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

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ABSTRACT

We show how to construct a ranking of U.S. undergraduate programs based on students' revealed preferences. We construct examples of national and regional rankings, using hand-collected data on 3,240 high- achieving students. Our statistical model extends models used for ranking players in tournaments, such as chess or 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. Our method produces a ranking that would be difficult for a college to manipulate. In contrast, it is easy to manipulate the matriculation rate and the admission rate, which are the common measures of preference that receive substantial weight in highly publicized college rating systems. If our ranking were used in place of these measures, the pressure on colleges to practice strategic admissions would be relieved.

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Executive Summary

We show how to construct a ranking of U.S. undergraduate programs based on how desirable students find them. We call this the revealed preference ranking of colleges. We construct examples of national and regional rankings, using data we collected on the college applications, admissions, and matriculation of 3,240 high- achieving students.

Our statistical model extends models used for ranking players in tournaments, such as chess or tennis. When a student decides to matriculate at one college, among those that have admitted him, he effectively decides which college "won" in head-to-head competition. The model efficiently combines the information contained in thousands of these wins and losses.

Our method produces a ranking that would be very difficult for a college to manipulate. In contrast, colleges can easily manipulate the matriculation rate and the admission rate, which are the crude proxies commonly used to measure colleges' desirability. Because there is a strong demand for measures of colleges' desirability, colleges are forced to advertise their matriculation and admissions rates. Moreover, college guides like *U.S. News* are forced to give substantial weight to the matriculation and admissions rates. These crude proxies are not only misleading; they induce colleges to engage in distorted conduct that decreases the colleges' *real* selectivity while increasing the colleges' *apparent* desirability. So long as colleges are judged based on their crude admissions and matriculation rates, they are unlikely to eliminate strategic admissions or roll back early decision programs, which are the key methods of manipulating the proxies. Many college administrators correctly perceive that they are in a bad equilibrium. Yet, so long as the crude proxies are used, the bad equilibrium is likely to persist. If our ranking method were used, the pressure on colleges to practice strategic admissions would be relieved.

We rank more than 100 colleges in the national ranking, and we show how each college is likely to fare in a head-to-head match up against specific rival colleges. We also show regional rankings and demonstrate that they combine up to generate a truly national ranking among colleges that are highly preferred. We explain how to think about niche colleges, such as California Institute of Technology, whose applicants are self-selected to an unusual degree; and we propose useful sub-rankings for certain types of colleges.

I. Why a Revealed Preference Ranking?

In this study, we show how to construct a ranking of U.S. undergraduate programs based on students' revealed preferences –that is, the colleges students prefer when they can choose among them. The result is a ranking of colleges based on their desirability. 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 construct an example of our ranking using data from a survey of 3,240 highly meritorious students that was specifically conducted for this study. Because we do not have a fully representative sample of college applicants, we rank only about a hundred undergraduate programs and our ranking is an example, not definitive. Nevertheless, we can show that our ranking has advantages. In particular, it is less manipulable than crude measures of revealed preference, such as the admissions rate and matriculation rate. A ranking constructed according to our method would be a good substitute for the preference indicators that receive substantial weight in formulas of high publicized college rating systems, like that of *U.S. News and World Report*. Many colleges currently feel compelled to engage in strategic admissions behavior in order to maximize their published college ratings. Use of our ranking method would relieve this pressure.

Rankings based on students' revealed preference measure a college's desirability in students' eyes. Such desirability may reflect a college's quality, but it is unlikely to be identical to quality. Indeed, the notion of what constitutes quality in a college is likely to differ from person to person. Faculty, parents, policy makers, and students may all assign different weights to colleges' characteristics. Why then construct a revealed preference ranking at all, which merely shows the value that *students* (in combination with their parents) put on colleges?

The primary reason that we are motivated to construct a revealed preference ranking is a practical one. Parents and students demand revealed preference information and college guides feel obliged to offer them some. The two measures of preference used by college guides are the crude matriculation rate and crude admissions rate. One objection to these measures is that they are inefficiently coarse. Our revealed preference ranking *efficiently* aggregates the information contained in individual students' decisions. Another serious objection to these measures is that colleges can manipulate them, though at a cost. Colleges do not necessarily want to manipulate their matriculation rate and admissions rate; they feel compelled to do so. A college that does not manipulate these rates, when its competitors do, loses ground in highly publicized college ratings. Such lost ground will eventually have real effects on the college's ability to recruit students, attract donations, and so on.[1] In short, U.S. colleges are in a bad equilibrium: colleges manipulate the rates even though they would all be better off if no college manipulated the rates. If a revealed preference ranking like ours were used, colleges would find it extremely hard to "defect" and the bad equilibrium would not arise. All parties (including the college guides) should be pleased to have a measure of revealed preference that limits or even eliminates manipulation.

We have attempted to justify constructing a good indicator of revealed preference by pointing out that one is demanded. But, why do students and their parents demand such measures? There are a few possible answers.

First, students believe and act as though their peers matter. This may be because peer quality affects the level of teaching that is offered. Alternatively, students may learn directly from their peers. If such channels for peer effects are important, then it is reasonable for students to care about whether they are surrounded by peers with high college aptitude. Students will want to see a revealed preference ranking because it will show them which colleges can offer the highest concentration of desirable peers. A more preferred college wins more often in matriculation tournaments. Thus, it can afford to be more selective and can offer peers with higher aptitude.

Second, students–especially the high achieving students on whom we focus–are not

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[1] See evidence on the real effects of the ratings, see Ehrenberg and Monks (1999).

ignorant about college quality. They gather information about colleges' quality from publications, older siblings, friends who are attending college, college counselors, and their own visits to colleges. A student may place the greatest weight on his own observations of quality, but he will also put some weight on the observations of other students, simply because his own sample of observations is too small to be representative. A revealed preference ranking efficiently aggregates observations about quality from thousands of students. There are parallels to other industries. For instance, people judge restaurant and hotel quality based partly on their own experiences, but they also want to know about other people's experiences. This is why there is a demand for guides like *Zagat's*, which aggregate people's observations about hotels and restaurants.

Third, it has long been hypothesized that specific colleges' degrees serve as signals of a student's aptitude, which is hard for future employers to observe directly [Spence, 1974]. In equilibrium, a college's degree signals the aptitude of the students who actually attend it. For instance, there will be an equilibrium only if a Princeton degree signals aptitude that is consistent with the actual distribution of aptitude among Princeton students. This is another reason for students to care about the ability of their peers and, thus, their college's tendency to attract students.[2]

In Section II of the paper, we further discuss the weaknesses of using the matriculation rate and the admissions rate as measures of revealed preference, and show how these measures can easily be manipulated. In Section III, we present our statistical model of college choice as a multiple comparison problem. We show how to account for the potentially confounding effects of tuition discounts, financial aid, and other factors that might make a college "win" when it would lose on the basis of its intrinsic desirability.

The data for our study was hand-collected in a survey of 510 high schools, with surveys

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[2] We do not know, however, that such signaling is actually important. Students may be able to 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.

returned for 3,240 students. Section IV describes the survey methodology and provides summary statistics for the sample. These data are used to estimate the model, with the results discussed in Section V. Section VI concludes the paper.

II. The Manipulability of Various Measures of Revealed Preference

One of the two common measures of revealed preference is the matriculation rate–the share of accepted students who matriculate at a college:

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

There are several methods by which a college can manipulate its matriculation rate. The reason that most methods work is that the matriculation rate is just an aggregate statistic and has no way of taking account of the composition of the pool of admittees (higher or lower merit?) and or of *which* students within the pool of admittees are matriculating (those with the best alternative offers or those with worst alternative offers?).

An early decision program is the most dramatic means by which a college can manipulate its matriculation rate. Every early decision admittee has a 100 percent probability of matriculating, so –mechanically– the more students whom a college admits under its early decision program, the higher is its matriculation rate. (It is important to distinguish between early decision, in which a student *commits* to matriculate if admitted, and early action, in which a student is admitted early but can apply to numerous other colleges and turn down the early admission offer.) An early decision program is not without costs for the college. As Avery, Fairbanks, and Zeckhauser (2003) show, college lowers their admissions standards for early decision applicants in order to induce them to pre-commit to matriculating and pre-commit to having no alternative offers when it comes to negotiating over financial aid. As a college admits more and more of its class under early decision, its actual admissions standards fall and students will therefore experience less meritorious peers. Yet, by the standard of the matriculation rate, the college's desirability will have risen.

