# A REVEALED PREFERENCE RANKING OF U.S. COLLEGES AND UNIVERSITIES

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**Abstract**

We construct a ranking of U.S. colleges and universities based on students' revealed preferences. That is, we show which college students prefer when they can choose among alternatives. The ranking shows students where their most talented peers are concentrated and what ability their college degree will signal. Also, because the ranking reflects information gathered by many students, it is a more reliable indicator than the observations of any individual student. Finally, our ranking is unbiased and non-manipulable, unlike crude indicators of preference such as the matriculation and admission rates. We use data from a survey of 3,240 highly meritorious students that was conducted specifically for this study. Although we account for the potentially confounding effects of tuition, financial aid packages, alumni preferences, and other preferences; these factors turn out not to affect the ranking significantly. We develop a statistical model that logically extends models used for ranking players in tournaments, such as chess and tennis. When a student makes his matriculation decision among colleges that have admitted him, he chooses which college "wins" in head-to-head competition. The model exploits the information contained in thousands of these "wins" and "losses." We simultaneously use information from colleges' admissions decisions, which implicitly rank students.

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## I. Why a Revealed Preference Ranking is Important

In this study, we construct a revealed preference ranking of American colleges and universities. In other words, we show which college students generally prefer when they can choose among alternatives. The result is a ranking of colleges based on their desirability. To construct the ranking, we use data from a survey of 3,240 highly meritorious students. The survey was conducted specifically for this study. We use a statistical model that we developed specifically for this application, but it is a logical extension of models used for ranking players in tournaments, such as chess and tennis. Essentially, when a student makes his matriculation decision among colleges that have admitted him, he determines which college "wins" in head-to-head competition. Our model exploits the information contained in thousands of these "wins" and "losses." We simultaneously use information from colleges' admissions decisions, which implicitly rank students. Although we account for the potentially confounding effects of tuition, financial aid packages, alumni preferences, and other preferences; these factors turn out not to affect the ranking significantly.

The revealed preference ranking has some obvious good qualities. Unlike rankings based on obscure and arbitrary formulas invented by self-appointed college guides, the revealed preference ranking is based on something that everyone can understand: actual students' behavior. Also, the ranking turns out to be well-defined and stable–that is, it does not turn on decisions such as how we account for financial aid offers. It is reasonable to ask, however, why we should care about a revealed preference ranking at all. Why should we care what value *students* place on a college? There are four answers to this question, two of which are fundamental and the fourth of which is purely practical.

First, students believe that their peers matter, and students act as though their peers matter. Many students argue that they learn from their peers as well as from faculty, books, and other course materials. They argue that learning spills over from other students in informal "teaching" that occurs when students discuss course material, study together, and share hints. If this argument is correct, then students want to be surrounded by peers who are knowledgeable and good at extracting new information from sources like faculty and books. In other words, students desire peers with high college aptitude. Therefore, students *should* care about a revealed preference ranking because it will show them which colleges can offer the highest concentration of desirable peers. (Because a more preferred college "wins" more often in the matriculation tournament, it can afford to be more selective and it can thus offer peers with higher aptitude.) Of course, college guides provide some proxies for the desirability of college peers (median SAT scores, for instance), but they weigh these arbitrarily.

Second, students–especially the meritorious students on whom we focus–are not ignorant. They gather information about colleges from numerous sources: published guides, older siblings, friends of similar merit who are attending college, college counselors, and their own visits to colleges. Each student's should value his own observations because he can, in making them, consider his own tastes, ask questions that particularly apply to him, and so on. Nevertheless, a student should also value the observations of other students who are reasonably like him in aptitude because his own sample of observations is too small to be representative. A revealed preference ranking aggregates the observations of thousands of students, and aggregation generates very valuable information. Readers should find this no surprise; there are many parallel cases for goods or services where a person's own observations are necessarily a small share of the number that would be needed to get an accurate sense of quality. For instance, people care about their own experience at a restaurant, but they also want to know about other people's experiences, simply because they contain information. When people choose cars, they care about their own test drives, but they also care about other people's experiences with the same model.

Third, it has long been hypothesized that specific colleges' degrees serve as signals of a student's ability, which is hard for future employers to observe directly [Spence, 1974]. In equilibrium, a college's degree signals the ability of the students who actually attend it. For instance, a Tufts' degree signals ability based on the actual distribution of ability among Tufts' students. This is another reason for students to care about the ability of their peers. Note, however, that the importance of signaling is more controversial than the other two fundamental reasons why students should care about revealed preference. Signaling may be unimportant if students can use indicators, other than their college degrees, to inform future employers about their abilities. For instance, a student whose abilities much exceed those of his college classmates could reveal his very high grades, his leadership, his ability to win national fellowships, and so on.

The fourth reason for a revealed preference ranking is a practical one: parents and students demand revealed preference information and college guides feel obliged to offer them some. However, colleges guides do not construct accurate revealed preference rankings. Instead, they use proxies for revealed preference that are not only inaccurate (in the sense of being noisy), but systematically biased, misleading, and manipulable. The two proxies most often used by college guides are the matriculation rate and admissions rate. These measures are noisy because they are crude aggregates. A true revealed preference ranking uses the *individual* decisions of students and colleges and aggregates the information contained in them in a far more efficient manner. Noisiness is not a serious problem, however, compared to the bias and manipulability of the matriculation rate and admissions rate.

For instance, consider the matriculation rate–the share of accepted students who matriculate at a college:

(1) $$\frac{\textit{number of students who matriculate}}{\textit{number of students who are admitted}}\ .$$

The matriculation rate is systematically biased against colleges that have close competitors because they will be less able to predict which students will accept their offer of matriculation. Such colleges must admit more students per matriculant in order to get a class of the right size. Moreover, a college can easily manipulate its matriculation rate in order to appear more valued than it really is. Consider just a few manipulation methods. A college can make itself a "niche college" so that students who apply have unusual tastes that make them unlikely to go elsewhere if admitted. A college can purposely not admit students who are likely to be admitted by close competitors or more highly preferred colleges. A college can institute an early decision program that forces applicants to pre-commit to matriculating if they are admitted. Suppose, for instance, that Princeton wanted to raise its matriculation rate. It could decide to admit only students who were very likely to fall just short of the admissions thresholds for Harvard, Yale, Stanford, MIT, Williams, and other close competitors. The students admitted would thus have no colleges in their "menus" that were close competitors to Princeton, and they would be likely to matriculate. (See Ehrenberg [2000] and Ehrenberg and Monks [1999] for evidence that such conduct really does occur.) Now, students who attend Princeton would almost certainly prefer that the university *not* pursue such a policy because it would reduce the peer quality of their fellow students. Yet, college guides would *raise* their assessment of Princeton's appeal just as its actual appeal fell. Any proxy for revealed preference is extremely flawed if it can be manipulated so that it goes in the opposite direction to students' true preference for a college.

Another popular but deeply flawed proxy for revealed preference is the admission rate–that is, the share of applicants who are admitted by a college:

$$\frac{\textit{number of students who are admitted}}{\textit{number of students who apply}} \quad (2)$$

We have already seen that colleges can manipulate the number of students whom they admit. They can also influence the number of students who apply by encouraging applications from students who have little chance of actually gaining admission. A college can advertize lenient or flexible admissions criteria, while actually applying strict criteria. For instance, a college can claim to take a generous view and to broadly consider a variety of abilities, achievements, and mitigating circumstances. Such a procedure will encourage marginal applicants who have little chance of admission based on their overall record, but who hope to be admitted because of a special talent or special circumstances. Clever advertising can increase a college's number of applications, its acceptance rate, and its apparent value to students. In reality, the college will not be any more preferred than it was previously.

In short, students and parents demand measures of revealed preference, and college guides typically respond with misleading proxies. Because the proxies are also manipulable , colleges may be induced to distort their conduct in order to appear to be more desirable, even if the conduct actually makes them less desirable. This is a game in which all parties lose. It would be very useful to have a measure of revealed preference that is accurate, unbiased, and not easily manipulated.

In the next section, we describe the statistical method we use to create a revealed preference ranking of colleges. In the formal exposition there, it will become clear why our revealed preference ranking does not suffer from the problems that plague proxies like the matriculation rate and acceptance rate. Here, we can give some intuition into why our method works better.

Our method is based on "wins" and "losses" in thousands of "tournaments" in which students are choosing the college at which to matriculate. Under this method, a college's ranking vis-a-vis a competitor is based on their record of wins and losses. Colleges that rarely compete directly in tournaments (because they are of very different selectivity) are ranked using the win/loss records of intermediate colleges that link them through series of tournaments: A routinely competes with B, B routinely competes with C, C routinely competes with D, and so on. Simultaneously, we use each student's admissions record to determine his merit; each student competes in one or more colleges' admissions contests. When ranking the most selective colleges, say, we automatically focus on the behavior of students who are actually choosing among them. Given our methods, there is no easy way for a college to artificially boost its ranking with no true change in its appeal to students. For instance, recall the example in which Princeton alters its acceptance decisions in order to avoid match-ups with Harvard, Yale, Stanford and so on. We would be unable to rank Princeton rank vis-a-vis its close competitors because its match-ups would always be against less selective colleges. That is, the standard errors on our estimates would reflect the fact that Princeton was not admitting the highly meritorious students for whom it should have been competing. We would see that, while it was consistently "winning," it was winning only among students who failed to get admitted to close competitors. In short, by simultaneously estimating the desirability of colleges and the desirability of students, we get a much clearer picture of revealed preference than one can get by simply looking at a matriculation rate or an admission rate.

For further intuition, it may be helpful for readers to think of some sport (tennis, golf, *et cetera*) or game (chess, bridge, *et cetera*) familiar to them. If a ranking system is properly constructed in a sport or game, there is no easy way for players to manipulate it. We are all familiar with the idea that a tennis or chess player should not be able to gain a top ranking if he avoids important tournaments and therefore never competes against the best players. We are all familiar with the idea that we can only judge the importance of a player's win or loss if we know something about the ability of his adversary. The statistical methods for constructing a revealed preference ranking of colleges are logically related to methods of ranking players. A good deal of familiar intuition carries over, even though college rankings are different in several dimensions (colleges' independent admissions decisions determine the colleges in any given tournament, students make matriculation decisions based on criteria that include but are not limited to a college's desirability, colleges' make admissions decisions based on criteria that include but are not limited to a student's merit, and so on).[1]

In the remainder of the paper, we describe our survey, our data, our statistical method, and the revealed preference ranking itself. After presenting the basic results, we consider the potentially confounding effects of tuition, financial aid packages, alumni preferences, and a variety of other factors that might make a college or student "win" when it (he) would lose on the basis of its (his) intrinsic desirability. In this version of the paper, we do not deal explicitly with early decision applicants who apply to only one college. They make up about 10 percent of our sample. However, we do have a method for dealing with these students, and our preliminary results suggest that they do not significantly affect the ranking. Because dealing with early decision applicants involves very considerable computational time, we await full results.

