College B the financial aid equation is just identified by the *peers* variable. For both College A and College B, the enrollment probability equation is identified by a subjective measure of student quality, *resid*.

[15] In this theoretical context, it is difficult to make the case for restrictions on the error covariances and / or other linear restrictions, therefore identification must be made from appropriate exclusion restrictions.

We were able to obtain subjective measures of student quality (*resid)* because each institution maintains a numerical rating scheme for each admitted student. The enrollment case manager responsible for the student's file assigns the academic rating and it is dependent on the student's academic record, recommendations, admission essay, and personal interviews. These ratings contain both objective and subjective elements. In order to separate the objective portion from the subjective portion, we regressed the ratings against the objective measures in each data set and then used the residual value from the model.[16] Since the residual is the variation in the academic rating that cannot be explained by the objective measures, it is argued that the residual reflects the evaluator's subjective evaluation of each student. The subjective evaluation of each student, *resid*, is employed as an independent variable in the structural scholarship model in the simultaneous system.

The results from these regressions are contained in Table 3. In each equation over one half (R-squared of 0.63 and 0.72) of the variation in the academic rating is explained by the objective variables such as SAT scores, high school class rank, high school grade point average, gender, minority status, and the year the evaluation was made. The results are consistent across both colleges with two major exceptions. First, being female has a positive influence on the evaluations at College A and a negative influence on the evaluations at College B. This is somewhat surprising given that the student body at each of the schools is fast approaching 60% female composition. Second, College A appears not to use racial characteristics in its evaluation while College B makes strong use of these characteristics. Again, this result is somewhat surprising in that College A's student body is comprised of less than 3% blacks and Hispanics while College B's student body is comprised approximately of 7% blacks and Hispanics. Since College A admits more minorities than College B, the minority enrollment yield is higher at College B than at College A. One other difference is that the coefficient for year is positive and significant at better than the .01 level at College A and is insignificant at College B. This result suggests that there has been inflation in the ratings at College A. However, this may

[16]Note that the scales for the ratings are very different for the two schools so that comparison of the magnitudes of the regression coefficients is not possible directly.

reflect unobserved factors causing ratings to increase over time.[17]

Murphy and Topel (1985) show that the standard errors in the two-step model are incorrect if we do not account for the fact that equations (6) and (7) contain estimates from the first-stage enrollment and scholarship equations. We compute the asymptotically correct standard errors for the two-step model as described in Greene [2003, pp. 509-512]. To the best of our knowledge, no empirical work exists that estimates a simultaneous probit-tobit model as outlined above.[18]

The probit results from the simultaneous model for both colleges are contained in Table 4. Controlling for the endogeneity of aid offers results in a reversal of coefficient sign for each school. The aid coefficient is insignificant for College A and negative and significant at better than the .01 level for College B. In other words, ignoring the simultaneous relationship between enrollment probabilities and aid offers causes us to overstate the impact of aid on enrollment probabilities in the single equation probit index. For students receiving the mean amount of financial aid at College A, the single equation specification infers that students receiving $1,000 more in financial aid than those at the mean, *ceteris paribus,* have a higher probability of enrolling. According to the simultaneous model, the aid variable is not significant. For College B, the probit coefficient fell from a positive and significant 0.27 to a negative and significant -0.08 – so ignoring the endoegeneity of the aid offers results in a complete misunderstanding of the impact that aid plays on enrollment probabilities at College B.

The sign of the need variable is positive in both equations, but is significant only in the equation for College B. The results for the objective measures of student academic quality are consistent with the single equation model for College A. Many of the objective academic quality measures have negative coefficients and are significant. The results are consistent with competition for higher quality students at College A. The student quality results are mixed at College B. The coefficient for the top 20% high school rank is negative and significant, but the coefficient for the SAT score and the scholars program are positive and significant. The coefficients for the minority control

[17] Such as an improvement in the quality of the applicant pool, or changes in the way that ratings are being assembled.