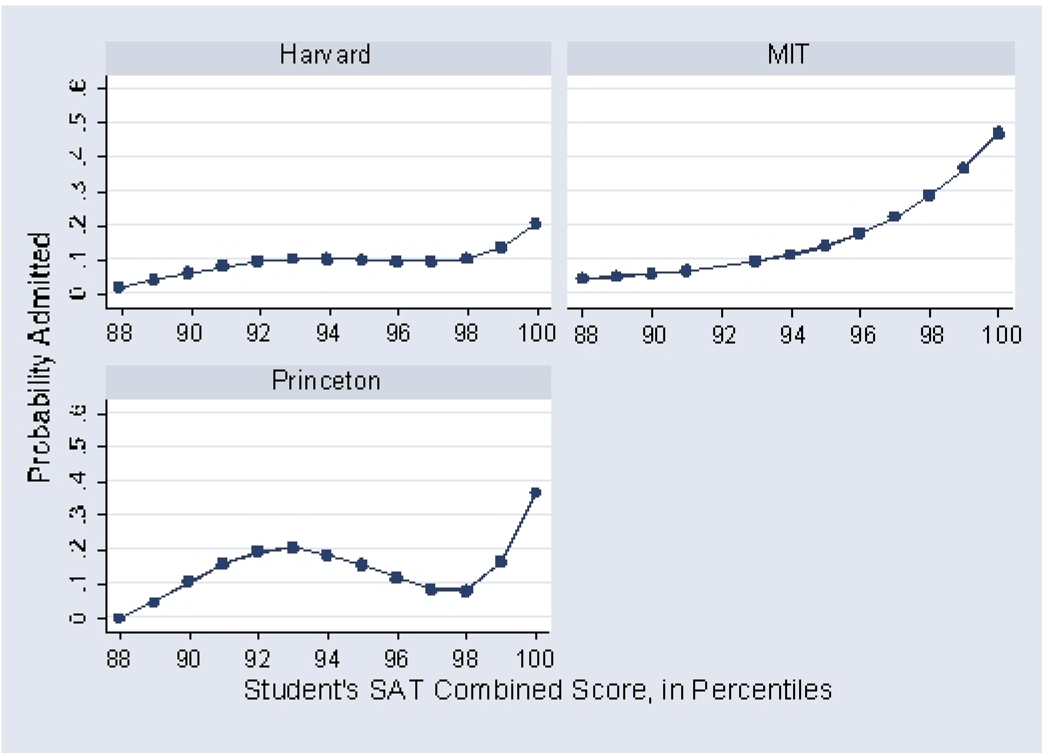
Another method by which a college can manipulate its matriculation rate is deliberately not admitting students who are likely to be admitted by close competitors or colleges that are often more highly preferred. A college administrator may say to himself, "My college will ultimately fail to attract good applicants unless I raise its matriculation rate. I can achieve this with a strategic policy that denies admission to students who seem likely to be accepted by colleges more desirable than mine. By systemically denying them admission, my college will of course lose of its some most desirable students (because some percentage of the highly desirable students would have matriculated). However, it is worthwhile to sacrifice the *actual* desirability of my college class in order to *appear* more desirable on a flawed indicator." To make this strategy concrete, suppose 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, 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. 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, by the standard of the matriculation rate, Princeton's measured appeal would rise just as its actual appeal fell.

We have not arbitrarily selected Princeton for our example. It is by no means alone in appearing to practice somewhat strategic admissions (for other examples, see "Glass Floor: How Colleges Reject the Top Applicants and Boost Their Status," 2001), but it makes for a particularly clear example in our data.[3] Consider Figure 1, which shows admissions at Harvard, MIT, and Princeton.   If a college is not practicing strategic admissions, then the probability that a student is admitted ought to rise monotonically in his or her merit. In contrast, a college that is strategic will have non-monotonic admissions probabilities. A student's probability of admission will first rise in his or her merit and then *fall* as his or her merit moves into the range in which the strategic college faces stiff competition. In other

[3] As described below, we have the most ample data on the colleges that are the most selective. Princeton provides the clearest example among the top several such colleges.

words, the college will avoid admitting students in the range in which it is likely to lose in a matriculation tournament. Finally, if the student's merit is high enough, a strategic college will probably admit the student even if the competition will be stiff. This is because the prospective gains from enrolling a "star" will more than make up for the prospective losses from a higher

Figure 1



admissions rate and lower matriculation rate. (Recall that the crude admissions rate and matriculation rate do not record *who* is admitted or matriculates.)

Although we realize that it is not a definitive measure of a student's merit, for the sake of these purely illustrative figures, we use a student's combined SAT I score, measured in national percentiles. This measure is at least readily understood and reasonably continuous. It is also wholly unrelated to our ranking method.

Examine MIT admissions in Figure 1. The probability of a student's being admitted rises steeply and monotonically in his or her combined SAT score, suggesting that MIT is not engaging in strategic admissions. Now examine Harvard admissions in Figure 1. The line has a flat region that suggests that the probability of a student's being admitted is about 10 percent regardless of where his SAT scores in the range between the 93rd and the 98th percentiles. Above the 98th percentile, a student's probability of admissions rises steeply. Finally, consider Princeton admissions in Figure 1. At Princeton, the admissions probability rises to 20 percent at the 93 percentile, then *falls* to 10 percent at the 98 percentile (precisely the region where competition is toughest), and then rises again for students with SAT scores in the top 2 percentiles.

In short, it appears that Princeton practices more strategic admissions than MIT or Harvard. When we see the revealed preference ranking later in the paper, we will see that Figure 1 makes sense because Harvard and MIT could benefit less from strategic admissions than Princeton could. While Figure 1 is not definitive, it provides suggestive evidence that even a highly prestigious school may practice potentially costly strategic admissions. Such behavior is potentially costly to the actual quality of an admissions class, with no clear benefit beyond a higher reported matriculation rate.

The second of the two common proxies for revealed preference is the admission rate–that is, the share of applicants who are admitted by a college:

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

There a several methods by which a college can manipulate its admissions rate. The reason that most methods work is that the admissions rate is just an aggregate statistic. It does not account for the composition of the pool of applicants (are they high or low merit?). It does not account for *which* applicants a college admits.

In forming a class of a given size, a college can admit fewer students if its matriculation rate is higher. Therefore, the methods discussed above for manipulating the matriculation rate are also methods for manipulating the admissions rate. For instance, if a college makes heavy use of an early decision program, it only needs to admit only slightly more students than the number that it actually wishes to enroll. This is because the early decision admittees are pre-committed to enrolling. The technique of *not* admitting applicants who are likely to be admitted by close competitors also allows a college to publish a lower (better) admissions rate.

In addition, colleges can manipulate their admissions rate by encouraging applications from students who have little chance of actually gaining admission. A college can advertise less stringent criteria than it actually applies. By doing so, it encourages marginal students to apply, increases its number of applications, decreases its admissions rate, and raises its apparent desirability, even though its real desirability has not changed. For instance, this is how Toor (2000) described her job as an admissions officer at Duke University: "The job of admissions officers is to recruit, to boost application numbers. The more applications, the lower the admit rate, the higher the institutional ranking. Increasing application numbers is usually the No. 1 mandate of the recruiting season. Partly, that means trying to get the very best students to apply. But it also means trying to persuade those regular, old Bright Well-Rounded Kids (B.W.R.K.'s, in admissionese) to apply -- so that the college can reject them and bolster its selectivity rating."

In short, the two conventional measures are manipulable by colleges, though at a cost. If the goal of college admissions is to admit the optimal class, then colleges must systemically deviate from this goal in order to manipulate their matriculation and admissions rates. Colleges must sacrifice actual desirability for apparent desirability. Even if all colleges prefer not to manipulate the crude rates, each college will lose if it refrains from manipulation when other colleges do not refrain.

How might colleges escape this bad equilibrium? If the measure of revealed preference is not manipulable (or manipulable only by very complex, costly means), then all parties could be better off. In the next section, we formally describe the statistical method we use to create a revealed preference ranking of colleges. Here, we can give some intuition into why a ranking based on our method is not prey to simple forms of manipulation. For this exercise, it may be helpful for readers to think of some sport or game familiar to them.

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 its 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, etc. 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, 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.

Readers might also find it helpful if we stated what a college would need to do if it were to manipulate our ranking successfully. None of the crude methods of manipulation described above would work. A college would need to do something more subtle. Return to the Princeton example, for concreteness. Princeton would need to find students in its applicant pool who were likely to attend Princeton even if admitted to Harvard, Yale, MIT, Stanford, and so on. Such students would have to exist exogenously; they could not be "created" by Princeton's giving them extra aid to induce them to matriculate. (Giving them extra aid would not work because we can observe and account for aid.) Moreover, Princeton would have to identify these students using characteristics not observable to other colleges. If the trait that Princeton used to pick out likely matriculators was observable (such as being a Princeton alumnus' child), then this trait could be used as a control in any revealed preference ranking, as we will do below with some characteristics collected in our study. Without an early decision program to bind students or "secret" traits that distinguished its likely matriculators, a college could not identify students whose matriculation tournaments it would win.