Although we have argued that a revealed preference ranking of colleges is useful, we wish to state clearly that we are *not* recommending that students choose colleges wholly or mainly on the basis of such a ranking. When making college decisions, one student may give great weight to indicators of revealed preference; another student may give negligible weight to them. We do not claim to know which student is right; we do not even claim to know whether there *is* some optimal weight. Our interest in revealed preference for colleges should not be taken as an endorsement for any particular use of the revealed preference ranking. We support students using all available information about colleges to make their application and matriculation decisions. Although we have been critical of college guides' use of proxies for revealed preference, we believe that college guides perform a valuable function by gathering and publishing uniform measures of a variety of other college characteristics (costs, housing, faculty,

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[1] Based on the dimensions we list, ranking colleges is a more complex statistical problem than is ranking players in sports or games. However, sports and games present one problem that college rankings do not: tournaments are typically spread out over time, and players' abilities can change over the relevant time period. In the college problem, students make matriculation decisions in a relatively concentrated time period (5 months at most) over which colleges' true quality is essentially static.

*et cetera*) that interest prospective students.

## II. The Desirability of Colleges and Students

The exercise of ranking colleges or students is necessarily predicated on the notion that there is some unidimensional index of desirability on which they *can* be ranked. In the language of econometrics, the exercise is necessarily based on the assumption there is a latent variable that indicates the desirability of each college or student. We shall call the latent variable "desirability" to remind readers that the indicator is based on revealed preference. However, readers may find it useful to think of desirability as some overall construct of merit. We do not claim to know (or need not know) how these constructs of merit are created or whether they are optimal constructions, in terms of advancing either private self-interest or social good. We simply assert that, to the extent that students and colleges act in accordance with the existence of these indices of desirability, we will construct rankings around them.

Colleges' and students' desirability are *latent* variables because we not expect ever to see them concretely. That is, they do not correspond to variables that we observe. However, we can speculate about what factors they are likely to encompass (although with unknown weights) and we can be definite about factors that are excluded. For instance, consider the desirability of a college. It is likely to comprise numerous factors that students take to be indicators of a college's quality: expected spillovers and other benefits from peers, classroom and library resources, laboratories, computing and communications technology, faculty who are successful teachers, faculty who are successful researchers and authors, advisors who have a record of successfully counseling students about curricular choices and career plans, and so on. The desirability of a college excludes factors that measure price rather than quality: tuition; room and board; discounts in the form of grants, subsidized loans, or work-study commitments; costs of being transported to the college; and so on. We recognize that such price factor influence college choice, but they are not indicators of quality. We want to have an index of desirability that is free from prices so that we can say whether a college is more likely to be picked on a "price-considered" or "price-not-considered" basis.

Now consider the desirability of a student. It is likely to comprise factors that colleges take to be indicators of a student's quality: measured aptitude, measured academic achievement, demonstrated leadership, demonstrated talent or achievement in an extracurricular activity, emotional maturity, intellectual maturity, demonstration of unusual motivation or perseverance, unusual experiences that could be shared with classmates (from travel or an upbringing), and so on. We define a student's desirability to exclude factors that may make give a student preference in admissions but which are not meritorious *in and of themselves*. Also, by definition, a latent student desirability is a unidimensional aggregate and therefore must exclude factors to which not every student can aspire. These two criteria give us a list of factors that should be excluded: being the child of an alumnus, being from an underrepresented group, being from in-state, having well-off parents, and so on. This is not the best place to discuss this point further because it will be easier to understand when the statistical model has been presented. However, we recognize that readers may be inclined to misinterpret this point, and we advise them to suspend their queries until they reach our discussion below.

For our exercise, is it necessary that all students identically perceive a college's desirability or that all college identically perceive a student's desirability? No. We will allow students' perception of a college's desirability to be distributed around a mean level, and we will allow colleges' perception of a student's desirability to be distributed around a mean level. Indeed, if there were no such distributions, all students would make identical matriculation decisions when offered the same choices and all colleges would make identical admissions decision when offered the same applicants. We know that this does not occur. What we need for our exercise is a pattern of wins and losses that would arise if colleges and students had latent desirabilities that were perceived with idiosyncratic noise added in.

What if no such latent variables influence students and colleges? Our exercise does not *impose* their existence; it simply will not work if they do not exist. To see this, suppose that there were no uniformity in how students perceived colleges' desirability. Each student would act as though he had been randomly assigned a ranking of colleges, where his ranking was independent of all other students' rankings. We would be able to find no pattern in the "wins" and "losses" because it would be random whether a college won or lost in head-to-head competition for a student. Moreover, we would find that all colleges were equally likely to appear with one another in students' choice sets. That is, Princeton would be no more likely to appear again and again with Yale in students' choice sets than it would be to appear again and again with the University of Akron. In short, our data would not be informative about the existence of latent desirability, and it would not allow us to estimate rankings with any precision.

Overall, we can afford to be agnostic about how and whether students develop preferences over colleges and colleges develop preferences over students. Our data will only reveal such preferences to the extent that they exist. We do not expect to be able to rank all colleges. For instance, it might be hard to rank Juilliard (a music school) and a pure engineering school because they are likely to have very few intermediating tournaments that indirectly connect them. For similar reasons, it might be hard to rank two colleges that draw from entirely different areas of the country. We will rank as many colleges as our data permit, but we acknowledge that–once outside a certain group of colleges with a national or broad regional draw–students' revealed preference might only help us rank colleges *within* a geographic area or type of school (music, engineering, and so on).

## III. A Statistical Method for Ranking Colleges

We want to use students' revealed preferences to rank colleges and colleges' revealed preferences to rank students. Although we are not interested in the student ranking *per se*, performing both rankings simultaneously generates the best estimates, as will be seen.

A. Ranking Colleges is a Paired and Multiple Comparison Problem

The problem of ranking colleges can be framed as a collection of paired and multiple comparisons. We obtain comparison data from any competition in which alternatives are compared and an outcome indicates that one alternative has been preferred over the others. Many sports and games fall into this framework because players are compared via competition, and the winner of a competition is deemed the "preferred alternative." Also, marketing applications, including experiments in which consumers choose among products or services, are well-suited to paired and multiple comparison models. As we describe below, college choice fits into this framework as well, though not in a conventional manner. An important problem addressed by paired and multiple comparison models is how to rank objects, recognizing that many direct comparisons do not take place. For example, in the context of a "Swiss system" chess tournament, every competitor competes against only a few other individuals rather than against every other competitor. That is, player A competes against B, and B competes against C, but A does not compete against C. Yet, an inference is still desired for the comparison of A versus C. In the context of college choice, every college does not compete directly with every other college, though the goal is to draw conclusions about all colleges' desirability.

To understand how college choice can be viewed as a paired/multiple comparison problem, suppose that a fixed collection of students are applying to a set of schools. Suppose that each student and each school is a competitor entered in two tournaments, in sequence. In the first tournament, each student is paired against each school to which he applied. A "game" occurs between the student and the school. If the student is admitted to the school, then this outcome is equivalent to the student having won the game. If the student is denied admission, then the school has won the competition. Intuitively, when a student is admitted to a school, then he has, in some sense, higher desirability than the school; if the converse, then the student is not "good enough" for the school. In the second tournament, the collection of schools that admitted a student compete against each other in a "multi-player" game. When a student matriculates at a particular school among the those that admitted him, that school has won the multi-player game. A reasonable inference, therefore, is that (assuming no confounding variables) the school that wins the multi-player game is generally preferred to the other schools in that competition. By aggregating the information in these two "tournaments" through an appropriate statistical model, inferences about the desirability of schools and students can be constructed from the comparison data. In principle, in this framework, students and schools can be ranked on the same scale relative to each other. However, only the ranking of colleges is useful to report.

To understand how a probability model for comparison data is constructed, suppose that each student and each college owns a box containing slips of papers with numbers written on them. The mean value of the slips of paper within a box is an indication of overall desirability. When a student applies for admission at a college, the comparison model, in effect, assumes that the student and the college randomly draw a slip of paper from their own boxes, and the higher value "wins" the game. Even if the college is more desirable than the student (that is, the values in the college's box are *generally* higher than that of the student's), there is still a non-zero probability that the student would win, even if the likelihood is that the student would lose and not be admitted to the school. Similarly, during the matriculation choice when colleges compete in a multi-player competition, each draws a slip from its own box, and the highest one wins (that is, the student matriculates at that college). The slips of papers that are drawn in a game are the observed performances for that game. The set of values in each box is the *distribution* of potentially observed desirability for that student or college. The goal of statistical modeling from comparison data is to infer the mean values in all of the boxes, though we will report only the mean values for the colleges.

There is a rich body of work on paired comparison modeling, and extensions to multiple comparison modeling, surveyed by David (1988). While no one has previous modeled college choice using comparison models, there are abundant applications for divining chess ability from tournament data-- see, for example, Zermelo (1929), Good (1955), Elo (1978) and Glickman (1993, 1999, 2001).

We build on the Bradley-Terry (1952) model for paired comparisons and the Luce (1959) extension for multiple comparisons, in which the distribution of desirability for a college or student is an extreme value distribution, having the same shape but centered at a different value depending on the college's or student's overall desirability. The assumption of an extreme value distribution for the potentially observed desirability leads to a logit model for paired comparisons, and to a multinomial logit model for multiple comparisons.

The main alternative to the assumption of an extreme value distribution for potentially observed desirability is a normal distribution. This leads to a class of models studied by Thurstone (1927) and Mosteller (1951) in the context of paired comparisons. When analyzing paired comparison data in practice, it makes almost no difference whether one assumes that the distribution of potentially observed desirability is extreme value or normal (see Stern, 1992). Models based on extreme value distributions tend to be more tractable and computationally efficient, which guides our choice.

Assuming each college's and student's potentially observed desirability follows an extreme value distribution with the same scale and shape, the only relevant parameter is the location parameter of the distribution. These are the latent variables described in the previous section:

$\theta_i$ , which is the desirability parameter of college *i*; and

$\eta_j$ , which is the desirability parameter of student *j*.

We index colleges with $i$=1,2,...,$I$ and index students with $j$=1,2,...,$J$.