[18] Singell (2002) estimated models of financial aid packaging at the University of Oregon that controlled for the selection of students that filed a FAFSA. However, these models did not include controls for student enrollment probabilities.

variables are negative at College A, but are not significant. The coefficient for black students is positive and significant at College B. The quadratic distance function is significant in the model for College A. The *peers* coefficient is positive and significant in both models.

The tobit results for the financial aid equations are contained in Table 5. One speculates there are three motives for awarding financial aid to prospective students: The student is a need based candidate, the student is a merit based candidate, or the student is a diversity candidate. The need variable is defined to be the total cost of attendance less the expected family contribution that has been computed on the Free Application for Federal Student Aid Form (FAFSA). Therefore, all students that have not filed a FAFSA are assumed to have no need. This variable is positive and significant at better than the .01 level in both equations. The measures of merit based financial aid, such as SAT scores, grade point averages, class rank, and the subjective variable resid are positive and significant in each equation. These results are consistent with the allocation of financial aid according to need and merit.

Diversity can be defined by racial/ethnic characteristics, gender, or spatial characteristics. The black and Hispanic coefficients for College A are positive and significant, as is the Hispanic coefficient for College B. Curiously, the black coefficient is negative and significant for College B. The female zero/one variable is positive and significant for College A, but not significant for College B. Given the relative scarcity of male students attending college versus the number of female students attending college, this result is also somewhat curious. Generally, the out of state residency variables are positive and significant, which is consistent with a preference for geographic diversity.

The most important anomaly in the aid model occurs in both equations: The enrollment probability variable is positive and significant in both equations. [19] This is exactly the opposite of what theory predicts. If the colleges are economizing on their use of financial aid funds, they should be using financial aid to induce attractive students who are on the enrollment margin by offering them more financial aid. Other things equal, if the student is more likely to enroll, she should receive less financial aid. To the extent

[19] This result is robust to the specification of a simultaneous system. Single equation tobit estimates also show a significant positive impact of enrollment probabilities on financial aid awards.

that that does not happen, the college has less financial aid to allocate to students based on their need, their merit, and the institution's diversity goals. Furthermore, the college has fewer financial resources to ensure the quality of the student's educational experience. This result suggests that these two colleges are not making the most efficient use possible of their financial aid budgets. They may be awarding more aid than is required to attract the number of students they need and the student mix they require.

IV. Estimation Problems, Agency, Production Externalities, and Culture

The most surprising and robust empirical finding in this study is that financial aid awards increase as the probability a student will enroll increases. This result contradicts the theory of financial aid allocation, which predicts that financial aid awards decline, as the probability a student will enroll increases. The intuition from the theory is clear: financial aid awards are an incentive to induce students to enroll. If a student is very likely to enroll, the enrollment manager can increase expected enrollment, provide more aid to students in need, and/or increase average student quality by allocating financial aid away from students who are likely to enroll towards students in need, to higher quality students, or to diversity students. Since this empirical conclusion is robust for both college A and college B, it requires closer examination. There are several potential explanations.

The empirical result may be an estimation problem. The data consists of those students accepted by the institutions under study. It does not include the students who choose not to apply to the institutions. We do not model the application decision. When deciding where to apply, students make a subjective decision about the expected financial aid award relative to the known total cost of attendance at each institution. Students with the greatest relative need are the least likely to apply and the students with the greatest relative need are the ones who are most sensitive to the cost of attendance. Many of the students who choose not to apply are the students whose probability of enrollment is most sensitive to financial aid awards. Hence, our samples may be subject to prior selection bias due to the absence of the students who are in the greatest need.[20] While this is a

[20] In fact, Curs and Singell (2002) find that by ignoring the inquiry/application decision, single equation enrollment probability models substantially underestimate the price sensitivity of admitted students.

possible explanation, the results are so robust to specification that we do not believe this is the complete answer. College A is a much more selective and expensive college than college B; therefore, fewer price sensitive students would be hesitant to apply to college B than college A. The results are robust in either case.