III. The Model

A. The Desirability of Colleges

The exercise of ranking colleges is necessarily predicated on the notion that there are latent indices of desirability on which college *can* be ranked. In the language of econometrics, the exercise is based on the assumption there are latent variables that indicate the desirability of each college (perhaps on multiple dimensions). Our measure of desirability encompasses all characteristics of a school, including (perceived) educational quality, campus location, and tuition. We do not claim to know how latent desirability is constructed. We simply assert that, to the extent that students act in accordance with it, we can construct rankings.

We suspect that latent desirability is well defined on a national basis for the most academically elite colleges in the United States. We also suspect that latent desirability is defined on a national basis for the most elite specialized colleges in the United States: engineering schools, music schools, and so on. We would not be surprised to find, however, that once we move below the most academically elite colleges, latent desirability is only well-defined within regions of the country and perhaps within other dimensions. If we had a very large, random sample of all college applicants, we could construct rankings within regions and specialties and show where they joined up to become a national ranking. Given that the data we use for our exercise is focused on high achieving students who do not apply much outside the group of the most academically elite colleges, we will start by constructing a national ranking of such colleges. We will rank only those that the data suggest have a national draw. Subsequently, we construct regional rankings and discuss specialized rankings. Until then, however, we encourage the reader to think of a college's latent desirability as being unidimensional.

For our exercise, is it necessary that all students identically perceive a college's desirability? No. We will allow students' perception of a college'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. 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 had latent desirabilities that were perceived with idiosyncratic noise added in.

Finally, note that our exercise does not *impose* the existence of latent desirability; our method simply will not work if widespread agreement on desirability does 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 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. Overall, we can afford to be agnostic about how students develop preferences over colleges. Our data will only reveal such preferences to the extent that they are systematic.

The problem of ranking colleges can be framed as a collection of multiple comparisons. Comparison data come from competitions 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 multiple comparison models. An important problem addressed by multiple comparison models is how to rank objects when 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.

B. Matriculation Tournaments as a Multiple Comparison Problem

To understand how college choice can be viewed as a multiple comparison problem, suppose that a collection of students has been admitted to a set of schools. Each schools' desirability is modeled as a latent distribution of values. Each student effectively holds a tournament among the collection of schools that have admitted him; in our model this tournament is played by taking one draw from each school's distribution. The school with the highest draw has "won" the multi-player tournament, and the student matriculates at that school. Assuming that there are no confounding variables, a reasonable inference is that the school that wins the multi-player tournament is preferred to the other schools in that competition. By aggregating the information from all students' tournaments, inferences about the desirability of schools can be constructed.

David (1988) surveys the rich body of work on multiple comparison modeling, which mainly focuses on paired comparison models, where each tournament contains only two players. While no one has previously attempted to rank colleges 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).[4]

We build on the Bradley-Terry (1952) and the Luce (1959) models in which the distribution of desirability is an extreme value distribution. The assumption of an extreme value distribution for potentially observed desirability leads to a logit model. 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.

It is worth noting that the extreme-value or normal distribution of potential desirabilities is a probabilistic assumption about the merit of an individual school, not an

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[4] Statistical comparison models have also been used to study which college characteristics students like and which student characteristics colleges like. See, for example, Manski and Wise (1983), Long (2003), Avery and Hoxby (2004).

assumption about the distribution of mean desirabilities across schools. Because college comparison data can provide strong information about the relative desirabilities of colleges, any assumptions made about the distribution of mean desirabilities should be weak. Our modeling approach allows for the possibility, for example, that a small number of schools are estimated to have mean desirabilities substantially greater than the remaining schools considered.

C. The Matriculation Model

Assuming that each college's potentially observed desirability follows an extreme value distribution with the same scale and shape, the relevant parameter is the location parameter of the distribution. The latent variable is:

$$\theta_i = \text{the desirability parameter of college } i,$$

where we index colleges with i=1,2,...,I.

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:

$$(3) \qquad Y_{ij} = \left\{ \begin{array}{ll} 1 & \textit{if student } j \textit{ matriculates at college } i \\ 0 & \textit{otherwise} \end{array} \right\} .$$

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

$$(4) \qquad (Y_{1j},\ldots,Y_{m_j j}) \sim \textit{Multinomial}\,(1,(p_{1j},\ldots,p_{m_j j})) ,$$

where p_{ij} is the probability that student j chooses to matriculate at college i among his m_j college choices.[5] We assume Luce's choice model, of the form:

$$(5) \qquad p_{i^*j} = \frac{\exp(\theta_{i^*})}{\sum_{i \in S_j} \exp(\theta_i)} , \qquad i^* \in S_j .$$

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[5] For expositional convenience, we have reindexed the colleges in student j set S_j, so that they can be written 1,...,m_j.

This model can be rewritten as a conditional logit model, sometimes called McFadden's choice model.

The θ_is include all characteristics that do not vary within each college: such characteristics include *average* perceptions about the quality of the education and the *average* cost of attendance. For some characteristics, we can measure variation across applicants: tuition, room fees, board fees, grants to the student, the subsidy value of loans to the student, the subsidy value of the work-study it offers the student, the cost associated with its distance from the student's home, its being in-state, its being in-region, and its being the *alma mater* of one or more of the student's parents. We add these characteristics to the model to gain extra explanatory power.[6]

Let the vector $\boldsymbol{x}_{ij} = (x_{1ij}, x_{2ij}, \ldots, x_{Kij})'$ be the K characteristics that can vary among admittees and that are faced by admittee j who is considering whether to matriculate at college i. Note well that each characteristic is de-meaned so that we obtain the college's desirability at its average level in the data. It is not possible to separately identify the effect of these average characteristics from the θ_i for each school. We treat $\boldsymbol{x}_{ij}$ as a vector of covariates which are allowed to enter the model linearly. Specifically, the probabilities for the matriculation model become:

(6)
$$p_{i^*j} = \frac{\exp(\theta_{i^*} + \boldsymbol{x}_{ij}'\boldsymbol{\delta})}{\sum_{i \in S_j} \exp(\theta_i + \boldsymbol{x}_{ij}'\boldsymbol{\delta})}, \qquad i^* \in S_j .$$

In fitting the model, not only are the θ_i inferred, but so are the $\boldsymbol{\delta}$, which are the effects of the characteristics on matriculation.

D. Self-Selection and the Application Decision

We estimate the θ_i from matriculation decisions of admitted applicants. Of course, to be admitted, one must first apply, so our underlying data for each school is not a random sample of all students, but rather of all students *conditional* on their application to that school. This is a

[6] In practice, the covariates have a trivial effect on the rankings. Estimates of the model without covariates are available from the authors.

self-selected group, and we expect a group of applicants to find a school more desirable than an otherwise identical set of non-applicants. Such self-selection does not induce any bias if the applicant pool for every school is shifted equivalently: that is, if we are estimating a θ_i for every school based on the applicant pool, but the equivalent parameter for all students (applicants and non-applicants) is θ_i - α_i, and the α_i is the same for all schools, i. Since our ratings are unique only up to a constant, such a shift would not change the interpretation of our results.

Self-selection would cause a problem if the applicant pools are induced differently across schools. This would appear to be a major issue only for "niche schools" that attract applications from only the most interested students. Any speciality school could fall into this category, with engineering schools, school with a religious affiliation, or single-sex schools being the most likely. These schools might attract applicant pools with stronger preferences – because students who are lukewarm about the speciality don't bother to apply – and effectively have a higher α_i, leading the estimated θ_i to be biased upward.

The ideal way to handle these selection issues would be to explicitly model the application decision, but this is not feasible without many further assumptions. With thousands of schools to choose from, even artificial constraints on the number of applications leads to a complex combinatorial problem. In this case, the modeler – like the applicants themselves – is forced to use shortcuts and assumptions. Since these assumptions would ultimately drive the extent of selection bias, it seems more straightforward to acknowledge this potential bias and discuss its implications where it is appropriate. Thus, we proceed under the baseline assumption that the α_i are identical across schools. In Section V, we discuss the implications of deviations from this assumption, point out specific schools for which these deviations may make a difference, and propose a practical method for dealing with them.

