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Abstract

I measure the spillover effect of intercollegiate athletics on the quantity and quality of applicants to institutions of higher education in the United States, popularly known as the "Flutie Effect." I treat athletic success as a stock of goodwill that decays over time, similar to that of advertising. A major challenge is that privacy laws prevent us from observing information about the applicant pool. I overcome this challenge by using order statistic distribution to infer applicant quality from information on enrolled students. Using a flexible random coefficients aggregate discrete choice model that accommodates heterogeneity in preferences for school quality and athletic success, and an extensive set of school fixed effects to control for unobserved quality in athletics and academics, I estimate the impact of athletic success on applicant quality and quantity. Overall, athletic success has a significant long-term goodwill effect on future applications and quality. However, students with lower than average SAT scores tend to have a stronger preference for athletic success, while students with higher SAT scores have a greater preference for academic quality. Furthermore, the decay rate of athletics goodwill is significant only for students with lower SAT scores, suggesting that the goodwill created by intercollegiate athletics resides more extensively with low-ability students than with their high-ability counterparts. But, surprisingly, athletic success impacts applications even among academically stronger students.

1. Introduction

On a stormy day in November 1984, Boston College and the University of Miami played an extraordinary football game, an electrifying shootout with 1,273 yards of total offense and multiple lead changes throughout. However, it was the final play of the game that has persisted for decades in the minds of sports fans nationwide. The score was Miami 45, Boston College 41; with six seconds remaining, Boston College quarterback Doug Flutie made a miraculous, Hail Mary touchdown pass to win the game.[1] Nationally televised the day after Thanksgiving, the game had a huge viewing audience. The win qualified Boston College, which finished the season with a 10–2 record and top-five AP (Associated Press) Poll ranking, to compete in the Cotton Bowl, one of the New Year's bowl games.[2] Doug Flutie won the Heisman Trophy, the most prestigious individual award in college football, and subsequently enjoyed a successful career as a professional football player and TV analyst.

Two years after this extraordinary game, Boston College experienced an approximately 30 percent surge in applications. Ever since, the popular media have called this phenomenon the "Flutie Effect," referring to an increase in exposure and prominence of an academic institution due to the success of its athletics program. As *USA Today* described it, "Whether it's called the 'Flutie factor' or 'mission-driven intercollegiate athletics', the effect of having a winning sports team is showing up at admissions offices nationwide."[3]

Boston College has not been alone in witnessing a surge of applications due to success on the playing field. Applications at Georgetown University rose 45 percent between 1983 and 1986, a period during which it enjoyed tremendous success in men's basketball, appearing three times in the National Collegiate Athletic Association (NCAA) championship finals. Similarly, Northwestern University experienced a 21 percent increase in applications in 1996, a year after winning the Big Ten Championship in football.

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[1] A Hail Mary pass is a term used to describe a long forward pass that has a very small probability of success. It usually is called into play toward the end of a game in which it is the only option for winning.

[2] At the time, the schools with the most successful regular seasons were invited to one of five New Year's bowl games: the Cotton, Fiesta, Orange, Rose, and Sugar Bowls. The rankings of schools in college football are determined by multiple polls including the AP Poll, Coaches Poll, and Harris Interactive Poll. The oldest of these, the AP Poll, which is compiled by sports writers throughout the United States, is most commonly used to determine the success of a particular school's football season.

[3] Source: "Winning One for the Admissions Office," *USA Today*, July 11, 1997.

More recently, an 18 percent increase in applications followed Boise State University's successful 2006–07 football season, which included a win over college football powerhouse University of Oklahoma in the 2007 Fiesta Bowl to cap a perfect 13–0 season. Texas Christian University (TCU), after decades of mediocrity in college football, was able to land in the AP Top 25 rankings for the first time in over 40 years in 2000. Ever since, TCU has frequently been in the top of the college football rankings, enjoying media exposure with many nationally televised games. Its admissions office also enjoyed a whopping 105-percent increase in applications from 2000 to 2008.

However, is the so-called "Flutie Effect" for real? Boston College's then admissions director John Maguire does not seem to think so. "Doug Flutie cemented things, but the J. Donald Monan factor and the Frank Campanella factor are the real story," he said, referring to Boston College's former president and executive vice president. Maguire believes that Boston College experienced a surge in applications in the mid-1980s due to its investments in residence halls, academic facilities, and financial aid. So he claims that the "Flutie Effect" was minimal, at best, and did not contribute as much as the popular press claimed it had.[4]

The primary form of mass media advertising by academic institutions in the United States is, arguably, through its athletics program. Therefore, this study investigates the possible advertising effects of intercollegiate athletics. Specifically, it looks at the spillover effect, if any, and the magnitude and divergence that athletic success has on the quantity and quality of applications received by an academic institution of higher education in the United States. Furthermore, I look at how students of different abilities place heterogeneous values on athletic success versus academic quality.