The empirical result may be evidence of an agency problem. Senior administrators use three criteria to evaluate enrollment managers: The size of the incoming class, the quality of that class, and the amount of tuition discounting expended to recruit the class. After the students enroll, the size of the incoming class and the quality of that class are easily measured. The number of students enrolled, their college entrance examination scores, their high school grade point averages, their high school class rank, gender, minority status, and need for financial aid are all obvious. In sharp contrast, it is very difficult to determine if the enrollment manager "paid too much for the class."

In order to measure excessive discounting, the institution needs some estimate of the minimum financial aid award required to induce each student to enroll. The summation of the difference between the actual financial aid awarded and the minimum aid required would represent the dollar value of excess discounting. Dividing that sum by the total tuition discount yields a measure of excess discounting. Unfortunately, the excess discounting is very difficult to measure, so difficult that most institutions do not attempt to measure it.

The rational response among enrollment managers is to direct their efforts towards the measurable criteria and to ignore the criteria that cannot, or is not, measured. Indeed, an enrollment manager can insure a superior result in terms of the quantity and the quality of the students enrolled by aggressive discounting. If this agency problem is widespread, normal recruiting competition among institutions can produce a collective spiral in tuition discounting. Furthermore, if academic rankings focus more on the quality of the inputs rather than value added, senior administrators will be hesitant to criticize the enrollment manager as long as student quality remains high.

Consider the effect of the 'Overlap Group's policies on this agency problem. If institutions are sharing financial aid information about students whose applications overlap, that shared information provides a ready measure of the excessive discounting for each overlapping student. The Overlap Group's policies served to insure that all

enrollment management criteria are measurable. Hence, it is not surprising that the era of aggressive discounting began after the demise of the Overlap Group. While the decision only directly affected the institutions that composed the Overlap Group, the signal to other institutions that public policy had shifted from cooperation with respect to financial aid awards to competition would be unmistakable. Any informal arrangements for sharing information would stop.

The empirical anomaly may also be the result of a production externality. The additional aid provided to enthusiastic students can be a reward for enthusiasm. Attitude plays an important role in the education process for both individual students and the class as a whole. A large cohort of enthusiastic students means a better educational experience. Hence, enthusiasm is a positive production externality. Alternatively, a large cohort of students paid to attend may lead to negative externalities in production if the financial aid was the primary reason for their matriculation and not academic or extracurricular characteristics of the IHE. If this explains the positive correlation between the probability of enrollment and the aid awarded, then, one cannot conclude that the aid awards are inefficient since they are a reward for positive production externalities.

Finally, higher education institutions frequently do not consider efficiency when addressing problems, particularly when it concerns pricing across individuals. Fairness is a core value for many academics and 'price discrimination' based on willingness to attend does not set well with some faculty and administrators. The notion will be alien to many decision makers.

V. Conclusion

This paper contains empirical models of financial aid allocation and enrollment demand. The data are generally consistent with what theory would lead us to expect. There is one major exception: for both College A and B, students that are more likely to enroll in the college receive higher financial aid offers. This contradicts theory and suggests that both colleges tend to offer higher tuition discounts than are necessary to attract students in need, have merit, or are diversity students. Though the two schools in our study are quite different, we caution that this result may not be generalizable to the

approximately 4,000 colleges and universities in the United States - thus this question is fertile ground for future research.

We speculate that this result is likely due to traditional institutional practices. Enrollment managers are most concerned about meeting their minimum enrollment numbers and student quality objectives. If they meet those numbers and enroll a good class, they are not likely to be criticized for paying too much for the students enrolled. The collective effect of excessive discounting across many colleges is to weaken the financial condition of all colleges. This seems consistent with those who view the current level of discounting to be excessive. Our results suggest that the situation can be improved by having each institution's chief financial officer take a more active role in the financial aid process and having admissions and financial aid officers more fully embracing a data driven approach to the enrollment management process.