While we do not believe that self-selection is a major issue for the θ_i estimates, it is of greater concern for inference on the δ coefficients For instance, suppose that price sensitivity is heterogeneous and students who are especially price sensitive seek out colleges that offer them substantial discounts. We might overestimate the effects of prices because the variation in the data comes disproportionately from price-sensitive students. For this reason, we will not give strong interpretations to the coefficients on these characteristics. It is still useful to include these characteristics in the regression, especially because they may proxy for otherwise unobservable variables.

E. Model Fitting

The complexity of our model lends itself naturally to fitting the model in the Bayesian framework. We fit our model by computing the posterior distribution of model parameters followed by summarizing important features of the distribution. The posterior distribution of parameters is proportional to the product of the likelihood function with a prior distribution. The likelihood can be written as a product of multinomial logit probabilities derived from equation (6). We assume a locally uniform but proper prior distribution that factors into independent densities. The prior distribution consists of the following components:

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

$$\frac{1}{\sigma^2} \sim Gamma(0.1, 0.1) \qquad (7)$$

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

where δ_k indexes the k^{th} element of the vector delta.

We summarize estimated college desirability by computing the posterior modes of the θ_i. These were carried out using a Newton-Raphson algorithm for multinomial logit models, as implemented in Stata. The posterior modes are presented in Tables 3, 5 and 6. We also fit the model using Markov chain Monte Carlo(MCMC) simulation from the posterior distribution to infer more complex quantities of interest. For example, to answer questions like "is there a meaningful distinction in desirability between the college ranked 15th and the college ranked 20th?" we cannot simply rely on comparing posterior modes. Instead, MCMC produces simulated values from the posterior distribution of model parameters. Thus, using MCMC simulation, pairs of values can be generated from the posterior distribution of (θ_{15}, θ_{20}), and the probability that θ_{15} is greater than θ_{20} can be evaluated by computing the proportion of pairs in which θ_{15} is greater than θ_{20}. An answer like 95 percent or more – analogous to a 95%

significance test – tells us that the colleges are substantially more distinct than an answer like 55 percent.

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. 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 posterior distribution. A recent example of MCMC methods applied to paired comparison models is Glickman (2001).

We implemented the MCMC algorithm using the program BUGS (Spiegelhalter et al., 1996). For each model, a burn-in period of 10,000 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, 10,000 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 on which to calculate parameter summaries. In Table 4, which shows pairwise match-ups for each college we rank, we display summaries based on MCMC draws from the posterior distribution.

IV. Data

To construct an example of our revealed preference ranking, we use from the College Admissions Project survey, in which we surveyed high school seniors in the college graduating class of 2004.[7] We designed the survey to gather data on 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,

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

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 colleges with a national draw to construct a revealed preference ranking among them.

We reemphasize that we use the College Admissions Project data to construct an *example* of a revealed preference ranking. If we had had much greater resources, we would have surveyed a more fully representative sample of students in the United States. With more data, our national ranking would be more definitive, and we would be able to rank many more colleges (most of them in regional or specialized rankings, not the national ranking). At the end of this section, we describe the cut-offs we used to determine which colleges we could reasonably rank.

A. 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 selected had a record of sending several students to selective colleges each year, and they were identified using published guides to secondary schools, such as Peterson's and the experience of admissions experts. 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.[8] The counselors distributed the surveys to students, collected the completed surveys, and returned them to us for coding.[9] Students were tracked

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[8] 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.

[9] 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.

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.

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 (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.[10]

The College Admissions Project survey produced a response rate of approximately 65%, including full information for 3,240 students from 396 high schools.[11] The final sample contains

[10] See Avery and Hoxby [2004] for a complete description of administrative data sources.

[11] 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.

students from 43 states plus the District of Columbia.[12] 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 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, 2004], we have found that students who make it into the sample act very much like one another when they make college decisions, regardless of whether they come from more or less advantaged 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. Sample Statistics

The summary statistics shown in Tables 1 and 2 demonstrate show the students in the sample are high achieving. 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.[13] 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

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

[13] 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.

at least one college. 45 percent of the students attended private school, and their parents' income averaged $119,929 in 1999.[14] However, 76 percent of the sample had incomes below the cut-off where a family is considered for aid by selective private colleges, and 59 percent of the students applied for need-based financial aid.[15]

Table 1

Description of the Students in the College Admission Project Data

Variable	Mean	Std. Dev.	Minimum	Maximum
Male	0.41	0.49	0.00	1.00
White, non-Hispanic	0.73	0.44	0.00	1.00
Black, non-Hispanic	0.04	0.18	0.00	1.00
Asian	0.16	0.36	0.00	1.00
Hispanic	0.04	0.19	0.00	1.00
Native American	0.00	0.03	0.00	1.00
Other race/ethnicity	0.04	0.19	0.00	1.00
Parents are married	0.83	0.38	0.00	1.00
Sibling(s) enrolled in college	0.23	0.42	0.00	1.00
Parents' income	119,929	65,518	9,186	240,000
Expected family contribution	27,653	16,524	0	120,000
Applied for financial aid?	0.59	0.49	0.00	1.00
National Merit Scholarship winner	0.05	0.22	0.00	1.00
Student's combined SAT score	1357	139	780	1600
Student's SAT score, in national percentiles	90.4	12.3	12.0	100.0
Median SAT score at *most* selective college to which student was admitted	86.4	10.4	33.5	98.0
Median SAT score at *least* selective college to which student was admitted	73.8	14.6	14.3	97.0
Student's high school was private	0.45	0.50	0.00	1.00

[14] See Avery and Hoxby [2004] for descriptions of how the aid variables were hand checked and how some parents' income was estimated based on their Expected Family Contribution, a federal financial aid measure.

[15] The cut-off was approximately $160,000, but the actual cut-off depends on family circumstances.

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.

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 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.

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	0.28	0.45	0.18	0.39	1.00	0.00
Admitted to this college	1.00	0.00	0.66	0.47	1.00	0.00
Grants from 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	0.04	0.20	0.03	0.17	0.07	0.25
Mother is an alumna of this college	0.03	0.17	0.02	0.14	0.04	0.19
Sibling attended or attends this college	0.05	0.21	0.04	0.19	0.08	0.28
College is public	0.3325	0.4711	0.2631	0.4403	0.2843	0.4512
College's median SAT score, in percentiles	80.5947	12.5188	83.8816	12.0390	83.4215	12.5494
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
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

We can see that the students made logical application decisions. The mean college to which they *applied* had a median SAT score at the 83rd percentile; the mean college to which they were *admitted* had median SAT score at the 81st 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 83.4th percentile, as opposed to the 81st 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 often did not matriculate at them. 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.

V. Results

We show a college in the national ranking if it was not a military academy and if, in our sample, it competed in matriculation tournaments in at least six of the nine regions of the U.S. 106 colleges met these criteria. The mean college shown in the national ranking competed in 73 matriculation tournaments, and the median college competed in 57. Admittedly, the six region cut-off is somewhat arbitrary, but we show regional rankings after showing the national rankings. The regional rankings pick up extra colleges. Please note that if a small college fails to appear in the rankings, one should not conclude that its ranking is below 106 or that it does not have a national draw. For a small college, our sample might fail to pick up enough applicants to include the college in the national ranking, even if its draw is national in character.

A. National Ranking

Table 3 presents the revealed preference ranking of colleges and universities with a national draw. For each college, we present its mean desirability among students. Keep in mind that Table 3 shows only an example of our ranking method. With more data, we would produce a more definitive ranking. The rankings are on an arbitrary numerical scale of value, Elo points, which are used in chess and other game rankings. The conversion multiplies the θ_is by 173 and then adds whatever number gives 2800 points to the highest ranked college.[16] The following table contains rule-of-thumb relationships between point differences and probability of winning:

400	.919
300	.853
200	.758
100	.637
50	.569
0	.500
-50	.431
-100	.363
-200	.242
-300	.147
-400	.081

Note that Elo point differences tell us only about the college versus its *mean* competitor. Put another way, attaching standard errors to the estimates in Table 3 would not be very useful

[16]We choose 2800 as the maximum number because this is approximately the rating for the highest-rated chess player in the world. We use the Elo scale because of its familiarity. In addition to serving as the main rating system for chess and many other board games, the Elo scale has also been used in a wide variety of sports. A partial list includes soccer (www.eloratings.net/), college football (www.usatoday.com/sports/sagarin/fbt01.htm), cricket (www.ultra-sports.com/Cricket/UC4/UC4abselo.html), and racquetball (www.eqp.com/pubs/rb/PlayerRankByELO.asp).

because they would not reliably indicate whether any two colleges' rankings were statistically distinct. This is because the statistical significance of the difference between any two colleges' ranks depends on the overlap between their two groups of admittees. For this reason, it is best to use Table 4 for head-to-head comparisons between colleges.