For many people residing in the United States, intercollegiate athletics is a big part of their everyday lives. During the college football season, it is common to see live college football games being broadcast in prime time slots by not only sports-affiliated cable channel

[4] Source: "The 'Flutie factor' is now received wisdom. But is it true?" *Boston College Magazine*, Spring 2003.

networks (e.g., ESPN and Fox Sports), but also major over-the-air networks (ABC, NBC, and CBS).[5] Yet, it is surprising to see very limited research in this area.

McCormick and Tinsley (1987) were the first to examine the possible link between athletics and academics. They find that, on average, schools in major athletic conferences tend to attract higher-quality students than those in non-major conferences and that the trend in the percentage of conference wins in football is positively correlated with the increase in the quality of incoming students. They hypothesize that intercollegiate athletics has an advertising effect and, as a result, suggest that schools with athletic success may receive a greater number of applications, thus allowing them to be more selective in admissions. Similar to McCormick and Tinsley (1987), Tucker and Amato (1993), using a different time frame for the data, find that football success increases the quality of incoming students. Using only a single year of school information, however, these studies rely primarily on cross-sectional identification to determine the impact of historical athletic success on the quality of the incoming freshman class, essentially ignoring any unobserved school-specific effects that might be correlated with athletic success.

In comparison, Murphy and Trandel (1994) and Pope and Pope (2009), using panel data, focus more on short-term episodic athletic success and its impact on academics. While these studies, in aggregate, are able to control for unobserved school-specific effects, by relying solely on a descriptive model, they are unable to precisely capture shifts in preferences by potential students. In addition, aside from Pope and Pope (2009), all of the foregoing studies ignore any heterogeneous effects of athletics on students of different ability. Furthermore, these studies use institutional-level data, disregarding any specific market-level characteristics that would likely affect demand for higher education in different markets. That is, both Murphy and Trandel (1994) and Pope and Pope (2009) use the aggregate number of applications per institution per year as their observation points, while I use market-level (state-level) data to infer school preferences for students who reside in different markets. Moreover, by examining only changes in the aggregate, these studies do not account for any heterogeneity

[5] ABC's *Saturday Night Football*, which broadcasts major college football games live, runs from 8:00 PM to 12:00 AM on Saturday evenings during the college football season. More information about the popularity of college football is given in the following sections.

in preferences for athletic success that is likely to exist among high school seniors applying to colleges and universities in the United States. Most importantly, none of the above studies accounts for the relative value of athletic success compared to other factors (monetary/psychological costs, academic quality, etc.) that determine an applicant's choice of demand for higher education.

I distinguish from these studies and treat athletic success as a stock of goodwill that decays over time, similar to that of advertising. Relying on the utility-maximizing behavior of high school seniors applying to colleges and universities in the United States, I build and estimate a structural model of demand for higher education to determine the effect and magnitude that these goodwill stocks can have on the outcome of school admissions. My goal is twofold: to determine if there is, indeed, an advertising spillover effect from athletic success and, if so, to identify the magnitude of the effect on the quality and quantity of applications and impact on school selectivity rates. Furthermore, using market-level data, I examine the relative importance of athletic success compared to other factors (academic quality, tuition costs, distance from home, etc.) that influence students of different abilities.

From a modeling perspective, using an extensive set of school fixed effects to control for unobserved quality in athletics and academics, I apply a flexible random coefficients aggregate discrete choice model to allow for heterogeneity in preferences where athletic success shifts school preferences for high school seniors applying to colleges and universities. A major challenge is that privacy laws prevent us from observing information about the applicant pool. I overcome this challenge by developing an order statistics based approach to infer applicant quality from information on enrolled students.