The data driven approach is not without influential adversaries. As Gordon Winston, Economist at Williams College bluntly said of enrollment management, "It's a brilliant analytical process of screwing poor kids."[21] These remarks seemed to have been directed at those schools that are "buying the best", but they are increasingly being directed at the enrollment management industry in general. Now that 75% of four year colleges and universities employ enrollment managers to oversee admissions and financial aid[22] the criticism is that enrollment managers instill market driven competition into the recruitment process and that this has the pernicious effect of leaving well-qualified, low-income students behind. However, the question we are addressing in this paper is efficiency of institutional behavior in the sense that it does not waste resources. We find IHE's may be wasting considerable resources because they are insufficiently bottom line oriented. Thus, these arguments ignore the fact that additional revenues generated through effective enrollment management can lead to an increase in need based aid – making college more accessible to the needy, yet academically qualified, minority of students.

---

[21] *Atlantic Monthly*, November 2005, "The Best Class Money Can Buy".
[22] Ibid.

References

Allen, Robert F. and Jianshou Shen. 1999. "Some New Evidence of the Character of Competition Among Higher Education Institutions." *Economics of Education Review 18(4)*: pp. 465-470.

Amemiya, T. 1979. "The Estimation of a Simultaneous-Equation Tobit Model", *International EconomicReview,* 20: 169-181.

_____ 1978. "The Estimation of a Simultaneous Equation Generalized Probit Model", *Econometrica,* 46: 1193-1206.

Brewer, Dominic J., Susan M.Gates and Charles A. Goldman. 2002. *In Pursuit of Prestige: Strategy and Competition in U.S. Higher Education.* New Brunswick: Transaction Publishers.

Buss, Christian, Jeffrey Parker and Jon Rivenburgm. 2004. "Cost, Quality and Enrollment Demand at Liberal Arts Colleges." *Economics of Education Review 23:* 57-65.

Cook, Phillip J., and Robert H. Frank. 1993. "The Growing Concentration of Top Students at Elite Institutions." In *Studies of Supply and Demand in Higher Education* (ed. Charles T. Clotfelter and Michael Rothschild). Chicago: University of Chicago Press.

Curs, B., and Larry Singell, Jr. 2002. "An Analysis of the Application and Enrollment Processes for In-State and Out-of-State Students at a Large Public University." *Economics of Education Review 21:* 111-124.

Deis, D.R., and R.C. Hill, R.C. 1998. "An Application of the Bootstrap Method to the Simultaneous Equations Model of the Demand and Supply of Audit Services", *Contemporary Accounting Research,* 15: 83-99.

Desjardins, Stephen L. 2001. "Assessing the Effects of Changing Institutional Aid Policy." *Research in Higher Education 42(6):* pp. 653-678.

Duffy, Elizabeth A. and Idana Goldberg. 1998. *Crafting A Class: College Admissions & Financial Aid, 1955-1994.* Princeton, New Jersey: Princeton University Press.

Ehrenberg, Ronald G. 2000. *Tuition Rising: Why College Costs So Much*. Cambridge, MA: Harvard University Press.

Ehrenberg, Ronald G. and Daniel R. Sherman. 1984. "Optimal Financial Aid Policies for a Selective University." *The Journal of Human Resources*, 19(2), 202-230.

Esposito, Frances Ferguson and Louis Esposito. 1995. "Monopolization, Social Welfare, and Overlap." *The Antitrust Bulletin*, 433-451.

Greene, W.H., 2003. *Econometric Analysis,* New Jersey: Prentice Hall.

Grossman, Herschel. 1995. "Scholarships: Need or Merit?" *Cato Journal*, 14(3), 519-525.

Heller, Donald E. 1997. "Student Price Response in Higher Education: An Update to Leslie and Brinkman." *Journal of Higher Education*, 68(6): 624-659.

Hoenack, Stephen. 1971. "The Efficient Allocation of Subsidies to Higher Education." *American Economic Review* 61: 302-311.

Hopkins, David S. P. and William E. Massy. 1981. *Planning Models for Colleges and Universities*. Stanford, California: Stanford University Press.

James, Estelle. 1990. "Decision Processes and Priorities in Higher Education," in Hoenack, Stephen A., and Eileen L. Collings, *The Economics of American Universities*. Buffalo, NY: State University of New York Press.

Mallar, C. 2000. "The Estimation of Simultaneous Probit Models", *Econometrica,* 58: 173-188.