A common misconception about ranking systems such as ours is that we impose some theoretical distribution of desirability, such as the normal or logistic distribution, across colleges or students. We do not impose any distribution on desirability. We only make an assumption about the distribution of potential desirability that a college or student might display in a tournament. This is an assumption about the range of desirability displayed by a single player, not an assumption about the range of average desirabilities across players.

B. The Admissions Model

Our model has two components: an admissions model where students "compete against" colleges, and a matriculation model where colleges "compete against" each other. The two components of the model are fit simultaneously, but we present them separately.

Let $W_{ij}$ be an indicator variable that tells us whether college *i* admits student *j*:

(3) $$W_{ij} = \begin{Bmatrix} 1 \;\; \textit{if school } i \textit{ admits student } j \\ 0 \;\; \textit{if school } i \textit{ rejects student } j \end{Bmatrix} .$$

We assume that $W_{ij}$, given the student and college desirability parameters, can be written in the form of a Bradley-Terry model:

(4) $$P(W_{ij} = 1) \; = \; \frac{\exp(\eta_j)}{\exp(\eta_j) + \exp(\theta_i)}.$$

This model can be rewritten as a logit model:

(5) $$logit \; P\,(W_{ij} = 1 \mid \theta_i , \eta_j) \; = \; \eta_j - \theta_i \; ,$$

Thus, as can be seen from equation (5), the probability that a student gains admission to a college is a function of the difference between the student's desirability parameter and the college's desirability parameter: $\eta_j - \theta_i$. Put another way, the better the student is relative to the college, the more likely he is be admitted.

C. The Matriculation Model

Our matriculation model follows naturally from our admissions model. Students prefer colleges with higher desirability, among those in their choice set. Suppose that student *j* is admitted to a set of colleges $S_j$ consisting of $m_j$ schools. Let the indicator variable $Y_{ij}$ tell us which college the student chooses:

$$(6) \qquad Y_{ij} = \left\{ \begin{array}{ll} 1 & \textit{if student } j \textit{ matriculates at college } i \\ 0 & \textit{otherwise} \end{array} \right\} .$$

The result of the multi-player competition among the $m_j$ colleges that admitted student *j* is assumed to follow a multinomial distribution:

$$(7) \qquad (Y_{1j}, \dots, Y_{m_j j}) \sim \textit{Multinomial}\,(1, (p_{1j}, \dots, p_{m_j j})) \ ,$$

where $p_{ij}$ is the probability that student *j* chooses to matriculate at college *i* among his $m_j$ college choices.[2] We assume Luce's choice model, of the form:

$$(8) \qquad p_{i^* j} = \frac{\exp(\theta_{i^*})}{\sum_{i \in S_j} \exp(\theta_i)} \ , \qquad i^* \in S_j \ .$$

Analogously to the previous sub-section, this model can be rewritten as a multinomial logit model.

D. Factors Other than Quality and Merit that Affect Admissions and Matriculation

So far, we have written the model as though admissions decisions were made purely on the basis of a student's desirability and matriculation decisions were made purely on the basis of a college's desirability, but this is unlikely to be true. Colleges have preferences for students on the basis of factors that do not correspond to notions of merit; students have preferences for

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[2] Merely for expositional convenience, we have reindexed the colleges in student *j* set $S_j$, so that they can be written $1, \dots, m_j$.

colleges on the basis of factors that do not correspond to notions of quality. Readers will probably find it intuitive to think of these other factors as prices (and, indeed, some of them *are* prices). We are all familiar with ratings that are "price-considered" and "price-not-considered." We understand that a "price-not-considered" rating is an attempt to measure pure quality, and that a "price-considered" rating attempts to account for price differences. Both types of ratings are interesting. Although we are primarily interested in a pure ("price-not-considered") college ranking, we are also interested in a "price-considered" ranking. If there are factors other than pure desirability that affect admissions and matriculation, and we estimate our model as though these factors did not exist, we will produce a "price-considered" ranking. Intuitively, this is because a college may "win" often because it offers big price discounts; if we do account for those price discounts, we will ascribe its wins to its desirability and produce a "price-considered" ranking. Similarly, factors other than pure desirability that made a student attractive in admissions tournaments would cause us to ascribe "wins" to the student's desirability and produce a "price-considered" ranking.

There are several factors other than a college's desirability that we expect to affect matriculation. They are a college's tuition, room and board fee, grants to the student, loans to the student, work-study commitment to the student, distance from the student's home, being in-state, being in-region, and being the *alma mater* of one or more of the student's parents. Most of these factors *are* prices or price discounts–for instance, when a college gives a student a grant, it is essentially offering a price discount. The factors that are not explicitly prices can be usefully thought of as proxies for prices. For instance, distance matters because it affects the transportation costs associated with getting to and from college. Being in-state or in-region is like getting a price discount if students enjoy attending a college that has local connections. For instance, students may enjoy cheering for a familiar team or derive benefits from being part of a local alumni network. Having an alumni parent may also be like getting a better price–that is, parents may be willing to pay more for a college or accept lower quality from a college if they derive pleasure from seeing their child walk in their footsteps.

There are several factors other than a student's desirability that we expect to affect his admissions outcomes. They are a student's being a alumni child; having parents who are rich or influential; applying for financial aid; being from an underrepresented racial, ethnic, or gender group; being from an underrepresented state; being from in-state; being from in-region; and distance from the college. Most of these factors are not prices, *per se*, but they all function like prices. For instance, if a college expects donations to increase when it grants admission to children of alumni or influential parents, then it is getting a bonus on top of whatever tuition the student pays. Similarly, if the college expects to get more tuition from richer students or students who do not apply for financial aid, it is getting a sort of price bonus. A college that admits students from underrepresented minority groups, underrepresented states, or the local area may get rewards through political channels, public relations channels, or from its own faculty (if they have tastes for a diverse student body, say).

At this point, it is useful to clear up a common misinterpretation of the previous paragraph. We do *not* claim that the only reason why an admissions officer might look differently at an application from, say, a minority student is that there are price-like rewards for admitting such students. Suppose an admissions officer cares solely about pure desirability. He might derive a measure of pure desirability by combining a student's achievement measures (like SAT scores) with measures of how advantaged his family background was. For instance, an admissions officer might conclude that a student with top SAT scores has more merit if he attained those scores despite coming from a poor family and attending a deficient high school. It is this pure but latent assessment of desirability that we are attempting to estimate. It is important to distinguish our exercise, where we let colleges' revealed preferences generate estimates of student desirability, from an exercise where SAT scores, say, are *assumed* to index student desirability and people then argue about how much SAT scores should be adjusted for family background.

Another way for readers to get a firm grasp on our exercise is to consider the factors for which we should *not* control. We want to control for factors *other* than desirability that influence matriculation and admissions. We do not want to control for variables that are indicators of merit or quality. For instance, we would not want to control for measures of student's aptitude or achievement, like his SAT1, SAT2, or Advanced Placement scores. We would not want to control for measures of a college's resources, like its faculty-student ratio. The point of estimating revealed preference rankings is using students' and colleges' actual conduct to weigh indicators of colleges' value and students' merit. We expect students to create their valuations using indicators of colleges' quality, both indicators that are observable to us and indicators that students observe but we do not. Thus, indicators of a college's value are *already* embodied in the rankings generated by revealed preference; they do not need to be accounted for in any other way. A parallel logic holds for colleges' creating their valuations of students.

E. Accounting for "Prices" (Factors Other than Desirability that Affect Matriculation and Admissions)

From here onwards, we will use "prices" as shorthand for the factors other than pure desirability that affect matriculation and admissions. Having described the "prices" for which we need to account in order to generate pure rankings, we can now include them in our model.

Let the vector $\boldsymbol{x}_{ij} = (x_{1ij}, x_{2ij}, \dots, x_{Kij})'$ include the $K$ "prices" that might affect student $j$'s probability of admission at college $i$ or his probability of matriculating at college $i$. We account for "prices" by treating $\boldsymbol{x}_{ij}$ as a vector of covariates which are allowed to enter the model linearly. Specifically, the admissions model becomes:

$$\text{(9)} \qquad logit\ P(W_{ij} = 1 \mid \theta_i, \eta_j) = \eta_j - \theta_i + \boldsymbol{x}_{ij}'\beta \ ,$$

and the probabilities for the matriculation model become:

(10) $$p_{i^* j} = \frac{\exp(\theta_{i^*} + \boldsymbol{x}_{ij}^{/}\boldsymbol{\delta})}{\sum_{i \in S_j} \exp(\theta_i + \boldsymbol{x}_{ij}^{/}\boldsymbol{\delta})}, \qquad i^* \in S_j .$$

It is worth noting that, in the two model components, different sets of "prices" may be appropriate to incorporate as factors affecting admission and matriculation. To recognize this difference, $x_{ij}$ is constructed to include all the "prices" (both those that are relevant for admission and those that are relevant for matriculation), but we set some of the price parameters to 0. For instance, if a price is appropriate for inclusion in the admission model, but not in the matriculation model, then its component of $\boldsymbol{\beta}$ will be a free parameter, but its component of $\boldsymbol{\delta}$ will be set to 0. In fitting the model, not only are the $\theta_i$ and $\eta_j$ inferred, but so are the $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$, which are the effects of the "prices" on admissions and matriculations.

F. Model Fitting

The complexity of our model lends itself naturally to fitting the model in the Bayesian framework. This allows the use of recent computation tools for model fitting, and, in particular, the use of Markov chain Monte Carlo (MCMC) simulation from the posterior distribution to obtain parameter summaries. Recent examples of MCMC methods applied to paired comparison models include Glickman (2001) and Glickman and Stern (1998).

The posterior distribution of parameters is proportional to the product of the likelihood function with the prior distribution. The likelihood can be written as a product of binomial logit probabilities derived from equation (4) times the product of multinomial logit probabilities derived from equation (8). We assume a diffuse but proper prior distribution that factors into independent densities. The prior distribution consists of the following components:

(11) $$\theta_i \sim N(0, \sigma^2)$$

(12) $$\frac{1}{\sigma^2} \sim Gamma(0.1, 0.1)$$

(13) $$\eta_j \sim N(0, \tau^2)$$

(14) $$\frac{1}{\tau^2} \sim Gamma(0.1, 0.1)$$

(15) $$\beta_k \sim N(0, 100) \qquad \textit{for } k = 1, 2, \ldots, K$$

(16) $$\delta_k \sim N(0, 100) \qquad \textit{for } k = 1, 2, \ldots, K$$

It should be noted that, when we model admission and matriculation data without prices, the prior components for $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ do not appear in the model.