Overall, I find that athletic success has a significant impact on the quantity and quality of applicants that a school receives. However, I find that students with lower than average SAT scores have a stronger preference for athletic success, while students with higher SAT scores have a greater preference for academic quality. Furthermore, I find that the carryover rate of goodwill stocks for athletic success is evident only for students with lower SAT scores, suggesting that students of low ability inter-temporally value the success of intercollegiate athletics more and discount it less than their high-ability counterparts. In addition, I find that when a school goes from being "mediocre" to being "great" on the football field, applications increase by 17.7 percent, with the vast proportion of the increase coming from low-ability students. However, there is also an increase in applications from students at the highest ability level. In order to attain similar effects, a school must either decrease tuition by 3.8 percent or increase the quality of education by recruiting higher-quality faculty who are paid 5.1 percent more in the academic labor market. I also find that schools become more selective with athletic success. For the mid-level school in terms of average SAT scores, the admissions rate would decline by 4.8 percent with high-level athletic success.

The rest of the paper proceeds as follows. Section 2 presents an overview of collegiate athletics and the data used for empirical analysis. Sections 3 and 4 present the model and estimation methodology, respectively. Section 5 discusses the results and counterfactual analysis. Section 6 concludes.

2. Collegiate Athletics and Data

2.1 Collegiate Athletics

The first college football game was played between Rutgers University and Princeton University in 1869. The last years in which a non-athletic scholarship granting school claimed a major title in college football were 1944–1946, when the United States Military Academy, and 1950, when Princeton University, won the College Football National Championship. In those days, collegiate athletics served mainly to increase diversity and boost pride and self-awareness among the student body and alumni.

Things have changed significantly over the past several decades. Although one of its missions continues to be to increase diversity and morale, collegiate athletics today is a multi-billion dollar industry that rakes in huge amounts of revenue for the participating institutions. It acts as a huge catalyst in boosting the regional economy and at public institutions, it is not uncommon to see the head coaches as one of the highest-paid state employees. In terms of mere numbers, college football topped \$2 billion in revenue and \$1.1 billion in profit in 2010, and the single highest revenue-generating institution, the University of Texas at Austin, generated $94 million of revenue in football alone.[6] Nick Saban, the head football coach at the University of Alabama, is the highest paid coach, with an annual income of close to $6 million.[7] The total fan base for college football, 103 million people, represents approximately one-third of the U.S. population, and 43 percent of U.S. residents viewed at least one of the 35 post-season bowl games in the 2010–11 (hereafter referred to as the 2010) football season.[8] The University of Nebraska holds the longest home game sell-out streak, dating back to 1962 (306 as of the end of the 2010 football season), and the average home game ticket price in the secondary market in 2009 for Ohio State was $524, the highest among all schools. Though not the original goal when it was institutionalized, intercollegiate athletics has become both commercialized and a significant part of regional economies.

To investigate the effect of a successful athletics program on admissions, I utilize multiple datasets, each compiled to match one of the 120 institutions that participate in the NCAA Division 1 FBS (Football Bowl Subdivision). Collegiate athletics, like professional sports, is organized as a hierarchy of divisions, Division 1 being the highest level of competition. Within Division 1 are Division 1 FBS and Division 1 FCS (Football Championship Subdivision).[9] Division 1 FBS is the strongest of all divisions and is considered as the main division. Therefore, my analysis focuses only on the set of institutions that participates in this division.[10] Figure 1 outlines the subdivisions and conferences within Division 1.

Presently, Division 1 FBS is further subdivided into the AQ (automatic qualifying) and non-AQ (also known as mid-majors) conferences.[11] The main difference between them is

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[6] Source: "College football's $1.1 billion profit," CNNMoney.com, December, 2010.

[7] Source: "Football Bowl Subdivision coaches salaries for 2010," *USA Today*, December, 2010.

[8] Source: "Behind the Numbers: College Football Business Grows Exponentially," CNBC.com, March, 2011.

[9] These two subdivisions were formerly known as Division 1-A and Division 1-AA. The key organizational difference is that the former relies on bowl games after the regular season to determine the champion while the latter determines the champion through a playoff system. The substantive difference is that the former utilizes many more resources than the latter and can award up to 85 athletic scholarships, compared to the former's 63. Furthermore, Division 1 FBS teams have better facilities and a bigger alumni base, which results in larger amounts of contributions to support their athletic programs.

[10] Although most schools in Division 1 FBS jointly operate football and basketball programs, some schools with basketball programs considered high profile are not part of this division (e.g., Georgetown and Gonzaga).