Manski, Charles F. and David A. Wise. 1983. *College Choice in America*. Cambridge, Mass: Harvard University Press.

Martin, Robert E. 2005. *Cost Control, College Access, and Competition in Higher Education*. North Hampton, MA: Edward Elgar, Ltd.

McPherson, Michael S. and Morton Owen Schapiro. 1999. "Gaining Control of the Free-for-all in Financial Aid." *The Chronicle of Higher Education*, (July 2), A48.

_____. 1991. "Does Student Aid Affect College Enrollment? New Evidence on a Persistent Controversy." *American Economic Review*, 81(1): 309-318.

Moore, R. L., A. H. Studenmund and T. Slobko. 1991. "The Effect of the Financial Aid Package on the Choice of a Selective College." *Economics of Education Review*, 10(4): 311-321.

Murphy, K., and R.Topel. 1985. "Estimation and Inference in Two Step Econometric Models", *Journal of Business and Economic Statistics,* 3: 370-379.

Nelson, F., and L. Olson. 1978. "Specification and Estimation of a Simultaneous-Equation Model with Limited Dependent Variables", *International Economic*

Review, 19: 695-709.

Quirk, Matthew. 2005. "The Best Class Money Can Buy." *The Atlantic Monthly,* November:128-134.

Redd, Kenneth E. 2000. "Discounting Toward Disaster: Tuition Discounting, College Finances, and Enrollments of Low-Income Undergraduates." *New Agenda Series*: USA Group Foundation, 3(2) December.

Rothschild, M. and L. J.White. 1995. "The Analytics of Pricing in Higher Education and Other Services in Which Customers are Inputs." *Journal of Political Economy,* 103 (June): 573-586.

Singell, Larry D. and Joe A. Stone. 2002. "The Good, The Poor and the Wealthy: Who Responds Most to College Financial Aid?" *Bulletin of Economic Research 54(4)*: 393-407.

Singell, Jr., Larry D. 2002. "Merit, Need and Student Self-Selection: Is There Discretion in the Packaging of Aid at a Large Public University?" *Economics of Education Review 21:* 445-454.

St. John, E. P. 1990. "Price Response in Enrollment Decisions: An Analysis of the High School and Beyond Sophomore Cohort." *Research in Higher Education*, 31(2): 161-176.

_____ and J.B. Starkey. 1995. "An Alternative to Net Price." *Journal of Higher Education*, 66: 156-186.

Tiffany, Frederick G. and Jeff A. Ankrom. 1998. "The Competitive Use of Price Discrimination by Colleges." *Eastern Economic Journal*, (Winter), 24(1): 99-110.

van der Klaauw, W. 2002. "Estimating the Effect of Financial Aid Offers on College Enrollment: A Regression-Discontinuity Approach." *International Economic Review 43(4).*

Zimmer, M. 2001. "Disability Reposting Choices by Married Couples: Evidence from Census Data", *Southern Economic Journal*, 67: 922-937.

Table 1
Mean Institutional Characteristics
Academic Year 2003-2004

Panel A: Institutional Characteristics

	College A	College B
Total Enrollment	1,069	5,687
Student-Faculty Ratio	11.5	43.7
Tuition Dependence[a]	28.70%	50.30%
Discount Rate[b]	34.90%	11.60%
Percent receiving Aid[c]	88.30%	75.40%
Endowment per Student	$140, 237	$9,377
Acceptance Rate[d]	68.50%	72.90%
Enrollment Yield[e]	27.00%	33.90%
Cost of Attendance	$30,900	$17,150
Weighted Average Faculty Salaries	$60,562	$63,908
Instruction Percent[f]	37.00%	43.10%
Academic Support Percent[f]	6.90%	9.80%

Panel B: Admitted Student Characteristics

	College A	College B
Total Grant Aid	$8, 971	$2,699
Need	$5, 743	$3, 541
Expected Family Contribution	$31, 578	$14, 257
Internal Grant Aid	$7, 251	-
External Grant Aid	$1, 720	-
Merit Aid Recipients	-	15.47%
Top 10% of High School Class	84.08%	23.43%
SAT	1,221	1,081
Female	52.00%	56.39%
Minority	4.68%	2.09%

[a] Tuition and fees as a percent of total revenues.
[b] Discount rate for entering class, total federal, state, local, and institutional grants per entering student divided by total price.
[c] Percent of entering class receiving aid.
[d] Total admitted students as a percent of total applications.
[e] Total enrolled students as a percent of total admitted students.
[f] Activity as a percent of total expenditures.