The MCMC algorithm proceeds as follows. Initial values of all parameters are set to the prior mean values (though the initial values can be set arbitrarily). Then values are simulated from the conditional posterior distributions of each model parameter. The result is a set of simulated values of all parameters. This process is repeated until the distributions of values for individual parameters stabilize. The values simulated beyond this point can be viewed as coming from the joint posterior distribution. We implement the MCMC algorithm using the program BUGS (Spiegelhalter et al., 1996).

Parameter summaries are obtained from the simulated values from the posterior. A burn-in period of 2000 iterations was run, and parameter summaries were based on every 5th iteration of a subsequent 30,000 iterations. Based on trace plots from our data analyses, 2000 iterations was sufficient to reach the stationary distribution. Every 5th iteration was sampled to reduce the autocorrelation in successive parameter draws. This process produced 6000 values per parameter. Posterior means, percentiles, correlations, and so on, can be computed based on the simulated values using standard sample calculations.

A few of our "price" variables have a modest number of missing observations: race (5 percent missing), parents' income (0.7 percent missing), and distance from home to the college (3 percent missing). In these cases, we performed multiple hot-deck imputation. This was carried out in the following manner. For each variable where data was missing, we imputed values from the empirical distribution of the observed values on from the remaining cases. This process resulted in a completed data set with no missing values. To account for the uncertainty in the missing values, the imputation was repeated three times resulting in three completed data sets. The MCMC simulation from the posterior distribution was run separately on each completed data set, and the three sets of simulated values were combined into one set from which inferences were based. Multiple imputation based on hot-deck is a sensible approach if the prices are uncorrelated. Further modeling will involve investigating regression models for missing "prices" as part of model fitting.

## IV. The College Admissions Project Data

Our data comes from our College Admissions Project survey, in which we surveyed high school seniors applying to college during the 1999-2000 academic year.[3] The survey was designed to gather data on an unusual group of students: students with very high college aptitude who are likely to gain admission to the colleges with a national or broad regional draw that are most appropriate for ranking. While such students are represented in surveys that attempt to be nationally representative, such as the National Educational Longitudinal Survey, they are a very small share of the population of American students. As a result, the number of such students is so small in typical surveys that their behavior cannot be analyzed, even if the survey contains a large number of students. By focusing on students with very strong academic credentials, we end up with a sufficient number of tournaments among college with a national draw to construct a revealed preference ranking.

### A. The Survey Design

In order to find students who were appropriate candidates for the survey, we worked with counselors from 510 high schools around the United States. The high schools that were

[3] See Avery and Hoxby [2000] for additional detail.

selected had a record of sending several students to selective colleges each year, and they were identified using published sources (such as Peterson's guides to secondary schools) and the experience of admissions experts (Andrew Fairbanks, Michael Behnke, and Larry Momo). Each counselor selected ten students at random from the top of his senior class as measured by grade point average. Counselors at public schools selected students at random from the top 10% of the senior class, while counselors at private schools (which tend to be smaller and have higher mean college aptitude) selected students at random from the top 20% of the senior class.[4] The counselors distributed the surveys to students, collected the completed surveys, and returned them to us for coding.[5] Students were tracked using a randomly assigned number; we never learned the names of the students who participated.

Survey participants completed two questionnaires over the course of the academic year. The first questionnaire was administered in January 2000. It asked for information on the student's background and college applications; the majority of these questions were taken directly from the Common Application, which is accepted by many colleges in place of their proprietary application forms. Each student listed up to ten colleges where he had applied, his test scores, and race. In addition, each student listed the colleges and graduate schools (if any) attended by each parent and the colleges (if any) attended by older siblings along with their expected graduation dates.

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[4] The counselors were given detailed instructions for random sampling from the top 20, 30, 40, or 50 students in the senior class depending on the size of the school. For example, a counselor from a public school with 157 students was asked to select 10 students at random from the top 20 students in the senior class, with the suggestion that the counselor select students ranked #1, 3, 5, 7, 9, 11, 13, 15, 17, and 19.

[5] The exception was the parent survey, which parents mailed directly to us in an addressed, postage-paid envelope so that they would not have to give possibly sensitive financial information to the high school counselor. Because counselors have access to the information on the students' surveys (and must, in order to support their applications competently), we were not as concerned about students' giving information to their counselors.

The second questionnaire was administered in May 2000 and asked for information about the student's admission outcomes, financial aid offers, scholarship offers, and matriculation decision. Each student listed their financial aid packages with the amounts offered in three categories: grants, loans, and Work Study. We obtained detailed information on grants and scholarships. On a third questionnaire distributed to a parent of each survey participant, we collected information on parents' income range in 1999 (see Table 1 for the income categories.)

We matched the survey to colleges' administrative data on tuition, room and board, location, and other college characteristics. In all cases, the ultimate source for the administrative data was the college itself and the data were for the 2000-01 school year, which corresponds to the survey participants' freshmen year.[6]

The College Admissions Project survey produced a response rate of approximately 65%, including full information for 3,240 students from 396 high schools.[7] The final sample contains students from 43 states plus the District of Columbia.[8] Although the sample was constructed to include students from every region of the country, it is intentionally representative of applicants to highly selective colleges and therefore non-representative of American high school students as a whole. Regions and states that produce a disproportionate share of the students who apply to

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[6] We collected the administrative data from the following sources in order: The College Board's annual survey (ACS), the United States Department of Education's Integrated Postsecondary Education Data System (IPEDS), the United States Department of Education's College Opportunities Online system (COOL), the 2001 edition of Peterson's Guide to Colleges, and colleges themselves. That is, we attempted to fill in each observation using the first source first; missing observations were filled in using one of the remaining sources, in order.

[7] The most common reasons for failure to return the survey were changes of high school administration, an illness contracted by the counselor, and other administrative problems that were unrelated to the college admissions outcomes of students who had been selected to participate.

[8] The states missing from the sample are Alaska, Delaware, Iowa, Mississippi, North Dakota, South Dakota, and West Virginia.

selective colleges are given a weight in the sample that is approximately proportionate to their weight at very selective colleges, not their weight in the population of American high school students. Of course, all of the students in the sample have very strong academic records.

Because the students are drawn from schools that send several students to selective colleges each year (though not necessarily to *very* selective colleges), the students in the sample are probably slightly better informed than the typical high aptitude applicant. However, in other work [Avery and Hoxby, 2002], we have found that students who make it into the sample on the basis of their achievement act very much like one another when they make college decisions, regardless of whether they come from more or less disadvantaged backgrounds. This suggests that a revealed preference ranking based on our sample may reflect slightly more information than one based on the typical applicant, but the difference in the information embodied in the ranking is probably small.

B. The Typical Student in the College Admissions Project

The summary statistics shown in Tables 1 and 2 demonstrate that the sample is quite special. The average (combined verbal and math) SAT score among participants was 1357, which put the average student in the sample at the 90th percentile of all SAT takers.[9] About 5 percent of the students won a National Merit Scholarship; 20 percent of them won a portable outside scholarship; and 46 percent of them won a merit-based grant from at least one college.[10] 45

[9] We converted American College Test (ACT) scores to SAT scores using the cross-walk provided by The College Board. We converted all college admissions scores into national percentile scores using the national distribution of SAT scores for the freshman class of 2000-01.

[10] Because the aid variables are important, we hand-checked every observation to ensure that no grant was counted twice (as a need-based grant and again as a merit-based grant), recorded incorrectly as a four-year total rather than an annual amount, or recorded with insufficient restrictions. In many cases, we were able to double-check or clarify students' responses because they were offered named grants with known parameters (for instance, "Morehouse Scholars" at the University of North Carolina).

percent of the students attended private school, and their parents' income averaged $119,929 in 1999.[11] However, 76 percent of the sample had incomes below the cut-off where a family is considered for aid by selective private colleges (the cut-off is approximately $160,000, but the actual cut-off depends on family circumstances). 59 percent of the students applied for need-based financial aid, and 41 percent of the families reported that finances influenced their college choice.[12] Of course, a college may offer a student a grant to persuade him to matriculate, regardless of whether he has applied for aid.

83 percent of the student's parents were currently married, and 23 percent of the students had at least one sibling currently enrolled in college. The racial composition of the survey participants was 73 percent white, 16 percent Asian, 3.5 percent black, and 3.8 percent Hispanic.

C. The Typical College in the College Admissions Project

Looking at Table 2, which shows descriptive statistics on the colleges where the students applied, were admitted, and matriculated; we can see that the survey participants applied to a

[11] We used parents' reports of their own incomes whenever available. When a parent report of income was unavailable, we substituted an estimate of parents' income based on the Expected Family Contribution reported by the student. (The Expected Family Contribution is the standardized federal estimate of the amount that parents should be able to contribute towards the student's college education.) We can explain 88 percent of the variation in the Expected Family Contribution using just two variables: parents' income and likely current expenditures for the college education of older siblings. We know about siblings' enrollment and likely expenditures for their education. Therefore, our estimates of parents' income based on the Expected Family Contribution and siblings' college expenses are highly accurate. For families that reported both parents' income and an Expected Family Contribution, our estimate of parents' income based on Expected Family Contribution placed families into the correct income category 97 percent of the time. A remaining 3.4 percent of families had neither a reported parents' income nor a reported Expected Family Contribution. For these families, we estimated parents' income by assigning parents the mean incomes for people with the same detailed occupation in the March 2000 Current Population Survey (which asks about a person's 1999 income from his occupation). For families for which we could check this method, we found that it assigned them to the correct income category 91 percent of the time.

[12] That is, either the parent, the student, or both claimed that finances influenced the college choice decision.

range of colleges that included "safety schools" (the mean college to which a student applied had a median SAT score 8.5 percentiles below the student's own). However, the participants also made ambitious applications: 47.5 percent of them applied to at least one Ivy League college.

We can see that the students made logical application decisions. The mean college to which they *applied* had a median SAT score at the $83^{rd}$ percentile; the mean college to which they were *admitted* had median SAT score at the $81^{st}$ percentile. This small difference suggests that the students aimed a little high in their applications, a procedure that is optimal. 66 percent of the colleges to which students were admitted were private, and their mean tuition was $17,671. Notice that we show the colleges' in-state tuition, out-of-state tuition, and the tuition that actually applies to the students in the sample (in-state or out-of-state as appropriate).

The final column of Table 2 shows descriptive statistics for the colleges at which the students matriculated. They are more selective, on average, than the colleges to which the students were admitted: their median SAT score is at the $83.4^{th}$ percentile, as opposed to the $81^{st}$ percentile median SAT score of the colleges to which students were admitted. This makes sense because it implies that students included "safety schools" in their choice sets, but that they did not actually matriculate at their "safety schools" when they did not need to. One measure of the unusual college aptitude of the survey participants is the list of colleges at which the largest numbers of participants enrolled. Seventeen institutions enrolled at least 50 students from the sample: Harvard, Yale, University of Pennsylvania, Stanford, Brown, Cornell, University of Virginia, Columbia, University of California–Berkeley, Northwestern, Princeton, Duke, University of Illinois, New York University, University of Michigan, Dartmouth, and Georgetown.