[11] As of December 2010, the AQ conferences (also referred to as the Bowl Championship Series, or BCS, conferences) included the Atlantic Coast Conference (ACC), Big East Conference, Big Ten Conference, Big 12 Conference,

that the conference champions of the AQ conferences are automatically invited to a BCS (Bowl Championship Series) bowl game at the end of the regular season, whereas invitations to such bowl games are more difficult to obtain for non-AQ conference teams. Although the definition of success varies with school and pre-season expectations, a season is generally deemed successful if a team goes to a BCS bowl game.[12] Hence, AQ conference schools tend to have superior facilities and funding and, as a result, attract more talented student athletes to their athletic programs.

2.2 Data

The primary data for admissions were collected through the Integrated Postsecondary Education Data System (IPEDS). The core of the postsecondary education data collection program for the National Center for Educational Statistics (NCES), IPEDS contains data on the number of applications received, number of applicants admitted, and number and distribution of SAT scores for students enrolled at each institution of higher education. To ascertain the origin of applications, I manually collected data from the annual state-level report "College-Bound Seniors," compiled by the College Board (the implementer of the SAT). This dataset contains the exact number of SAT score reports sent by high school seniors in each state seeking admission to colleges and universities throughout the United States. It also contains the distribution of overall SAT scores by state.

Institutional characteristics such as average faculty salary, whether the school is a public or private institution, size of the student body, total number of faculty, and published in-state and out-of-state tuition costs were also collected through IPEDS. The historical number of high school graduates by state for each year over the sample period was collected through the NCES. The college-going rate by state per year, which represents the proportion of high school students in each state that goes to college, was obtained from the National Center for Higher Education Management Systems (NCHEMS) Information Center. To

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Pacific (Pac)-10 Conference, and Southeastern Conference (SEC); the non-AQ conferences included the Conference USA (C-USA), Mid-American Conference (MAC), Mountain West Conference (MWC), Sun Belt Conference, and Western Athletic Conference (WAC).

[12] Currently, the BCS bowl games are the Fiesta, Orange, Rose, and Sugar, and the BCS National Championship Game.

control for inflation, the history of the consumer price index, obtained from the U.S. Bureau of Labor Statistics, was used to convert any monetary variables in the analysis to 2009 U.S. dollars. The distance from a specific state to an institution was manually obtained using publicly available software.[13]

Athletic performance data were hand-collected from multiple data sources including Wikipedia, STASSEN.COM College Football Information, and Sports-Reference. As a measure of athletic performance, I use the total number of wins per season for the school's football program. Although slightly different by conference and season, Division 1 FBS teams typically play 12 games in a regular season.[14] In bigger conferences with sub-conferences, a conference championship game is held between the sub-conference champions.[15] After the regular season, teams with six or more wins qualify for a post-season bowl game; for each bowl game, a bowl committee selects the teams that will participate. As previously noted, the conference champions of AQ conferences automatically qualify for a BCS bowl game, and the two top-ranking teams in the BCS standings play for the BCS National Championship. Thus, the maximum number of games a team can win is 14, that is, regular-season games (12) plus a conference championship (1) plus a bowl game (1). I hypothesize that with each additional win, a team would receive greater media exposure via TV, newspapers, and other media outlets, which would translate into an advertising effect for the school. I therefore use the total number of games won in a season to measure the success of a particular school's athletic performance.

Table 1 presents the descriptive statistics of the data. The AQ conference schools tend to receive more applications and have larger student bodies. The difference is clearer for private schools, those in AQ conferences receiving twice as many applications as their non-AQ counterparts, despite similar enrollments. Private schools are generally more selective in both subdivisions (AQ and non-AQ). They also tend to have better standards of education quality,

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[13] The web tool Distance From To (http://distancefromto.net) was used to calculate distances from students' home states to each institution.

[14] Teams that play at Hawaii have the option of scheduling a 13th regular-season game to offset travel costs. This rule, referred to as the "Hawaii Exemption," also gives the University of Hawaii the option of playing a 13th game.

[15] As of the 2010 season, the ACC, Big-12, C-USA, MAC, and SEC have a conference championship game in Division 1 FBS.

with higher average faculty salaries and faculty–student ratios, and consequently to exhibit a propensity for attracting higher-quality students, as evidenced by higher average SAT scores. Overall, schools in the AQ conferences are generally larger, have higher standards of education, and tend to attract superior students, consistent with the results of past cross-sectional studies (e.g., McCormick and Tinsley, 1987) that find that schools with successful athletics programs tend to attract higher-quality students.