Table 2
Single Equation Probit Models
Dependent Variable is Probability of Enrollment

	College A		College B	
Variable	Estimate	Standard Error	Estimate	Standard Error
Intercept	1.081	0.251*	-1.465	0.158*
Need	-0.039	0.005*	-0.093	0.007*
Grant Aid	0.080	0.005*	0.270	0.012*
Loans	0.184	0.016*		
Distance	-0.049	0.018*		
Distance Sq.	0.002	0.001**		
SAT	-0.088	0.014*	-0.006	0.013
High School GPA	-0.308	0.054*		
Top 20% HS Rank	-0.359	0.095*	-0.332	0.047*
Top 40% HS Rank	-0.219	0.098***	0.048	0.038
Top 20% HS Size	-0.171	0.047*		
Top 40% HS Size	0.055	0.04		
Scholars Program	-0.177	0.05*	1.455	0.046*
Peers	0.001	0.00	0.001	0.000*
Legacy	0.609	0.07*		
Campus Visit	0.496	0.04*		
Black	-0.388	0.12*	-0.872	0.146*
Hispanic	-0.295	0.19	-0.207	0.119
Female	-0.010	0.03	-0.036	0.033
State 1	-0.075	0.08		
State 2	-0.191	0.11		
State 3	-0.199	0.09**		
State 4	-0.616	0.20*		
State 5	-0.224	0.08*		
State 6			0.185	0.110
State 7			0.010	0.075
State 8			-0.250	0.082
State 9			0.061	0.073*
State 10			-0.035	0.073
FAFSA Filer	0.274	0.04*	0.034	0.046
Log-Likelhood	-3,972		-4,000	
Observations	7,699		11,304	

* Significant at the .01 or better level.

** Significant at the .02 or better level.

*** Significant at the .05 or better level.

Table 3
Determinants of Academic Student Ratings
Ordinary Least Squares Regressions

	College A		College B	
Variable	Estimate	Standard Error	Estimate	Standard Error
Intercept	-897.30	29.03*	17.83	26.33
SAT	1.74	0.03*	0.87	0.01*
Top 20% HS Rank	2.37	0.20*	0.83	0.03*
Top 40% HS Rank	0.02	0.21	0.11	0.03*
High School GPA	3.67	0.11*		
National Merit Semi-Finalist	1.76	0.16*		
National Merit Nominee	1.29	0.12*		
Black	0.02	0.25	6.20	0.05*
Hispanic	0.69	0.38	5.67	0.07*
Female	0.33	0.07*	-0.04	0.02**
Year	0.44	0.01*	-0.01	0.01
Adjusted R^2	0.63317		0.7171	
Observations	7,699		11,304	

* Significant at the .01 or better level.

** Significant at the .02 or better level.

*** Significant at the .05 or better level.

Table 4
Simultaneous Equation Probit Models
Dependent Variable is Probability of Enrollment