Table 4 summarizes the results of posterior draws: the Bayesian analogue to a set of paired significance tests. For instance, in 96 percent of the draws from the posterior distribution, Harvard's ranking was higher than Yale's, and for 95 percent of the draws Harvard was higher than Cal Tech. For all other colleges, Harvard's ranking was higher in at least 99 percent of the draws. Put another way, we are 96 percent confident that Harvard's ranking is higher than Yale's, 95 percent confident it is higher than Cal Tech, and at least 99 percent confident that it is higher than that of other colleges. For Yale, in turn, we are 88 percent confident that its ranking is higher than Stanford's, 78 percent confident that its ranking is higher than Cal Tech's, and 91 percent confident that its ranking is higher than MIT's.

Table 4 helps us to understand the results for Cal Tech, which are somewhat problematic. Because students self-select into applying to Cal Tech based on an orientation toward math and science, Cal Tech's pool of admittees overlaps only slightly with that of most other institutions, except for MIT, with which Cal Tech has substantial overlap. MIT, on the other hand, does have substantial overlap with other top schools. Unlike the other institutions in the top twenty, Cal Tech appears to draw a more focused group of applicants. In Section III.D, we discussed how such self-selection might bias inference for some speciality schools, with the possibility of some upward bias in the θ_i estimate.

All of the top twenty are private institutions and four-fifths are universities (the exceptions being Amherst, Wellesley, Williams, and Swarthmore). The next twenty institutions

Table 3

A Revealed Preference Ranking of Colleges

rank	College Name	Elo pts
1	Harvard	2800
2	Yale	2738
3	Stanford	2694
4	Cal Tech	2632
5	MIT	2624
6	Princeton	2608
7	Brown	2433
8	Columbia	2392
9	Amherst	2363
10	Dartmouth	2357
11	Wellesley	2346
12	U Penn	2325
13	U Notre Dame	2279
14	Swarthmore	2270
15	Cornell	2236
16	Georgetown	2218
17	Rice	2214
18	Williams	2213
19	Duke	2209
20	U Virginia	2197
21	Northwestern	2136
22	Pomona	2132
23	Berkeley	2115
24	Georgia Tech	2115
25	Middlebury	2114
26	Wesleyan	2111
27	U Chicago	2104
28	Johns Hopkins	2096
29	USC	2072
30	Furman	2061
31	UNC	2045
32	Barnard	2034
33	Oberlin	2027
34	Carleton	2022
35	Vanderbilt	2016
36	UCLA	2012
37	Davidson	2010
38	U Texas	2008
39	NYU	1992
40	Tufts	1986
41	Washington & Lee	1983
42	U Michigan	1978
43	Vassar	1978

Table 3
A Revealed Preference Ranking of Colleges

rank	College Name	Elo pts
44	Grinnell	1977
45	U Illinois	1974
46	Carnegie Mellon	1957
47	U Maryland	1956
48	William & Mary	1954
49	Bowdoin	1953
50	Wake Forest	1940
51	Claremont	1936
52	Macalester	1926
53	Colgate	1925
54	Smith	1921
55	U Miami	1914
56	Haverford	1910
57	Mt Holyoke	1909
58	Connecticut College	1906
59	Bates	1903
60	Kenyon	1903
61	Emory	1888
62	Washington U	1887
63	Occidental	1883
64	Bryn Mawr	1871
65	SMU	1860
66	Lehigh	1858
67	Holy Cross	1839
68	Reed College	1837
69	RPI	1835
70	Florida State	1834
71	Colby	1820
72	UCSB	1818
73	GWU	1798
74	Fordham	1796
75	Sarah Lawrence	1788
76	Bucknell	1784
77	Catholic U	1784
78	U Colorado	1784
79	U Wisconsin	1780
80	Arizona State	1774
81	Wheaton (Il)	1750
82	Rose Hulman	1745
83	UCSC	1736
84	Boston U	1736
85	UCSD	1732
86	Tulane	1727

Table 3
A Revealed Preference Ranking of Colleges

rank	College Name	Elo pts
87	U Richmond	1714
88	CWRU	1704
89	Trinity College	1703
90	Colorado College	1698
91	Indiana U	1689
92	Penn State	1686
93	American U	1681
94	Hamilton	1674
95	U Washington	1629
96	U Rochester	1619
97	Lewis & Clark	1593
98	Wheaton (MA)	1564
99	Clark	1551
100	Skidmore	1548
101	Purdue	1525
102	Colorado State	1513
103	Syracuse	1506
104	Scripps	1479
105	Loyola U	1221
	Tuition (In Thousands, In-state or Out-of-state, Whichever Applies)	-6.443
		(3.129)
	Grants (In Thousands)	28.156
		(2.104)
	Loans (In Thousands)	12.629
		(3.018)
	Work-study	3.023
		(13.091)
	Indicator: Is Dad's College	70.458
		(29.450)
	Indicator: Is Mom's College	34.432
		(24.797)
	Indicator: Is a Sibling's College	94.743
		(25.290)
	Indicator: College in Home State	25.646
		(38.033)
	Indicator: College in Home Region	15.191
		(20.533)
	Distance from Home (Hundreds of Miles)	4.276
		(2.137)

Notes: Estimates based on equation (6) converted into Elo points (see text). Standard errors are in parentheses.

Table 4: Share of Draws in Which College in the Row is Ranked Higher than the College Various Places Below It

	Number of Places Below																			
College	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Harvard	96	100	95	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Yale	88	78	91	95	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Stanford	58	62	76	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Cal Tech	51	57	89	94	96	96	96	98	98	99	100	100	100	100	100	100	100	100	100	100
MIT	63	99	100	100	100	99	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Princeton	96	99	99	99	99	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Brown	80	87	90	88	97	96	98	100	100	100	100	100	100	100	100	100	100	100	100	100
Columbia	65	66	72	80	85	92	99	99	99	98	100	100	100	100	100	100	100	100	100	100
Amherst	50	59	62	74	85	92	95	97	95	98	97	100	99	100	100	99	98	100	100	100
Dartmouth	60	65	76	86	95	97	98	96	99	98	100	100	100	100	100	99	100	100	100	99
Wellesley	50	64	75	82	85	93	90	92	90	98	98	98	99	97	94	99	99	99	97	100
U Penn	68	81	94	96	97	94	99	98	100	99	100	100	100	98	100	100	100	99	100	100
Notre Dame	65	73	78	89	84	88	85	97	96	98	98	95	91	99	99	99	96	100	99	100
Swarthmore	53	60	78	73	74	68	90	90	91	93	87	80	95	94	95	91	97	98	98	98
Cornell	61	82	75	81	73	97	95	98	97	94	85	99	99	99	94	100	99	100	99	100
Georgetown	77	68	71	62	93	91	95	95	89	78	97	97	98	91	99	99	99	99	100	100
Rice	45	38	31	62	68	64	75	60	49	75	75	76	77	86	87	89	89	92	93	92
Williams	46	39	67	73	69	79	66	56	78	79	79	80	89	89	90	91	94	93	94	94
Duke	40	81	82	84	89	77	63	91	91	92	86	97	96	97	96	99	99	98	99	100
U Virginia	88	87	90	92	83	70	95	94	96	89	98	98	98	98	100	100	99	99	100	100
Northwestern	62	54	71	49	35	72	72	74	74	88	88	90	90	96	96	93	95	99	98	90
Pomona	40	58	39	28	55	56	55	64	74	75	78	79	83	84	84	85	89	89	83	88
Berkeley	69	47	33	69	69	72	73	86	88	89	89	95	98	93	95	99	98	90	99	96
Georgia Tech	31	22	45	47	45	59	67	70	71	74	78	78	81	82	85	86	79	84	82	80
Middlebury	37	67	69	69	72	84	85	88	87	92	92	92	92	96	96	89	96	94	90	97
Wesleyan	78	79	80	79	90	90	91	92	95	96	94	95	98	98	92	97	97	93	98	98
UChicago	52	52	63	74	76	79	80	85	86	86	87	93	93	83	92	90	85	95	95	91
Johns Hopkins	49	62	72	74	77	78	83	84	84	85	91	91	81	91	88	83	93	94	89	95

Table 4: Share of Draws in Which College in the Row is Ranked Higher than the College Various Places Below It