2.3 Model-free Analysis

Figure 2 shows the aggregate number of high school graduates in the United States over the past decade. The upward trend in the number of graduates is due mainly to the population increase in the relevant age bracket. To get a glimpse of how athletic success influences admissions, figure 3a shows the number of applications received by the two main public universities in the state of Alabama, the University of Alabama and Auburn University. These two institutions are chosen for illustration because many consider them to be the greatest college football rivals in the United States, clashing each year in the historic Iron Bowl.[16] Both are public universities of roughly equal enrollment and academic ranking. In addition, college football is one of the biggest attractions, if not the *biggest* attraction, in the state of Alabama, with the BCS National Championship having been won by the University of Alabama in the 2009, and Auburn University in the 2010 season. The early years of this decade, during which the school had to deal with NCAA sanctions for recruiting violations, are referred to as the "dark ages" in Crimson Tide (University of Alabama's nickname) football. During this period, Alabama lost the Iron Bowl to Auburn for seven consecutive years. Alabama's football program was rejuvenated in the latter years of the decade and has been on the national scene ever since. It was during this time that Alabama surpassed Auburn in the number of applications received.

The most established and well-known institution in college football is, arguably, the University of Notre Dame, with 13 recognized national championships under its belt and 96 All-Americans and seven Heisman Trophy winners throughout its history. Notre Dame has

[16] There are other big rivalries considered to be equal to the rivalry of Alabama and Auburn; Yale vs. Harvard, Army vs. Navy, Ohio State vs. Michigan, USC vs. Notre Dame, Stanford vs. California, Texas vs. Texas A&M.

had somewhat of a rollercoaster ride in the past decade in terms of football success. One can see in table 2, which shows overall football wins per season for a select number of schools, that Notre Dame did quite well in the 2002, 2005, and 2006 seasons, with ten, nine, and ten wins, respectively. Because the football season begins with the start of the academic year in the fall and ends with the conclusion of the national championship game in early January, and applications for admission are usually submitted between late fall and early spring of the previous academic year, the effect, if any, of football success on the number of applications is expected to appear the following academic year.[17] Figure 3b shows substantial increases in numbers of applications in 2003, 2006, and 2007, the years immediately following Notre Dame's successful football seasons; other years show only a limited increase, and in some instances a decrease, in numbers of applications.

This phenomenon is not limited to the case of Notre Dame. Figure 3c shows the trend of applications at two large public institutions with rich traditions in football, the University of Texas and Pennsylvania State University. Similar to the application trends of Notre Dame, the number of applications for both Texas and Penn State increased significantly, immediately following years of football success. Specifically, there was a huge increase in the number of applications for Texas in the year following the BCS National Championship at the end of the 2005 football season. Likewise, there was a huge increase in applications for Penn State in the year following its win in a BCS bowl game, the Orange Bowl, at the end of the 2005 football season.

Would this phenomenon hold for smaller schools with less history of football success prior to the recent decade? The University of Oregon and University of West Virginia, with their high-tempo powering offenses, have gained popularity among college football fans and enjoyed huge success on the football field during the past decade. Figure 3d shows application trends for both schools, at which the number of applications has risen substantially over the past decade, with peaks in the years following successful football seasons.

Finally, a glimpse of what happens when a less sports-affiliated institution (member of the non-AQ conference) excels in athletics is given in figure 3b, which shows the number of

[17] A detailed description of timing is provided in the following section.

applications for TCU over the past decade.[18] We see a huge increase in applications, far greater than the increase in high school graduates shown in figure 2. During this period, in contrast to previous decades, TCU did quite well on the field, being ranked in the top 10 twice and in the top 25 seven times in the final AP Poll.

One thing to consider is that there may have been a national temporal trend in the number of applications over the past decade due to record-low interest rates and the federal government's emphasis on postsecondary education. Figure 2 shows that the total number of applications for 1,277 U.S. institutions that offered associate degrees or above in the aggregate increased substantially. Additionally, Figure 2 shows the ratio of the number of applications to the total number of U.S. high school graduates over the past decade. The average number of applications per student increased steadily, from 1.4 applications per student in 2001 to 1.8 in 2009, possibly due to the macroeconomic variables mentioned above.