D. The Colleges We Rank

In this version of the paper, we ranked 79 colleges. We picked the 79 colleges because each one competed in at least 10 "multi-player" tournaments, and we were confident that we could obtain reasonably precise results with these colleges. The mean college in this group competed in 78 "multi-player" tournaments, and the median college completed in 65. In future versions of this paper, we may attempt to rank more colleges, but ranking becomes difficult and computationally time-consuming as we attempt to include more colleges on which we observe little information.

If a student's choice set includes colleges in our group of 79, but he matriculates at another college, we call this other college "Other College." It is important to realize that is mere relabeling and not the creation of a fictional college: each such college is included in the data with its real characteristics for each student. The "Other College's" mean desirability is just the average for colleges relabeled in this way. Although we show "Other College's" mean desirability in the note following each table, readers will probably want to ignore it, as it is not readily interpretable.

## V. A Revealed Preference Ranking of American Colleges and Universities (The Pure, Price-Not-Considered, Ranking)

Table 3 presents the pure, or "price-not-considered" ranking of colleges and universities. For each college, we present its mean desirability among students–that is, the mean of its posterior distribution. We also show a 95 percent confidence interval around each mean, and we indicate whether the college's mean desirability is statistically significantly different from the mean desirability of the college listed below it (at the 0.01, 0.05, and 0.10 levels). Readers should not attempt to interpret the mean desirability except as an arbitrary numerical scale of value. The desirabilities do not, for instance, translate into dollar values. The order of the ranking is interpretable (except when two colleges do not have statistically significantly different means); the relative distance between colleges' estimated desirabilities is interpretable; but the overall scale of value is arbitrary. Negative values imply nothing negative: they exist simply because desirability is arbitrarily centered on zero.

It is important to keep in mind that what Table 3 shows is the *revealed preference* ranking of colleges. Although the colleges that appear relatively high on our ranking also tend to appear relatively high on college guides' ranking, there is no reason why there must be a correlation. Moreover, the revealed preference ordering within the 79 colleges is quite different from orderings in college guides' rankings.

Table 3 shows that the top ten are, in order: Harvard, Yale, Stanford, Princeton, MIT, Brown, Columbia, Dartmouth, California Institute of Technology, and University of Pennsylvania. Except for California Institute of Technology and University of Pennsylvania, they all have mean desirability that is statistically significantly different from the desirability of the college listed beneath them. Interestingly, all of the top ten are universities.

The next ten, however, include a mix of college and universities: Amherst, Williams, Georgetown, Swarthmore, Cornell, Duke, Pomona, Tufts, John Hopkins, and Wesleyan; in that order. Georgetown's mean value is not statistically significantly different from Swarthmore's, and Cornell's is not statistically significantly different than Duke's. Otherwise, the differences are statistically significant. All of the top 20 are private institutions and near either the American East Coast or the West Coast.

The next 20, however, are a mix of public and private, small and large, colleges and universities. They are also more geographically diverse. University of California-Berkeley is the first public institution to appear, but University of California-Los Angeles and University of Virginia are not far below it. Institutions that are near neither the East nor West Coasts include Notre Dame, Rice, Northwestern, University of Chicago, Emory, and Washington University (St. Louis). Wellesley happens to be the highest ranked women's college.

The remaining 39 colleges include a good number of states' "flagship" universities, numerous liberal arts colleges, several private universities, and a few more institutes of technology.

In the next two tables, we show estimates of the effects of "prices" on admissions and matriculation probabilities. Because the scale of the merit parameter is arbitrary, we discourage readers from interpreting the scale of the point estimates. Instead, focus on the signs of the estimates, their *relative* scale, and whether their confidence regions include zero.

The estimates of the parameter $\boldsymbol{\delta}$ are not terribly revealing, but we show them in Table 4. Half of them have 95 percent confidence regions that include zero, and the other half either have small effects or very imprecisely estimated effects. These estimates suggest that controlling for "prices" is likely to have relatively little effect on the ranking. Put more bluntly, the price-not-considered and price-considered rankings are likely to be similar. Below, we explain why this is so.

Table 5 shows our estimates of the parameter $\boldsymbol{\beta}$. A sizable minority have 95 percent confidence regions that include zero, but some do not. Several are worthy of interpretation. A student's being male does not affect admissions. Being Asian is a mild advantage in admissions. (This is interesting, because there are anecdotes that suggests that being Asian is a disadvantage in admissions at California's public universities. Evidently these anecdotes are just anecdotes or whatever systematic phenomenon exists is specific to the University of California.) Being black or Hispanic appears to be a larger advantage in admissions than being Asian, but the black and Hispanic confidence regions overlap considerably, as do the Asian and Hispanic confidence regions. Having a father who is an alumnus conveys an advantage of approximately the same magnitude as being black or Hispanic, and a mother who is an alumna conveys a lesser advantage. Parent's income does not appear to have an effect, but having a parent with a graduate degree is helpful and so is applying for aid, apparently. *However*, we strongly warn readers against interpreting the parent characteristics (alumni status, income, graduate degrees, and aid applications) literally. They are too collinear to be interpreted literally as partial effects.

A student's being from the college's own state is an advantage in admissions. Being from a sparsely populated state (a proxy for being from an underrepresented state) is not a significant advantage.

On the whole, our estimates of $\boldsymbol{\delta}$ fit reasonably well into the existing literature on factors that affect a student's admissions probability. We do not expect them to be very similar to estimates in the existing literature because our sample is different from the samples typically analyzed in that literature.

## VI. A "Price-Considered" Revealed Preference Ranking of American Colleges and Universities

Table 6 shows the "price-considered" ranking of colleges and universities. On the whole, the ranking is similar to the "pure" ranking, but there are numerous small changes in the ordering. Let us examine institutions that move up or down at least five places to see whether college characteristics ("prices") affect the ranking in the way we would have expected.

The list of colleges that are substantially more preferred when price *is* considered are: Furman, Georgia Institute of Technology, University of Illinois, University of Maryland, University of North Carolina, University of Oregon, University of Virginia, Washington and Lee, William and Mary. This is not a surprising array of institutions; most are public universities that charge very modest tuition to in-state students. The exceptions, Furman and Washington and Lee, are evidently attractive to students based on factors other than pure desirability (as well as pure desirability).

The list of colleges that are substantially more preferred when price is *not* considered are: Barnard, Boston University, Emory, George Washington University, Johns Hopkins, Lehigh, New York University, Rensselaer Polytechnic Institute, University of California-Davis, University of California-Santa Barbara, and University of California-San Diego, University of Michigan, Washington University (St. Louis). There are few surprises on this list, because most are high-priced private universities. Also, the University of Michigan is high-priced for a public university. The appearance of some campuses of the University of California suggests that a peculiar phenomenon may be affecting that multi-campus system: tuition is essentially the same on all campuses but the campuses differ in desirability and other dimensions. For instance, University of California-Davis has tuition that is, in some sense, too high, compared to University of California-Berkeley. As a result, Davis does better in the pure preference ranking than in the price-considered ranking.

Why are the pure and price-considered rankings so similar, overall? After all, price-considered and price-not-considered rankings of cars or lawnmowers are very different. The simple answer is that less preferred colleges do not, on the whole, charge much less than the most preferred. Put another way, the most preferred colleges do not appear to be charging as much, relative to the less preferred colleges, as a naive person would think they could. Although this phenomenon may appear puzzling at first glance, it is, in fact, understood. It reflects the fact that students are *inputs* into the production of college education as well as consumers of college education. Students who are better inputs must be paid higher "wages" in equilibrium, and relatively low prices of the most preferred colleges are an expression of these higher "wages." This is too large a topic to explore further here, but see Hoxby (2000).

## VII. Conclusions

In this paper, we present revealed preference rankings of American colleges and universities, both pure and "price-considered." These rankings are based on students' and colleges' *actual* choice behavior, which we aggregate statistically. Our rankings are *not* based on arbitrary formulas for weighting various college attributes, as are the rankings produced by college guides.

Students may care about revealed preference rankings because college classmates' knowledge spills over, because the rankings aggregate the observations of thousands of students, or because colleges' degrees are used as signals of ability. Given the very strong demand for measures of revealed preference among parents and students, it is clear that there should be an accurate, unbiased ranking available to them. In the absence of such a ranking, families use highly flawed, manipulable proxies such as the matriculation rate and admissions rate. These proxies are not only misleading, they also induce colleges to engage in distorted conduct that actually reduces the colleges' own desirability while making the colleges appear to be more desirable (as measured by the proxies).

Our revealed preference ranking is the first available indicator of revealed preference that can claim to be accurate and unbiased. It could be improved, but the only way to improve it significantly would be data from more students. We would be the first to advocate this improvement. Although our dataset is the largest available on students with high college aptitude, it was limited by practical constraints to be far less than universal. We did not attempt to gather data from students who were unlikely to be admitted to colleges with a national or broad regional draw, and we do not rank colleges outside this group. However, if we were–say–to have universal data on students, we could create additional rankings for smaller geographic areas and for specialized colleges (music schools, and so on). We could also add some colleges to the ranking we show in this paper, but colleges that do not have a national or broad regional draw are inherently unsuited for a national ranking.