	Number of Places Below																			
College	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
USC	62	73	76	79	80	86	89	85	87	94	93	82	94	90	84	96	96	91	96	93
Furman	54	56	59	61	62	61	68	66	68	70	68	67	70	69	70	76	67	78	74	82
UNC	54	58	61	63	61	70	68	73	75	69	71	71	71	76	82	70	84	79	88	72
Barnard	54	58	59	56	66	64	68	70	65	66	68	68	71	78	66	81	75	84	70	84
Oberlin	54	54	51	64	59	62	66	63	61	63	65	66	74	62	77	72	81	68	82	65
Carleton	49	47	58	55	57	60	59	55	58	62	60	68	55	72	66	75	64	77	59	65
Vanderbilt	47	61	57	61	64	60	59	61	63	65	74	60	79	70	82	65	81	64	68	81
UCLA	64	61	65	68	62	62	64	66	70	77	63	81	74	85	68	85	67	70	83	87
Davidson	46	45	49	50	44	48	53	49	58	46	64	57	66	57	69	50	56	67	74	60
U Texas	50	55	55	49	53	58	55	65	51	70	63	74	61	75	55	61	74	79	65	66
NYU	56	56	48	54	58	56	68	50	73	65	77	61	79	56	62	76	82	66	69	66
Tufts	51	42	48	54	49	61	44	68	60	71	58	73	50	57	71	78	62	63	61	83
Wash & Lee	44	47	52	48	56	45	62	56	64	55	67	48	54	65	71	60	58	57	75	80
U Michigan	54	59	58	70	52	74	66	79	62	79	58	63	77	83	68	70	67	87	96	98
Vassar	56	51	62	47	68	61	71	58	73	51	58	71	78	63	64	62	82	89	90	79
Grinnell	44	53	42	59	53	61	53	64	46	53	62	69	57	55	55	72	77	76	68	68
U Illinois	64	45	70	61	74	58	75	51	59	74	80	64	65	62	85	94	96	81	76	70
Carnegie Mell	34	57	50	61	51	65	40	49	64	71	55	53	52	75	85	85	71	69	63	76
U Maryland	72	64	75	61	76	55	62	74	80	65	67	64	85	93	95	82	78	72	86	79
William Mary	44	53	46	58	33	43	56	64	49	46	45	69	76	76	64	63	57	69	63	72
Bowdoin	59	51	62	41	49	62	68	54	52	51	73	80	80	69	68	62	74	68	76	79
Wake Forest	44	55	29	40	54	62	46	42	42	67	74	74	62	62	55	68	62	71	75	84
Claremont	59	43	49	58	64	52	51	50	68	72	71	63	64	59	68	63	71	74	80	74
Macalester	28	37	50	57	43	38	38	61	67	65	56	58	51	61	56	67	68	78	69	77
Colgate	58	71	77	62	63	61	82	89	90	78	75	69	83	76	82	87	93	89	95	96
Smith	62	69	55	54	52	73	78	77	68	69	62	73	68	75	78	85	80	85	88	60
U Miami	58	44	40	40	61	67	65	57	59	52	62	57	66	68	78	69	76	81	49	63
Haverford	37	32	32	53	57	56	49	52	45	54	49	59	61	71	62	69	72	42	56	66

Table 4: Share of Draws in Which College in the Row is Ranked Higher than the College Various Places Below It

	Number of Places Below																			
College	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Mt Holyoke	48	47	67	72	70	62	64	57	67	62	70	72	80	74	80	83	55	67	77	68
Connecticut C.	48	72	80	79	68	66	60	73	67	74	80	86	81	87	90	58	71	85	71	83
Bates	72	79	79	68	66	61	72	67	74	78	86	80	86	88	58	70	83	71	82	90
Kenyon	53	51	44	48	42	49	46	56	56	68	58	64	70	39	53	64	56	61	73	76
Emory	46	40	45	38	46	41	55	54	68	56	65	72	34	50	62	55	61	76	76	62
Wash. U	43	47	41	49	44	57	59	73	59	70	77	36	53	67	57	65	81	80	65	75
Occidental	53	46	55	50	61	62	73	64	72	76	42	57	69	60	67	79	80	68	76	81
Bryn Mawr	44	52	48	56	57	66	58	63	67	41	53	63	57	60	70	72	62	70	71	78
SMU	58	54	63	63	72	64	70	74	47	60	69	62	67	76	78	69	76	78	85	88
Lehigh	46	57	58	68	58	65	71	38	53	65	57	62	75	77	64	73	77	87	90	89
Holy Cross	60	60	70	62	67	72	42	56	67	59	65	76	77	66	74	77	85	89	88	87
Reed College	49	58	49	54	59	33	46	54	51	51	61	66	55	64	64	71	77	77	77	78
RPI	62	50	57	63	32	47	57	52	54	68	71	58	69	71	81	87	85	83	85	85
Florida State	38	43	49	24	37	45	43	41	53	60	47	59	58	67	74	74	74	76	75	68
Colby	57	64	31	47	57	51	54	68	71	57	68	70	81	87	86	84	86	86	79	88
UCSB	59	25	42	52	48	47	63	68	53	65	68	81	88	85	83	85	85	77	88	82
GWU	22	37	44	43	41	56	62	48	61	60	73	81	80	77	80	80	70	82	75	76
Fordham	63	73	64	72	81	82	71	78	82	89	92	91	90	91	91	87	93	90	89	89
Sarah Lawr.	59	53	56	66	70	60	68	69	76	81	81	81	82	81	76	83	79	79	80	91
Bucknell	47	46	60	65	51	63	63	74	80	80	78	81	81	73	82	76	78	78	92	94
Catholic U	51	60	64	54	63	62	67	73	74	73	74	73	69	75	70	72	73	84	87	78
U Colorado	64	69	54	66	68	80	86	84	83	84	84	77	86	81	81	81	94	97	87	57
U Wisconsin	58	44	57	54	67	75	75	73	76	76	67	79	70	72	72	90	93	80	48	82
Arizona St	39	51	45	53	63	63	64	65	64	57	66	58	61	63	80	85	71	43	74	83
Wheaton (IL)	60	59	67	73	74	73	75	74	69	76	69	72	73	86	89	79	53	82	88	87
Rose Hulman	46	52	59	60	61	62	61	56	62	55	58	60	75	79	68	42	72	78	77	48
UCSC	61	71	69	70	71	71	63	73	65	67	69	87	91	77	45	80	89	86	53	94
Boston U	64	63	63	66	65	56	68	55	61	62	85	91	73	40	77	87	84	45	95	81

Table 4: Share of Draws in Which College in the Row is Ranked Higher than the College Various Places Below It

	Number of Places Below																			
College	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Ucsd	51	53	55	53	46	55	43	49	52	77	83	65	34	69	79	78	37	89	74	89
Tulane	52	53	52	45	54	42	48	52	73	80	63	33	68	77	76	37	87	73	87	61
U Richmond	50	49	44	51	41	46	49	68	74	59	33	65	73	73	36	82	69	83	60	
CWRU	47	43	50	39	45	49	68	75	60	32	65	74	72	35	84	70	85	59		
Trinity Coll	44	52	40	46	51	72	78	62	33	66	76	74	36	85	71	86	61			
Colorado Coll	58	48	53	56	75	80	67	37	69	78	77	41	86	74	87	64				
Indiana U	38	45	48	71	77	60	32	66	75	74	34	85	70	86	60					
Penn State	56	59	81	87	69	37	73	83	81	42	92	77	91	66						
American U	54	75	80	65	34	69	78	76	39	88	74	87	63							
Hamilton	69	75	61	33	65	73	72	36	82	69	84	60								
U Washington	57	44	21	51	57	59	21	70	55	74	47									
U Rochester	38	17	46	51	52	17	64	50	70	43										
Lewis&Clark	26	55	61	61	28	72	59	75	51											
Wheaton (Ma)	77	82	82	56	87	79	88	72												
Clark	55	56	25	64	53	68	47													
Skidmore	52	18	62	49	67	43														
Purdue	19	60	48	64	41															
Colorado St	88	78	90	69																
Syracuse	39	58	35																	
Scripps	66	44																		
Loyola U	31																			

are, however, a mix of public and private, small and large, colleges and universities. They are also more geographically diverse. They include private schools from middle and southern states: University of Chicago, Furman, Carleton, Davidson, Northwestern, Oberlin, Vanderbilt. There are also several public universities: UC - Berkeley, UCLA, Georgia Tech, U Texas, North Carolina.