To account for this trend, and to conduct a more general and conclusive analysis of the relation between football success and applications, figure 4 presents a scatter plot and the best-fitting nonparametric smoothed polynomial (and its 95 percent confidence interval) of the fractional increase in applications (normalized by the total number of applications) against the change in the number of wins compared to the previous season. Normalization was done by dividing the number of applications for each institution by the total number of applications in a given year to account for macroeconomic temporal changes. Hence, the y-axis of figure 4 is the fractional increase in the normalized number of applications, specifically,

$$\left(\text{The increase in normalized applications for institution } j \text{ at } t\right) = \frac{\left(\dfrac{app_{jt}}{Tapp_t} - \dfrac{app_{j,t-1}}{Tapp_{t-1}}\right)}{\left(\dfrac{app_{j,t-1}}{Tapp_{t-1}}\right)},$$

where $Tapp_t = \sum_j app_{jt}$. The x-axis is institution j's change in the number of wins compared to the previous football season. One can see that when there is no significant change in football performance (near zero on the x-axis), changes in the number of applications are

[18] TCU was a member of the MWC. As of July 1, 2012, it became a member of one of the AQ conferences, the Big 12.

minimal. However, when there is a substantial increase in football success (the right side of zero on the x-axis), applications increase substantially. In contrast, when there are negative changes in football performance (the left side of zero on the x-axis) there is a decline in normalized applications.

3. Model

I propose a model of demand for higher education that allows for heterogeneity in students' tastes for school and market characteristics. I treat athletics and its cumulative performance as a stock of goodwill that decays over time but augments with current performance, similar to that of advertising.[19] In addition, I use order statistics to infer the quality of applicants from the observed distribution of the incoming freshman class and, thus, am able to formulate the relative importance of athletic success to students of different abilities.

Model of application choice conditional on the quality of applicants

The choice of postsecondary education is probably the biggest decision most high school seniors have faced in their young lives. The decision of where to apply is likely based on factors related to the quality of education, such as the quality of faculty and faculty–student ratio, and probably also takes into account the opportunity costs of postsecondary education and costs related to attending a particular institution, which can take the form of monetary costs, primarily represented by tuition, or the psychological costs of being away from home. Factors such as the diversity of the student body and the goodwill created by intercollegiate athletics may also impinge upon this decision.

Let the utility of person i with ability a residing in state s who decides to apply to institution j at time t be represented as u_{isjt}^{a}. Obviously, the utility obtained from applying is not limited to simply "applying," but is more a continuation value expected from enrolling in

[19] There have been numerous studies that deal with the long-term and carryover effects of advertising. These studies include de Kluyver and Brodie (1987), Givon and Horsky (1990), Dekimpe and Hanssens (1995), Lodish et al. (1995), Bruce (2008), and Rutz and Bucklin (2011). Clarke (1976) and Assmus et al. (1984) compare various models with regard to the long-term effect of advertising.

the school. Assume that the utility is additively separable between a deterministic and random component, and, hence, the utility function can be represented as

$$u^a_{isjt} = \sum_k \beta^a_k x_{sjkt} - \gamma^a p^T_{sjt} + G^a_{jt} + \xi^a_j + \Delta\xi^a_{sjt} + \sum_k \sigma^a_k x_{sjkt} \nu^a_{isk} + \sigma^a_p p^T_{sjt} \nu^a_{isp} + \varepsilon^a_{isjt}, \quad (1)$$

where x_{sjkt} is the k-th observed characteristic of the market institution-specific vector x_{sjt}. I define a market as the state in which a high school student currently resides. ξ^a_j is the time invariant unobserved (by the econometrician) utility component of j that is common across all individuals (with ability a) and across all markets, and $\Delta\xi^a_{sjt}$ is the time-varying unobserved utility component of j that is common across all individuals with ability a in market s at time t. The unobserved ξ captures difficult-to-quantify aspects, such as prestige, tradition, and reputation, that affect the demand of institution j. ε^a_{isjt} is the idiosyncratic random shock to utility that is assumed to be independently and identically distributed type I extreme value across individuals, states, schools and time. p^T_{sjt} is tuition costs, which are identical across markets for private institutions, but differ by market for public institutions. Specifically, for public institutions,

$$p^T_{sjt} = \begin{cases} \underline{p}^T_{sjt}, & \text{if institution } j \text{ is in state } s \\ \overline{p}^T_{sjt}, & \text{otherwise} \end{cases},$$

where $\underline{p}^T_{sjt}$ and $\overline{p}^T_{sjt}$ represent in-state and out-of-state tuition, respectively. G^a_{jt} is the stock of goodwill generated by past and current athletic performance, which follows the process:

$$G^a_{jt} = \lambda^a G^a_{j,t-1} + b^a A_{jt}, \quad (2)$$

where λ is the carry-over rate ($1-\lambda$ can be thought of as the decay rate), which is assumed to be $0 < \lambda < 1$, and A_{jt} is current athletic performance, which augments athletic goodwill. Recursively solving equation (2) results in,[20]