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**Table 1**
**Description of the Students in the College Admission Project Data**

| Variable | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| Male | 0.4120 | 0.4923 | 0 | 1 |
| White, non-Hispanic | 0.7321 | 0.4429 | 0 | 1 |
| Black, non-Hispanic | 0.0350 | 0.1837 | 0 | 1 |
| Asian | 0.1571 | 0.3640 | 0 | 1 |
| Hispanic | 0.0382 | 0.1918 | 0 | 1 |
| Native American | 0.0010 | 0.0313 | 0 | 1 |
| Other race/ethnicity | 0.0366 | 0.1878 | 0 | 1 |
| Parents are married | 0.8305 | 0.3752 | 0 | 1 |
| Sibling(s) enrolled in college | 0.2327 | 0.4226 | 0 | 1 |
| Parents' income, estimated if necessary | 119929 | 65518 | 9186 | 240000 |
| Expected family contribution, estimated if necessary | 27653 | 16524 | 0 | 120000 |
| Applied for financial aid? | 0.5946 | 0.4910 | 0 | 1 |
| National Merit Scholarship winner | 0.0494 | 0.2167 | 0 | 1 |
| Student's SAT score, sum of math and verbal, converted from ACT score if necessary | 1356.9110 | 138.8193 | 780 | 1600 |
| Student's SAT score, expressed as national percentile | 90.4013 | 12.3362 | 12 | 100 |
| Median SAT score at *most* selective college to which student was admitted | 86.4092 | 10.3836 | 34 | 98 |
| Median SAT score at *least* selective college to which student was admitted | 73.8469 | 14.5646 | 14 | 97 |
| Number of colleges to which student was admitted | 3.5250 | 2.1293 | 1 | 10 |
| Student's high school was private | 0.4534 | 0.4979 | 0 | 1 |
| Student's high school in AL | 0.0170 | 0.1292 | 0 | 1 |
| Student's high school in AR | 0.0028 | 0.0526 | 0 | 1 |
| Student's high school in AZ | 0.0093 | 0.0958 | 0 | 1 |
| Student's high school in CA | 0.1222 | 0.3276 | 0 | 1 |
| Student's high school in CO | 0.0120 | 0.1091 | 0 | 1 |
| Student's high school in CT | 0.0327 | 0.1779 | 0 | 1 |
| Student's high school in DC | 0.0096 | 0.0974 | 0 | 1 |
| Student's high school in FL | 0.0287 | 0.1670 | 0 | 1 |
| Student's high school in GA | 0.0111 | 0.1048 | 0 | 1 |

| Variable | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| Student's high school in HI | 0.0201 | 0.1402 | 0 | 1 |
| Student's high school in ID | 0.0031 | 0.0555 | 0 | 1 |
| Student's high school in IL | 0.0633 | 0.2435 | 0 | 1 |
| Student's high school in IN | 0.0086 | 0.0926 | 0 | 1 |
| Student's high school in KS | 0.0046 | 0.0679 | 0 | 1 |
| Student's high school in KY | 0.0031 | 0.0555 | 0 | 1 |
| Student's high school in LA | 0.0105 | 0.1019 | 0 | 1 |
| Student's high school in MA | 0.0855 | 0.2797 | 0 | 1 |
| Student's high school in MD | 0.0327 | 0.1779 | 0 | 1 |
| Student's high school in ME | 0.0052 | 0.0723 | 0 | 1 |
| Student's high school in MI | 0.0198 | 0.1392 | 0 | 1 |
| Student's high school in MN | 0.0056 | 0.0743 | 0 | 1 |
| Student's high school in MO | 0.0198 | 0.1392 | 0 | 1 |
| Student's high school in MT | 0.0019 | 0.0430 | 0 | 1 |
| Student's high school in NC | 0.0219 | 0.1464 | 0 | 1 |
| Student's high school in NE | 0.0031 | 0.0555 | 0 | 1 |
| Student's high school in NH | 0.0167 | 0.1280 | 0 | 1 |
| Student's high school in NJ | 0.0522 | 0.2224 | 0 | 1 |
| Student's high school in NM | 0.0102 | 0.1004 | 0 | 1 |
| Student's high school in NV | 0.0031 | 0.0555 | 0 | 1 |
| Student's high school in NY | 0.1278 | 0.3339 | 0 | 1 |
| Student's high school in OH | 0.0309 | 0.1730 | 0 | 1 |
| Student's high school in OK | 0.0062 | 0.0783 | 0 | 1 |
| Student's high school in OR | 0.0105 | 0.1019 | 0 | 1 |
| Student's high school in PA | 0.0472 | 0.2121 | 0 | 1 |
| Student's high school in RI | 0.0086 | 0.0926 | 0 | 1 |
| Student's high school in SC | 0.0031 | 0.0555 | 0 | 1 |
| Student's high school in TN | 0.0201 | 0.1402 | 0 | 1 |
| Student's high school in TX | 0.0395 | 0.1948 | 0 | 1 |
| Student's high school in UT | 0.0071 | 0.0840 | 0 | 1 |
| Student's high school in VA | 0.0333 | 0.1795 | 0 | 1 |
| Student's high school in VT | 0.0031 | 0.0555 | 0 | 1 |
| Student's high school in WA | 0.0160 | 0.1257 | 0 | 1 |
| Student's high school in WI | 0.0077 | 0.0875 | 0 | 1 |
| Student's high school in WY | 0.0028 | 0.0526 | 0 | 1 |

**Table 2**
**Description of the Colleges in the College Admission Project Data**

| | Colleges at Which Students | | | | | |
|---|---|---|---|---|---|---|
| | Applied | | Were Admitted | | Matricalated | |
| Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Matriculated at this college | 0.2825 | 0.4502 | 0.1813 | 0.3853 | 1.0000 | 0.0000 |
| Admitted to this college | 1.0000 | 0.0000 | 0.6566 | 0.4748 | 1.0000 | 0.0000 |
| Grants specific to this college | 2720 | 5870 | 1778 | 4933 | 4029 | 7051 |
| Loans from this college | 641 | 2282 | 413 | 1856 | 1020 | 2722 |
| Work study amount from this college | 172 | 593 | 111 | 483 | 296 | 768 |
| Father is an alumnus of this college | 0.0401 | 0.1962 | 0.0314 | 0.1744 | 0.0664 | 0.2491 |
| Mother is an alumna of this college | 0.0283 | 0.1659 | 0.0209 | 0.1431 | 0.0396 | 0.1949 |
| Sibling attended or attends this college | 0.0484 | 0.2146 | 0.0388 | 0.1932 | 0.0831 | 0.2761 |
| College is public | 0.3325 | 0.4711 | 0.2631 | 0.4403 | 0.2843 | 0.4512 |
| College is private not-for-profit | 0.6628 | 0.4737 | 0.7328 | 0.4436 | 0.7086 | 0.4562 |
| College is international, except for Canadian colleges which are treated as U.S. colleges | 0.0045 | 0.0672 | 0.0040 | 0.0633 | 0.0068 | 0.0822 |
| College's median SAT score, in national percentiles | 80.5947 | 12.5188 | 83.8816 | 12.0390 | 83.4215 | 12.5494 |
| Student's SAT score is this many percentiles *above* college's median SAT score | 11.2945 | 10.2160 | 8.7393 | 9.5927 | 8.4548 | 9.1831 |
| Student's SAT score is this many percentiles *below* college's median SAT score | 1.1006 | 4.3038 | 1.7454 | 5.6654 | 1.4351 | 4.8994 |
| In-state tuition | 16435 | 9594 | 18181 | 9199 | 17432 | 9513 |
| Out-of-state tuition | 19294 | 6191 | 20498 | 5891 | 19841 | 6371 |
| Tuition that applies to this student | 17671 | 8492 | 19277 | 7965 | 18340 | 8599 |
| Room and board at this college | 6809 | 1322 | 6976 | 1244 | 6822 | 1352 |
| In-state comprehensive cost of this college | 23785 | 10368 | 25746 | 9936 | 24881 | 10409 |
| Out-of-state comprehensive cost of this college | 26642 | 7033 | 28060 | 6681 | 27286 | 7335 |
| Comprehensive cost that applies to this student | 25022 | 9219 | 26842 | 8662 | 25792 | 9470 |

| | Colleges at Which Students | | | | | |
|---|---|---|---|---|---|---|
| | Applied | | Were Admitted | | Matricalated | |
| Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Total per-pupil expenditure of this college, in thousands | 58.3288 | 54.6237 | 68.4888 | 66.0989 | 67.5188 | 64.2833 |
| Educational and general per-pupil expenditure of this college, in thousands | 41.9290 | 24.4120 | 48.2225 | 26.2227 | 47.9875 | 26.4929 |
| Instructional per-pupil expenditure of this college, in thousands | 15.2391 | 10.5614 | 16.8792 | 10.4596 | 16.6971 | 10.2716 |
| College is in-state | 0.3270 | 0.4691 | 0.2666 | 0.4422 | 0.3368 | 0.4727 |
| Distance between student's high school and this college, in miles | 597 | 809 | 673 | 873 | 576 | 827 |
| College is in AK | 0.0000 | 0.0000 | 0.0001 | 0.0106 | 0.0000 | 0.0000 |
| College is in AL | 0.0053 | 0.0724 | 0.0038 | 0.0613 | 0.0050 | 0.0705 |
| College is in AR | 0.0004 | 0.0187 | 0.0003 | 0.0168 | 0.0006 | 0.0250 |
| College is in AZ | 0.0056 | 0.0748 | 0.0039 | 0.0622 | 0.0053 | 0.0727 |
| College is in CA | 0.1385 | 0.3454 | 0.1388 | 0.3458 | 0.1199 | 0.3249 |
| College is in CO | 0.0109 | 0.1038 | 0.0078 | 0.0881 | 0.0094 | 0.0963 |
| College is in CT | 0.0380 | 0.1913 | 0.0533 | 0.2246 | 0.0537 | 0.2255 |
| College is in DC | 0.0260 | 0.1591 | 0.0260 | 0.1591 | 0.0265 | 0.1608 |
| College is in DE | 0.0032 | 0.0561 | 0.0025 | 0.0497 | 0.0022 | 0.0467 |
| College is in FL | 0.0164 | 0.1271 | 0.0111 | 0.1047 | 0.0203 | 0.1410 |
| College is in GA | 0.0197 | 0.1389 | 0.0169 | 0.1290 | 0.0131 | 0.1138 |
| College is in HI | 0.0035 | 0.0592 | 0.0024 | 0.0491 | 0.0044 | 0.0660 |
| College is in IA | 0.0042 | 0.0648 | 0.0032 | 0.0561 | 0.0025 | 0.0499 |
| College is in ID | 0.0013 | 0.0363 | 0.0009 | 0.0300 | 0.0022 | 0.0467 |
| College is in IL | 0.0543 | 0.2265 | 0.0458 | 0.2090 | 0.0571 | 0.2321 |
| College is in IN | 0.0206 | 0.1422 | 0.0166 | 0.1278 | 0.0190 | 0.1367 |
| College is in KS | 0.0022 | 0.0468 | 0.0014 | 0.0375 | 0.0025 | 0.0499 |
| College is in KY | 0.0006 | 0.0248 | 0.0005 | 0.0212 | 0.0006 | 0.0250 |
| College is in LA | 0.0094 | 0.0965 | 0.0070 | 0.0836 | 0.0050 | 0.0705 |
| College is in MA | 0.1054 | 0.3070 | 0.1339 | 0.3406 | 0.1218 | 0.3271 |
| College is in MD | 0.0219 | 0.1462 | 0.0199 | 0.1395 | 0.0187 | 0.1356 |
| College is in ME | 0.0144 | 0.1191 | 0.0159 | 0.1250 | 0.0140 | 0.1177 |
| College is in MI | 0.0227 | 0.1488 | 0.0173 | 0.1303 | 0.0194 | 0.1378 |
| College is in MN | 0.0089 | 0.0938 | 0.0075 | 0.0865 | 0.0053 | 0.0727 |