The colleges ranked from 41 to 106 include a good number of states' "flagship" universities, numerous liberal arts colleges, several private universities, and a few more institutes of technology.[17] As a rule, the lower one goes in the revealed preference ranking, the less distinct is a college's desirability from that of its immediate neighbors in the ranking. Among the top ten colleges, we generally enjoy confidence of about 75 percent that a college is ranked higher than the college listed one below it. To achieve the same level of confidence for colleges ranked eleven to twenty, we need to compare a college with one that is about four places below it. To achieve 75 percent confidence with the colleges ranked twenty to 30, we need to compare a college with one that is about six places below it. In short, our confidence about the exact rank order falls with colleges' measured desirability. There are two reasons why our confidence falls. First, there may be less consensus among students about colleges' desirability as we move from the best known colleges to those with less wide reputations. Second, owing to the nature of our sample, our data are thickest for the most selective colleges. We did a simple test to determine whether data thickness was primarily responsible for the fall off in confidence: we randomly selected only 20 observations per college. With these data, we found that about two-thirds of the drop-off in confidence disappeared. That is, if our data were equally representative for all colleges, our confidence about the exact rank order would probably fall only about one third as fast as it does.

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[17] The students in our sample who had a Florida resident as a parent were the first cohort to receive Florida A-Plus Scholarships, which allowed them to attend public universities in Florida for free. The initiation of the scholarships generated considerable excitement and may have raised the ranking of public universities in Florida, such as Florida State, among students in our sample.

B. Comparing Measures of Revealed Preference

For the colleges that are in the top twenty based on revealed preference, Table 5 shows what their rankings would be if they were based on, respectively, the admissions and matriculation rates. We use crude admissions and matriculation rates from the College Board's Standard Research Complication, the same data as form the "Common Data Set" published on colleges' websites and used by college guides like *U.S. News*.

Table 5
A Comparison of the Revealed Preference Ranking of Colleges and Rankings Based on the Crude Admissions and Matriculation Rates

	National Rank Based On:		
	Revealed Preference (based on Matriculation Tournaments)	Admissions Rate	Matriculation Rate
Harvard	1	4	139
Yale	2	12	309
Stanford	3	7	297
Cal Tech	4	9	854
MIT	5	13	422
Princeton	6	5	266
Brown	7	14	561
Columbia	8	6	438
Amherst	9	19	916
Dartmouth	10	20	647
Wellesley	11	23	492
U Penn	12	104	794
U Notre Dame	13	58	459
Swarthmore	14	28	1016
Cornell	15	45	649
Georgetown	16	22	703
Rice	17	25	996
Williams	18	29	797
Duke	19	32	859
U Virginia	20	76	630

Notes: Left-hand column shows rank based on Table 3. The admissions and matriculation rates are based on the Common Data Set, used by most college guidebooks.

Looking at Table 5, we observe that most of the top twenty colleges based on revealed preference are not in the top twenty based on the admissions and matriculation rates. Indeed, the admissions rate puts 10 of them outside the top twenty and the matriculation rate puts all of them outside the top 100. Clearly, there are many colleges with low admissions rates or high matriculation rates that are not perceived to be highly desirable. Apart from convenience, we are unable to frame an argument for why the crude rates have any advantage over the procedures for revealing preference that we outline in this paper.

C. Regional Rankings

Table 6 shows the rankings we obtain if we estimate the matriculation model separately for students from each of the nine census divisions of the U.S. The nine divisions are:

Division 1: Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, Vermont;

Division 2: New Jersey, New York, Pennsylvania;

Division 3: Illinois, Indiana, Michigan, Ohio, Wisconsin;

Division 4: Kansas, Minnesota, Missouri, Nebraska;

Division 5: D.C., Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia;

Division 6: Alabama, Kentucky, Tennessee;

Division 7: Arkansas, Louisiana, Oklahoma, Texas;

Division 8: Arizona, Colorado, Idaho, Montana, New Mexico, Nevada, Utah, Wyoming;

Division 9: California, Hawaii, Oregon, Washington.

We make no great claims for these regional rankings because the sample for each region is small. Rather, we show Table 6 so that the reader can see how the regional rankings combine to form a truly national ranking at the top. Because the regional samples are small, some schools do not get ranked in some regions, and thus we have left spaces where Elo points suggest that a school ranked in other regions is missing. For instance, in division 6 (Alabama, Tennessee, Kentucky), neither Cal Tech nor Stanford is ranked. Because the regional samples are small, we merely group schools outside of the top 30 (see note below the table).

Looking at Table 6, the most noteworthy thing is the great consistency of the ranking of the top ten institutions. Each region reproduces the national ranking, with a couple of exceptions. In region 7 and 9, Stanford is ranked above MIT, whereas MIT is usually ranked higher. Also, Amherst and Dartmouth often trade places in the rankings. Among the

Table 6: An Example of Regional Preference Rankings of Colleges

Ranking among Students From:

	Region 1: CT, MA, ME, NH, RI, VT	Region 2: NJ, NY, PA	Region 3: IL, IN, MI, OH, WI	Region 4: KS, MN, MO, NE	Region 5: DC, FL, GA, MD, NC, SC, VA	Region 6: AL, KY, TN	Region 7: AR, LA, OK, TX	Region 8: AZ, CO, ID, MT, NM, NV, UT, WY	Region 9: CA, HI, OR, WA
1	Harvard	Harvard	Harvard	Harvard	Harvard	Harvard	Harvard	Harvard	Harvard
2	Cal Tech	Cal Tech	Cal Tech	Cal Tech	Cal Tech		Cal Tech	Cal Tech	Cal Tech
3	Yale	Yale	Yale	Yale	Yale	Yale	Yale	Yale	Yale
4	MIT	MIT	MIT	MIT	MIT	MIT	Stanford	Stanford	Stanford
5	Stanford	Princeton	Stanford	Princeton	Stanford		MIT	Princeton	MIT
6	Princeton	Stanford	Princeton	Stanford	Princeton	Princeton	Princeton	Brigham Young	Princeton
7	Brown	Brown	Brown	Brown	Brown	Brown	Brown	Brown	Brown
8	Columbia	Columbia	Columbia	Amherst	Columbia	Columbia	Columbia	Columbia	Columbia
9	Dartmouth	Dartmouth	Amherst	Dartmouth	Dartmouth	Dartmouth	Dartmouth	Dartmouth	Dartmouth
10	Amherst	Amherst	Dartmouth	Notre Dame	Amherst	Wellesley	Amherst	U Penn	Amherst
11	Wellesley	Wellesley	Wellesley	U Penn	Notre Dame	U Penn	Wellesley	Amherst	U Penn
12	Notre Dame	Notre Dame	U Penn	Swarthmore	Wellesley	Amherst	U Penn	Notre Dame	Wellesley
13	U Penn	U Penn	Notre Dame	Williams	U Penn	Duke	Notre Dame	Williams	Notre Dame
14	Swarthmore	Cooper Union	Swarthmore	Cornell	Swarthmore	Swarthmore	Cornell	Swarthmore	Cornell
15	Rice	Swarthmore	Cornell	Duke	Cornell	Cornell	Rice	Cornell	Swarthmore
16	Cornell	Cornell	Duke	Georgetown	Duke	Georgia Tech	Duke	Duke	Georgetown
17	Georgetown	Georgetown	Rice	U Virginia	Georgetown	Williams	Williams	Rice	Duke
18	Duke	Rice	Williams	Rice	Rice	Georgetown	Georgetown	U Virginia	Rice
19	Williams	Duke	Georgetown	Wesleyan	Williams	Rice	U Virginia	Georgetown	Cooper Union
20	U Virginia	Williams	U Virginia	USC	Harvey Mudd	U Virginia	Wesleyan	Wesleyan	Williams
21	Wesleyan	U Virginia	Wesleyan	Northwestern	U Virginia	Wesleyan	Northwestern	Pomona	U Virginia
22	Harvey Mudd	Harvey Mudd	Harvey Mudd	U Chicago	Wesleyan	Claremont	Berkeley	Middlebury	Harvey Mudd
23	Northwestern	Wesleyan	Northwestern	Pomona	Northwestern	Northwestern	Georgia Tech	Berkeley	Wesleyan
24	Pomona	Northwestern	Pomona	Georgia Tech	Pomona	Fordham	USC	Northwestern	Pomona
25	U Chicago	Pomona	Middlebury	Johns Hopkins	Georgia Tech	Berkeley	U Chicago	USC	Berkeley
26	Middlebury	U Chicago	Johns Hopkins	U Texas	Berkeley	USC	Johns Hopkins	U Chicago	Northwestern
27	Johns Hopkins	Middlebury	Berkeley	UNC	Middlebury	Pomona	Pomona	Georgia Tech	Johns Hopkins
28	USC	Berkeley	USC	Vanderbilt	U Chicago	U Chicago	Middlebury	UNC	USC
29	Berkeley	Johns Hopkins	U Chicago	Carleton	Johns Hopkins	UNC	U Texas	Johns Hopkins	U Chicago
30	Georgia Tech	Georgia Tech	U Texas	Oberlin	USC	Vanderbilt	UNC	Oberlin	Middlebury

Notes for Table 6

Next 30 colleges, for each region:

Region 1 (CT, MA, ME, NH, RI, VT): UNC, Oberlin, Vanderbilt, U Florida, Barnard, Carleton, Furman, George Mason, Davidson, U Michigan, UCLA, NYU, Tufts, Claremont Mckenna, U Illinois, Vassar, Washington and Lee, Grinnell, Pitzer, Carnegie Mellon, U Maryland, Wake Forest, Kenyon, Bowdoin, William and Mary, Colgate, SMU, Macalester, U Miami.