[20] With regard to identification of the carryover rate λ, if a school has more than two periods (current + 1st lag) of football performance, one can uniquely identify the marginal effect of football success and carryover rate separately. If there are more than two periods, these periods would act as over-identifying restrictions, hence, λ can be more precisely identified.

$$G_{jt}^{a} = \sum_{\ell=0}^{t-1} \left(\lambda^{a}\right)^{\ell} b^{a} A_{j,t-\ell} + \left(\lambda^{a}\right)^{t} G_{j0}^{a} . \quad (3)$$

I introduce individual-level preference heterogeneity by the sixth and seventh terms in equation (1), of which elements of ν are assumed to be distributed from a standard normal distribution. Hence, the characteristic x_{sjkt} factors into the utility function through the mean component $\beta_{k}^{a} x_{sjkt}$ plus any deviations from the mean $\sigma_{k}^{a} x_{sjkt} \nu_{isk}^{a}$ that differ by individual. Similarly, $\gamma^{a} p_{sjt}^{T}$ represents the mean disutility one gets from tuition expenses, and $\sigma_{p}^{a} p_{sjt}^{T} \nu_{isp}^{a}$ represents any deviations from this mean, thus allowing different price elasticities by individual. The utility one gets for not applying to college j is given as[21]

$$u_{is0t}^{a} = \xi_{s0t}^{a} + \sigma_{0}^{a} \nu_{is0}^{a} + \varepsilon_{is0t}^{a} . \quad (4)$$

One can think of ξ_{s0t}^{a} as common shocks within markets that influence choice. For example, in 2005 Hurricane Katrina made it difficult for students in Louisiana to apply to colleges. I capture individual-level heterogeneity in the value of not applying to school j by the second term in equation (4). Because the market shares in the logit model are a function of the differences in utility from the outside option (not to apply to j), naturally, in this formulation the random coefficient on the intercept term of the utility of option j captures the heterogeneity of the outside option of not applying to j.

The utility function in equation (1) can be decomposed as

$$\begin{aligned} u_{isjt}^{a} &= \delta(x_{sjt}, p_{sjt}^{T}, G_{jt}^{a}, \xi_{sjt}^{a}; \theta_{1}^{a}) + \mu(x_{sjt}, p_{sjt}^{T}, \nu_{is}^{a}; \theta_{2}^{a}) + \varepsilon_{isjt}^{a} \\ &= \delta_{sjt}^{a} + \mu_{isjt}^{a} + \varepsilon_{isjt}^{a}, \end{aligned}$$

where $\xi_{sjt}^{a} = \xi_{j}^{a} + \Delta\xi_{sjt}^{a}$ and $\delta(x_{sjt}, p_{sjt}^{T}, G_{jt}^{a}, \xi_{sjt}^{a}; \theta_{1}^{a})$ represents the mean utility, which is independent of individual characteristics $\nu_{is}^{a} = (\nu_{isp}^{a}, \nu_{is1}^{a}, ..., \nu_{isK}^{a})$, and $\mu(x_{sjt}, p_{sjt}^{T}, \nu_{is}^{a}; \theta_{2}^{a})$ is an individual's deviation from the mean. Correspondingly, $\theta_{1}^{a} = (\gamma^{a}, \beta_{1}^{a}, ..., \beta_{K}^{a}, \lambda^{a}, b^{a})$ is the vector of parameters that represents the marginal effect on utility for school-state

[21] More precisely, the outside option here would be not applying to one of the 120 universities in Division 1 FBS. Thus, deciding to apply to an Ivy League school would be captured by the outside option.

characteristics independent of individual characteristics, and $\theta_2^a = (\sigma_p^a, \sigma_1^a, ..., \sigma_K^a)$ is the vector of parameters associated with these individual characteristics.