| | Colleges at Which Students | | | | | |
|---|---|---|---|---|---|---|
| | Applied | | Were Admitted | | Matricalated | |
| Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| College is in MO | 0.0259 | 0.1589 | 0.0217 | 0.1456 | 0.0212 | 0.1442 |
| College is in MS | 0.0009 | 0.0296 | 0.0007 | 0.0260 | 0.0012 | 0.0353 |
| College is in MT | 0.0010 | 0.0311 | 0.0006 | 0.0249 | 0.0012 | 0.0353 |
| College is in NC | 0.0356 | 0.1852 | 0.0411 | 0.1986 | 0.0390 | 0.1937 |
| College is in NE | 0.0018 | 0.0419 | 0.0012 | 0.0344 | 0.0022 | 0.0467 |
| College is in NH | 0.0118 | 0.1078 | 0.0170 | 0.1293 | 0.0172 | 0.1299 |
| College is in NJ | 0.0217 | 0.1457 | 0.0311 | 0.1735 | 0.0284 | 0.1662 |
| College is in NM | 0.0017 | 0.0408 | 0.0011 | 0.0327 | 0.0009 | 0.0306 |
| College is in NV | 0.0008 | 0.0281 | 0.0005 | 0.0225 | 0.0022 | 0.0467 |
| College is in NY | 0.1212 | 0.3263 | 0.1187 | 0.3235 | 0.1065 | 0.3085 |
| College is in OH | 0.0273 | 0.1630 | 0.0201 | 0.1405 | 0.0178 | 0.1322 |
| College is in OK | 0.0018 | 0.0419 | 0.0011 | 0.0335 | 0.0022 | 0.0467 |
| College is in OR | 0.0087 | 0.0928 | 0.0058 | 0.0759 | 0.0078 | 0.0880 |
| College is in PA | 0.0713 | 0.2573 | 0.0723 | 0.2589 | 0.0743 | 0.2623 |
| College is in RI | 0.0193 | 0.1376 | 0.0320 | 0.1761 | 0.0300 | 0.1705 |
| College is in SC | 0.0049 | 0.0700 | 0.0037 | 0.0604 | 0.0066 | 0.0807 |
| College is in TN | 0.0139 | 0.1170 | 0.0106 | 0.1023 | 0.0140 | 0.1177 |
| College is in TX | 0.0222 | 0.1474 | 0.0185 | 0.1346 | 0.0225 | 0.1483 |
| College is in UT | 0.0045 | 0.0668 | 0.0032 | 0.0565 | 0.0091 | 0.0947 |
| College is in VA | 0.0391 | 0.1938 | 0.0361 | 0.1866 | 0.0406 | 0.1974 |
| College is in VT | 0.0104 | 0.1013 | 0.0110 | 0.1042 | 0.0106 | 0.1025 |
| College is in WA | 0.0122 | 0.1098 | 0.0088 | 0.0936 | 0.0094 | 0.0963 |
| College is in WI | 0.0090 | 0.0942 | 0.0061 | 0.0781 | 0.0059 | 0.0768 |
| College is in WV | 0.0000 | 0.0000 | 0.0001 | 0.0075 | 0.0000 | 0.0000 |
| College is in WY | 0.0003 | 0.0162 | 0.0003 | 0.0168 | 0.0006 | 0.0250 |

**Table 3**
**The Revealed Preference Ranking of Colleges**
**(The Pure or "Price-Not-Considered" Ranking)**

| | | Mean Rating | 95% Confidence Interval for Mean lower | 95% Confidence Interval for Mean upper | Diff. from Rating below? |
|---|---|---|---|---|---|
| 1 | Harvard | 2.199 | 2.193 | 2.205 | *** |
| 2 | Yale | 2.112 | 2.106 | 2.119 | *** |
| 3 | Stanford | 2.052 | 2.046 | 2.058 | *** |
| 4 | Princeton | 1.992 | 1.986 | 1.998 | *** |
| 5 | Massachusetts Institute of Tech. | 1.672 | 1.666 | 1.678 | *** |
| 6 | Brown | 1.617 | 1.611 | 1.624 | ** |
| 7 | Columbia | 1.608 | 1.602 | 1.614 | *** |
| 8 | Dartmouth | 1.499 | 1.493 | 1.505 | *** |
| 9 | California Institute of Technology | 1.350 | 1.344 | 1.356 | *** |
| 10 | University of Pennsylvania | 1.316 | 1.310 | 1.322 | |
| 11 | Amherst | 1.310 | 1.304 | 1.316 | ** |
| 12 | Williams | 1.299 | 1.293 | 1.305 | *** |
| 13 | Georgetown | 1.202 | 1.196 | 1.208 | |
| 14 | Swarthmore | 1.197 | 1.191 | 1.203 | *** |
| 15 | Cornell | 1.149 | 1.143 | 1.155 | |
| 16 | Duke | 1.148 | 1.142 | 1.154 | *** |
| 17 | Pomona | 0.890 | 0.884 | 0.896 | *** |
| 18 | Tufts | 0.863 | 0.856 | 0.869 | *** |
| 19 | Johns Hopkins | 0.781 | 0.775 | 0.787 | *** |
| 20 | Wesleyan | 0.764 | 0.758 | 0.770 | *** |
| 21 | Haverford | 0.700 | 0.694 | 0.707 | *** |
| 22 | Middlebury | 0.652 | 0.645 | 0.658 | *** |
| 23 | Notre Dame | 0.614 | 0.607 | 0.620 | *** |
| 24 | Wellesley | 0.594 | 0.588 | 0.600 | |
| 25 | Rice | 0.591 | 0.585 | 0.597 | *** |
| 26 | Northwestern | 0.544 | 0.537 | 0.550 | *** |
| 27 | Bates | 0.502 | 0.496 | 0.508 | *** |
| 28 | Bowdoin | 0.464 | 0.458 | 0.470 | *** |
| 29 | University of California, Berkeley | 0.446 | 0.439 | 0.452 | *** |
| 30 | Vassar | 0.364 | 0.358 | 0.370 | *** |
| 31 | University of California, Los Angeles | 0.266 | 0.260 | 0.272 | |
| 32 | University of Virginia | 0.262 | 0.256 | 0.268 | *** |
| 33 | University of Chicago | 0.208 | 0.202 | 0.215 | *** |
| 34 | Barnard | 0.168 | 0.162 | 0.174 | * |
| 35 | New York University | 0.160 | 0.154 | 0.166 | *** |
| 36 | Colgate | 0.083 | 0.077 | 0.089 | *** |

| | | Mean Rating | 95% Confidence Interval for Mean lower | upper | Diff. from Rating below? |
|---|---|---|---|---|---|
| 37 | Boston College | 0.069 | 0.063 | 0.075 | *** |
| 38 | Emory | 0.054 | 0.048 | 0.060 | *** |
| 39 | Washington University (St. Louis) | 0.023 | 0.017 | 0.030 | *** |
| 40 | Washington and Lee | -0.074 | -0.080 | -0.068 | *** |
| 41 | University of North Carolina | -0.099 | -0.105 | -0.093 | |
| 42 | Oberlin | -0.103 | -0.109 | -0.097 | *** |
| 43 | Connecticut College | -0.193 | -0.199 | -0.187 | *** |
| 44 | Colby | -0.208 | -0.214 | -0.202 | |
| 45 | Wake Forest University | -0.208 | -0.214 | -0.202 | *** |
| 46 | Vanderbilt | -0.254 | -0.260 | -0.248 | |
| 47 | William and Mary | -0.257 | -0.263 | -0.251 | *** |
| 48 | Carnegie-Mellon | -0.282 | -0.288 | -0.276 | *** |
| 49 | University of Michigan | -0.389 | -0.395 | -0.383 | *** |
| 50 | University of Southern California | -0.426 | -0.432 | -0.419 | *** |
| 51 | University of California, San Diego | -0.470 | -0.477 | -0.464 | *** |
| 52 | Brigham Young | -0.485 | -0.491 | -0.479 | *** |
| 53 | Furman | -0.568 | -0.574 | -0.562 | *** |
| 54 | University of California, Santa Barb. | -0.600 | -0.606 | -0.594 | *** |
| 55 | University of Texas | -0.695 | -0.701 | -0.688 | *** |
| 56 | Lehigh | -0.724 | -0.730 | -0.718 | *** |
| 57 | George Washington University | -0.788 | -0.794 | -0.782 | |
| 58 | Smith | -0.789 | -0.796 | -0.783 | *** |
| 59 | Boston University | -0.808 | -0.814 | -0.802 | *** |
| 60 | Georgia Institute of Technology | -0.876 | -0.882 | -0.870 | * |
| 61 | University of Maryland | -0.885 | -0.891 | -0.879 | *** |
| 62 | University of Illinois | -0.898 | -0.904 | -0.892 | |
| 63 | Occidental | -0.902 | -0.908 | -0.896 | *** |
| 64 | Texas A&M University | -0.990 | -0.997 | -0.984 | *** |
| 65 | Rensselaer Polytechnic Institute | -1.010 | -1.016 | -1.003 | *** |
| 66 | University of Florida | -1.090 | -1.096 | -1.084 | |
| 67 | University of Miami | -1.095 | -1.101 | -1.089 | *** |
| 68 | University of California, Davis | -1.118 | -1.124 | -1.112 | *** |
| 69 | University of Oregon | -1.177 | -1.183 | -1.171 | *** |
| 70 | University of Arizona | -1.222 | -1.228 | -1.216 | *** |
| 71 | Virginia Polytechnic University | -1.288 | -1.294 | -1.282 | * |
| 72 | University of Wisconsin | -1.296 | -1.302 | -1.290 | *** |
| 73 | University of Hawaii | -1.373 | -1.380 | -1.367 | *** |
| 74 | University of Washington | -1.419 | -1.425 | -1.413 | |
| 75 | Tulane | -1.426 | -1.432 | -1.420 | *** |

| | | Mean Rating | 95% Confidence Interval for Mean lower | upper | Diff. from Rating below? |
|---|---|---|---|---|---|
| 76 | University of Colorado | -1.450 | -1.456 | -1.444 | *** |
| 77 | Pennsylvania State University | -1.555 | -1.562 | -1.549 | *** |
| 78 | Indiana University | -1.712 | -1.718 | -1.705 | *** |
| 79 | Rutgers | -1.825 | -1.831 | -1.819 | n/a |

*** statistically significantly different from the rating of the college listed directly below at the 0.01 level
** statistically significantly different from the rating of the college listed directly below at the 0.05 level
* statistically significantly different from the rating of the college listed directly below at the 0.10 level

Notes: The table shows the "price-not-considered" ranking of colleges and universities. That is, we control for the effect of variables that might influence admissions or matriculation, but which are *not* indicators of college quality or student merit. See text. The mean value of the "Other College" was -1.111.