Region 2 (NJ, NY,PA): USC, U Texas, UNC, Carleton, Barnard, Vanderbilt, Oberlin, Davidson, Washington and Lee, UCLA, NYU, Tufts, U Michigan, U Florida, Furman, Vassar, Grinnell, U Illinois, St. John's, Bowdoin, U Maryland, Kenyon, William and Mary, Carnegie Mellon, Wake Forest, Claremont Mckenna, Smith, Colgate, Pitzer, Macalester.

Region 3 (IL, IN, MI, OH, WI): UNC, Claremont Mckenna, Fordham, Carleton, USC, Vanderbilt, Oberlin, Davidson, Barnard, UCLA, U Illinois, SMU, Washington and Lee, Bradley, U Florida, U Michigan, Tufts, Vassar, NYU, Grinnell, U Missouri, Wake Forest, Bowdoin, Carnegie Mellon, Illinois Wesleyan, U Oregon, Haverford, Macalester, Smith, William and Mary.

Region 4 (KS, MN, MO, NE): Washington and Lee, Vassar, Davidson, Tufts, Furman, Bowdoin, Colgate, Grinnell, U Michigan, New York, Rhodes, U Illinois, SMU, Haverford, Macalester, Kenyon, Wake Forest, U Missouri, Connecticut College, U Maryland, Carnegie Mellon, Bradley, Sarah Lawrence, Lehigh, Washington U., Bates, Bucknell, College of William and Mary, U Miami, Colby.

Region 5 (DC, FL, GA, MD, NC, SC, VA): UNC, U Texas, U Florida, Fordham, Barnard, Vanderbilt, Carleton, UCLA, Davidson, Oberlin, U Michigan, Tufts, Vassar, U Maryland, Furman, U Illinois, Washington and Lee, NYU, Grinnell, U. of the South, Bowdoin, Kenyon, Carnegie Mellon, William and Mary, Wake Forest, Macalester, Smith, U Miami, Colgate, Haverford.

Region 6 (AL, KY, TN): Furman, Johns Hopkins, Middlebury, UCLA, U Texas, Barnard, Davidson, U the South, Wake Forest, SMU, Carleton, Oberlin, U Michigan, U Illinois, Texas A&M, NYU, Rhodes, Vassar, Occidental, Smith, Clemson, Kenyon, Carnegie Mellon, Bowdoin, William and Mary, Bates, U Miami, Washington and Lee, Washington U., Haverford.

Region 7 (AR, LA, OK, TX): Furman, Oberlin, Carleton, UCLA, Rhodes, Vanderbilt, Barnard, Davidson, Fordham, U Michigan, Washington and Lee, Tufts, NYU, Wake Forest, U Illinois, Bowdoin, Vassar, Carnegie Mellon, Colgate, Smith, U Maryland, SMU, Macalester, Haverford, Washington U., Connecticut College, Emory, Mount Holyoke, Bucknell, Bryn Mawr.

Region 8 (AZ, CO, ID, MT, NM, NV, UT, WY): Barnard, Claremont Mckenna, Carleton, Vanderbilt, UCLA, NYU, Wake Forest, Tufts, Macalester, Washington and Lee, U Michigan, Bowdoin, U Oregon, Vassar, Colgate, U Miami, Mount Holyoke, Carnegie Mellon, Grinnell, Haverford, William and Mary, Emory, U Missouri, Whitman, U Colorado, Washington U., Santa Clara, U. Arizona, UCSB, Occidental.

Region 9 (CA, HI, OR, WA): U Texas, SMU, UNC, UCLA, Carleton, Barnard, Oberlin, Davidson, Vanderbilt, NYU, Washington and Lee, Tufts, U Illinois, U Michigan, U Oregon, Pitzer, Vassar, Bowdoin, Carnegie Mellon, Grinnell, Smith, Wake Forest, Macalester, Fordham, St. John's, Claremont Mckenna, William and Mary, Haverford, Emory, Whitman.

institutions ranked 11 to 30, there is considerable consistency overall, and nearly all of the changes in rank order appear to be noise, probably due to the small regional samples. The overall impression is one of consistency: the national ranking is truly national, at least at the top.

Regionalism is more evident in the colleges ranked 31 to 60, which are shown in the notes below Table 6. While much of the variation in the ranking is noise at this point, owing to the small regional samples, it is notable that Southern colleges do better in the South (U. of the South, Clemson, and Rhodes are the most obvious), Midwestern colleges do better in the Midwest (Bradley is the most obvious), and Western colleges do better in the West (Whitman, Santa Clara, Occidental, and Pitzer are the most obvious). In addition, flagship state universities are likely to show up in their region, even if not in distant regions (U Oregon, U Colorado, and U Arizona are the most obvious). However, for the colleges ranked 31 to 60, the overwhelming impression is that the regional rankings are not very regional. The regional favorites never represent more than ten percent of the 30, and most of the colleges that appear show up in every region.

Perhaps the single most interesting college in Table 6 is Brigham Young, which appears in the top 10, between Princeton and Brown, in region 8 (which contains Utah). We have checked and determined that, if we were to compute a Utah-specific ranking, Brigham Young would rank even higher. The dramatic appearance of Brigham Young in the top 10 almost certainly occurs because the college is particularly desirable in the eyes of Mormon students.[18] We cannot verify this conjecture because we did not ask students about their religion, but this leads us back to our general point about latent desirability and self-selection into applicant pools. The reason that Brigham Young wins so many tournaments with Utah students is that it is truly more desirable to them. Similarly, the reason that a bit of regionalism appears is that University of the South, say, is truly more desirable to Southerners. This is not a problem we

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[18] The reason that Brigham Young does not appear in the national ranking is that, in our sample, it competes in fewer than six regions.

need to "fix" in the national ranking. It is simply an indicator that, with sufficient data, it would be reasonable to compute sub-rankings for identifiable groups of students with well-defined tastes. We know now that these rankings will tend to join up at the top. A benefit of computing sub-rankings is that some colleges' performance in the national rankings depends on the fact that they are especially popular with a well-defined set of students who self-select into applying (think of Cal Tech). Self-selection does not appear to be an important concern with our national ranking, except perhaps for the engineering schools. However, we speculate that it would be appropriate to construct sub-rankings once we got much outside of this group.

VI. Conclusions

In this paper, we show how students' college choice behavior can be used to generate revealed preference rankings of American colleges and universities. Using a data set on the college application and matriculation choices of highly meritorious American students, we construct examples of a national revealed preference ranking and regional revealed preference rankings. Our procedure generates a revealed preference ranking which would be very difficult for a college to manipulate with strategic admissions behavior.

Given the strong demand for measures of revealed preference among parents and students, it is clear that colleges will be forced to provide some such information and college guides like *U.S. News* will be forced to give substantial weight to such information. In the absence of a revealed preference ranking method such as ours, colleges and college guides use two flawed, manipulable proxies: the crude admissions rate and crude matriculation rate. These proxies are not only misleading; they induce colleges to engage in distorted conduct that decreases the colleges' *real* selectivity while increasing the colleges' *apparent* desirability, as measured by the proxies. So long as colleges are judged based on the crude admissions and matriculation rates, it is unlikely that all colleges will eliminate strategic admissions or roll back early decision programs, which are key means for manipulating the proxies. Many college administrators correctly perceive that they are in a bad equilibrium. Yet, so long as colleges' find it advantageous to use early decision and other costly admissions strategies, the bad equilibrium is likely to persist.

Gathering our data was a moderately costly undertaking for researchers, but the cost would be a trivial share of the revenues associated with college guides. Moreover, at least some of the data are already compiled by organizations like The College Board and the ACT, so that gathering a highly representative sample should be very feasible. If a revealed preference ranking constructed using our procedure were used in place of manipulable indicators like the crude admissions rate and crude matriculation rate, much of the pressure on colleges to manipulate admissions would be relieved. In addition, students and parents would be informed by significantly more accurate measures of revealed preference. We close by reminding readers that measures of revealed preference are just that: measures of desirability based on students and families making college choices. They do not necessarily correspond to educational quality.

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