	College A		College B	
Variable	Estimate	Standard Error	Estimate	Standard Error
Intercept	-0.22	0.36	-2.48	0.20*
Need	0.01	0.01	0.03	0.01*
Grant Aid	-0.01	0.02	-0.08	0.02*
Loans	0.21	0.02*		
Distance	-0.04	0.02***		
Distance Sq.	0.00	0.00		
SAT	-0.02	0.02	0.09	0.02*
High School GPA	-0.12	0.06***		
Top 20% HS Rank	-0.26	0.10*	-0.16	0.05*
Top 40% HS Rank	-0.21	0.10***	0.08	0.04***
Top 20% HS Size	-0.15	0.05*		
Bottom 20% HS Size	0.08	0.04		
Scholars Program	-0.07	0.05	1.85	0.05*
Peers	0.00	0.00***	0.00	0.00*
Legacy	0.74	0.08*		
Campus Visit	0.39	0.04*		
Black	-0.04	0.14	0.85	0.17*
Hispanic	-0.12	0.20	-0.17	0.13
Female	0.01	0.03	-0.02	0.03
State 1	0.01	0.08		
State 2	-0.10	0.11		
State 3	-0.15	0.08		
State 4	-0.60	0.20*		
State 5	-0.16	0.08***		
State 6			0.02	0.11
State 7			0.05	0.07
State 8			-0.23	0.08*
State 9			0.13	0.07
State 10			-0.02	0.07
FAFSA Filer	0.43	0.05*	-0.18	0.04*
Log-Likelhood	-4097.47		-8904.53	
Observations	7,699		11,304	

* Significant at the .01 or better level.

** Significant at the .02 or better level.

*** Significant at the .05 or better level.

Table 5
Simultaneous Equation Tobit Models
Dependent Variable: Total Student Grant Aid Award

	College A		College B	
Variable	Estimate	Standard Error	Estimate	Standard Error
Intercept	-23.15	0.75*	-16.36	0.51*
Need	0.53	0.01*	0.53	0.01*
SAT	0.89	0.04*	0.96	0.04*
High School GPA	2.91	0.16*		
Top 20% HS Rank	1.85	0.34*	1.27	0.12*
Top 40% HS Rank	0.64	0.35	0.48	0.12*
Scholars Program	0.81	0.14*	3.24	0.33*
Black	4.65	0.34*	-0.78	0.35***
Hispanic	2.19	0.52*	0.39	0.34
Female	0.20	0.10***	0.16	0.09
State 1	0.97	0.14*		
State 2	1.28	0.31*		
State 3	0.56	0.22**		
State 4	0.62	0.51		
State 5	0.86	0.18*		
State 6			0.13	0.34
State 7			0.56	0.21*
State 8			0.76	0.23*
State 9			-0.80	0.21*
State 10			0.57	0.21*
FAFSA Filer	2.03	0.13*	-0.92	0.14*
RESID	0.36	0.02*	0.71	0.04*
Enroll	4.73	0.44*	3.38	0.60*
Log-Likelhood	-18,300.03		-8,904.53	
Observations	7,699		11,304	

* Significant at the .01 or better level.

** Significant at the .02 or better level.

*** Significant at the .05 or better level.

Appendix Table 1
Variable Descriptions

Academic ratings – Numerical ranking of each student provided by enrollment case managers.
Aid – Total institutional and external grant aid made available to each student (in $1,000s).
Black – minority status, zero/one.
Campus visit – Did the student visit the campus, zero/one.
Distance – linear distance from college zip code to student's zip code measured in hundreds of miles.
Enrollment – dichotomous enrollment result.
FAFSA – Did the student file a FAFSA form, zero/one.
Female – gender, zero/one.
Hispanic – minority status, zero/one.
HS class rank – Student's high school class rank upon graduation, percentile.
HS class size – size of student's high school graduation class.
HS gpa – Student's high school grade point average.
Legacy – Does the student have a close family member who attended the college, zero/one.
Loan – student loan amount (in $1,000s)
Minority – minority status, zero/one.
Need – Cost of attendance less expected family contribution for College B and also less state scholarship for College A (in $1,000s)
NM semi-final – National Merit finalist or semifinalist, zero/one.
NM nominee – National Merit nominee, zero/one.
Peers – number of students admitted from the student's same high school for College A and number of students admitted from the student's same zip code for College B.
Resid – Variation in the academic ranking of each student not explained by the objective factors.
SAT – Student's combined SAT math and verbal scores. Students who took the ACT had their scores converted to SAT equivalents per College Board conversion factors. Scholars prog – state sponsored high school scholars program.
State i – student is resident of the ith state, zero/one.
Top 20 – Top twenty percent of high school graduating class, zero/one.
Top 40 to 20 – Between top twenty and forty percent of high school graduating class, zero/one.