**Table 4**
**Coefficients on Colleges' "Price Variables"**
**(College Characteristics that Do Not Indicate Quality but May Influence Matriculation)**

| | | 95% Region from Posterior Distribution | |
|---|---|---|---|
| | Mean Estimate | Lower | Upper |
| tuition that applies to student | 0.4600* | 0.2163 | 0.7026 |
| room and board fee (in thousands) | -0.0400 | -0.1276 | 0.0500 |
| grants for student (in thousands) | -0.2427 | -0.3045 | -0.1815 |
| loans for student | 0.1713 | -0.0128 | 0.3586 |
| work study amount for student | 0.3148 | -0.0209 | 0.6453 |
| father is an alumnus | -0.0001* | -0.0001 | -0.0001 |
| mother is an alumna | 0.0200 | -0.1455 | 0.1861 |
| distance between high school and college (thousands of miles) | 0.1966* | 0.1831 | 0.2102 |
| college is in student's home state | 0.0005* | 0.0004 | 0.0006 |
| college is in student's home region (using 9 Census regions) | 0.0002* | 0.0001 | 0.0002 |

Notes: The table shows estimates of the parameter $\beta$ , which contains student characteristics that are not indicators of merit but may nevertheless affect admissions.

**Table 5**
**Coefficients on Students' "Price Variables"**
**(Student Characteristics that Do Not Indicate Merit but May Influence Admission)**

| | | 95% Confidence Region | |
|---|---|---|---|
| | Mean Estimate | Lower | Upper |
| male | 0.0729 | -0.0345 | 0.1823 |
| white, non-Hispanic | 0.2362 | -0.0417 | 0.5362 |
| Asian | 0.3738* | 0.0683 | 0.6946 |
| black, non-Hispanic | 1.2357* | 0.8244 | 1.6600 |
| Hispanic | 0.8156* | 0.4337 | 1.2042 |
| Native American | -2.3411 | -4.2585 | -0.5180 |
| father is an alumnus | 1.0878* | 0.7996 | 1.3873 |
| mother is an alumna | 0.4810* | 0.0893 | 0.8871 |
| parents' income (in thousands) | 0.0008 | -0.0002 | 0.0018 |
| student applied for aid | 0.3164* | 0.1856 | 0.4439 |
| at least parent has a graduate degree | 0.3170* | 0.1911 | 0.4434 |
| college is in student's home state | 0.6140* | 0.4971 | 0.7307 |
| population density of student home state (in thousands per square mile) | -0.0100 | -0.0688 | 0.0486 |

Notes: The table shows estimates of the parameter $\boldsymbol{\delta}$, which contains student characteristics that are not indicators of merit but may nevertheless affect admissions.

**Table 6**
**The "Price-Considered" Ranking of Colleges, based on Revealed Preference**

| | | Mean Rating | 95% Confidence Interval for Mean lower | upper | Diff. from Rating below? |
|---|---|---|---|---|---|
| 1 | Harvard | 0.692 | 0.687 | 0.698 | *** |
| 2 | Yale | 0.673 | 0.668 | 0.678 | *** |
| 3 | Princeton | 0.601 | 0.596 | 0.607 | *** |
| 4 | Stanford | 0.458 | 0.453 | 0.464 | *** |
| 5 | Brown | 0.306 | 0.301 | 0.311 | *** |
| 6 | Columbia | 0.291 | 0.285 | 0.296 | *** |
| 7 | California Institute of Technology | 0.280 | 0.275 | 0.286 | *** |
| 8 | Dartmouth | 0.250 | 0.245 | 0.255 | |
| 9 | Massachusetts Institute of Tech. | 0.248 | 0.242 | 0.253 | *** |
| 10 | Amherst | 0.178 | 0.173 | 0.183 | *** |
| 11 | Williams | 0.152 | 0.146 | 0.157 | *** |
| 12 | University of Pennsylvania | 0.132 | 0.127 | 0.137 | *** |
| 13 | Swarthmore | 0.007 | 0.001 | 0.012 | *** |
| 14 | Duke | -0.044 | -0.049 | -0.039 | *** |
| 15 | Georgetown | -0.097 | -0.103 | -0.092 | *** |
| 16 | Cornell | -0.188 | -0.193 | -0.183 | *** |
| 17 | Wesleyan | -0.231 | -0.237 | -0.226 | *** |
| 18 | Tufts | -0.291 | -0.296 | -0.285 | *** |
| 19 | Middlebury | -0.328 | -0.334 | -0.323 | *** |
| 20 | Pomona | -0.380 | -0.385 | -0.375 | ** |
| 21 | University of Virginia | -0.388 | -0.393 | -0.382 | *** |
| 22 | Haverford | -0.419 | -0.424 | -0.413 | *** |
| 23 | Rice | -0.444 | -0.449 | -0.439 | |
| 24 | Johns Hopkins | -0.447 | -0.452 | -0.441 | |
| 25 | Notre Dame | -0.451 | -0.456 | -0.446 | *** |
| 26 | Wellesley | -0.469 | -0.474 | -0.464 | |
| 27 | Bowdoin | -0.469 | -0.475 | -0.464 | *** |
| 28 | Bates | -0.506 | -0.512 | -0.501 | *** |
| 29 | Northwestern | -0.534 | -0.539 | -0.529 | *** |
| 30 | University of California, Berkeley | -0.565 | -0.571 | -0.560 | *** |
| 31 | Vassar | -0.690 | -0.695 | -0.684 | ** |
| 32 | University of North Carolina | -0.699 | -0.704 | -0.693 | *** |
| 33 | Washington and Lee | -0.768 | -0.773 | -0.762 | *** |
| 34 | University of California, Los Angel. | -0.810 | -0.815 | -0.804 | *** |
| 35 | Furman | -0.866 | -0.871 | -0.861 | |
| 36 | University of Chicago | -0.870 | -0.875 | -0.865 | *** |

| | | Mean Rating | 95% Confidence Interval for Mean lower | upper | Diff. from Rating below? |
|---|---|---|---|---|---|
| 37 | William and Mary | -0.884 | -0.889 | -0.879 | *** |
| 38 | Colgate | -0.901 | -0.906 | -0.895 | *** |
| 39 | Barnard | -0.910 | -0.916 | -0.905 | *** |
| 40 | New York University | -0.956 | -0.961 | -0.950 | *** |
| 41 | Boston College | -0.980 | -0.985 | -0.975 | ** |
| 42 | Connecticut College | -0.990 | -0.995 | -0.984 | *** |
| 43 | Oberlin | -1.003 | -1.008 | -0.998 | |
| 44 | Emory | -1.009 | -1.014 | -1.003 | *** |
| 45 | Colby | -1.076 | -1.082 | -1.071 | *** |
| 46 | Wake Forest University | -1.109 | -1.115 | -1.104 | *** |
| 47 | Washington University (St. Louis) | -1.134 | -1.139 | -1.128 | *** |
| 48 | Carnegie Mellon | -1.169 | -1.174 | -1.164 | |
| 49 | Vanderbilt | -1.170 | -1.175 | -1.165 | *** |
| 50 | University of Southern California | -1.220 | -1.225 | -1.215 | *** |
| 51 | University of Texas | -1.262 | -1.267 | -1.257 | * |
| 52 | Brigham Young | -1.269 | -1.274 | -1.264 | |
| 53 | Georgia Institute of Tech. | -1.275 | -1.280 | -1.269 | |
| 54 | University of Michigan | -1.277 | -1.282 | -1.271 | *** |
| 55 | University of Maryland | -1.430 | -1.435 | -1.425 | *** |
| 56 | University of Oregon | -1.443 | -1.448 | -1.438 | *** |
| 57 | University of Illinois | -1.463 | -1.468 | -1.458 | *** |
| 58 | University of California, San Diego | -1.485 | -1.490 | -1.480 | *** |
| 59 | Smith | -1.533 | -1.538 | -1.528 | * |
| 60 | Lehigh | -1.540 | -1.545 | -1.535 | *** |
| 61 | University of Florida | -1.583 | -1.588 | -1.578 | |
| 62 | University of California, Santa Barb. | -1.588 | -1.593 | -1.583 | *** |
| 63 | Occidental | -1.632 | -1.637 | -1.627 | |
| 64 | Texas A&M University | -1.634 | -1.639 | -1.628 | *** |
| 65 | University of Miami | -1.654 | -1.660 | -1.649 | *** |
| 66 | George Washington University | -1.664 | -1.670 | -1.659 | *** |
| 67 | Boston University | -1.703 | -1.708 | -1.698 | *** |
| 68 | University of Arizona | -1.830 | -1.835 | -1.824 | *** |
| 69 | Rensselaer Polytechnic Institute | -1.865 | -1.870 | -1.860 | *** |
| 70 | University of Washington | -1.894 | -1.900 | -1.889 | *** |
| 71 | Tulane | -1.948 | -1.954 | -1.943 | ** |
| 72 | Virginia Polytechnic Institute | -1.958 | -1.963 | -1.953 | *** |
| 73 | University of Wisconsin | -1.998 | -2.003 | -1.993 | *** |
| 74 | University of Colorado | -2.067 | -2.073 | -2.062 | *** |
| 75 | Pennsylvania State Univeristy | -2.106 | -2.111 | -2.101 | *** |

| | | Mean Rating | 95% Confidence Interval for Mean lower | upper | Diff. from Rating below? |
|---|---|---|---|---|---|
| 76 | University of Hawaii | -2.125 | -2.130 | -2.119 | * |
| 77 | University of California, Davis | -2.131 | -2.137 | -2.126 | *** |
| 78 | Rutgers | -2.312 | -2.317 | -2.306 | *** |
| 79 | Indiana University | -2.358 | -2.364 | -2.353 | n/a |

*** statistically significantly different from the rating of the college listed directly below at the 0.01 level
** statistically significantly different from the rating of the college listed directly below at the 0.05 level
* statistically significantly different from the rating of the college listed directly below at the 0.10 level

Notes: The table shows the "price-considered" ranking of colleges and universities. That is, we have not attempted to control for the effect of variables that might influence admissions or matriculation, but which are *not* indicators of college quality or student merit. See text. The mean value of the "Other College" was -1.513.