By the distributional assumption on the idiosyncratic shocks and the utility specification stated above, the probability of individual i with ability a who resides in state s applying to institution j is given as[22]

$$P_{isjt}^a = \frac{\exp(\delta_{sjt}^a + \mu_{isjt}^a)}{1 + \exp(\delta_{sjt}^a + \mu_{isjt}^a)}.$$

By integrating over the heterogeneity component, one can obtain the overall proportion of students of ability a in state s that applied to j,

$$S_{sjt}^a = \int \frac{\exp\left(\delta\left(x_{sjt}, p_{sjt}^T, G_{jt}^a, \xi_{sjt}^a; \theta_1^a\right) + \mu\left(x_{sjt}, p_{sjt}^T, \nu_i; \theta_2^a\right)\right)}{1 + \exp\left(\delta\left(x_{sjt}, p_{sjt}^T, G_{jt}^a, \xi_{sjt}^a; \theta_1^a\right) + \mu\left(x_{sjt}, p_{sjt}^T, \nu_i; \theta_2^a\right)\right)} h^a\left(\nu_i\right) d\nu_i\,, \qquad (5)$$

where $h^a\left(\nu_i\right)$ is the joint distribution of all heterogeneity elements $\nu_i^a = \left(\nu_{ip}^a, \nu_{i1}^a, ..., \nu_{iK}^a\right)$ for a student with ability a. Because the above equation involves solving a multidimensional integral that has no closed-form solution, one has to rely on simulations to obtain the overall application shares.

4. Estimation

Based on the specification outlined in the previous section, I estimate a model of demand for higher education that allows different preferences for students of different academic ability. In doing so, I make the following key assumptions, which are necessary due to data limitations.

A1. The likelihood of a student applying to a school after sending standardized test scores is the same across schools' geographical locations (state).

A2. Schools stochastically choose to admit students based on the order of students' standardized test scores.

A3. A random proportion of admitted students decides to enroll.

[22] The application decision is assumed to be independent across schools. This assumption may sound somewhat limited. However, since the cost of applications is extremely small compared to the cost of attendance, this assumption is not overly restrictive.

A4. The distribution of standardized test scores of applicants for a school is identical across states, formally stated as: for school i, let $F_j^i(x)$ and $F_k^i(x)$ be the distribution of standardized test scores of applicants from state j and k, respectively; then, $F_j^i(x) = F_k^i(x)$.

4.1 Constructing Application Shares

The IPEDS data contain the number of applications received by each institution in a given year. However, they do not contain the market (state) from which these applications originate. Therefore, the application shares (proportion of students in state s that applies to school j) are obtained by synchronizing the College Board SAT and IPEDS data, specifically, the percentage of SAT scores sent to each institution from each state and number of applications each school received. I hereafter refer to application shares as the proportion of high school students in state s that sends applications to a particular institution, formally defined as

$$S_{sjt} = \frac{\text{Number of high school students from state } s \text{ that applies to institution } j}{\text{Total number of high school students (seniors) in state } s}.$$

Naturally, these shares will not sum to one because an individual may choose to apply to more than one school; so the term 'share' is somewhat awkward. The application share can be thought of as the proportion of students who consider school j and, hence, apply to j from the total number of high school students in state s.

The College Board SAT data contain the exact number of SAT score reports sent to any institution from a particular state. Although merely sending one's SAT score report to a school is not the same as applying (but would probably be a superset), knowing the ratio of the SAT score reports sent to an institution from a specific state and total number of applications the institution received, we can infer for each institution the number of applications that come from a particular state. Specifically, suppose there are S markets and J institutions. Let the ratio of SAT score reports sent from students in market s to institution j be μ_j^s, formally defined as

$$\mu_j^s = \frac{\text{Number of students in } s \text{ who sent SAT scores to } j}{\text{Total number of students in } s \text{ who sent SAT scores}}.$$

In addition, let the total market size (i.e., total number of high school graduates) of state s be M^s and total number of applications received by j be A_j. Because μ_j^s reflects the popularity (in applications) of school j among students in s who have decided to apply to colleges, assuming A1, I can obtain the number of applications coming from state s for institution j by utilizing this ratio and weighing it by the total number of high school students in each state s that have decided to apply to colleges, such that

$$A_j^s = \frac{\mu_j^s \cdot M^s \pi^s}{\sum_{r=1}^{S} \mu_j^r \cdot M^r \pi^r} \cdot A_j, \tag{6}$$

where π^s is the proportion of students in state s that apply to postsecondary educational institutions; thus, $M^s \pi^s$ represents the number of students in state s that apply to colleges. For π^s, I use the college-going rate by state per year from the NCHEMS Information Center, which represents the proportion of high school students in each state that goes to college.[23] For clarification, I illustrate in the appendix how I construct application shares.

4.2 Order Statistics to Infer the Quality of Applicants

Federal law protects the data associated with individual information about applicants to each institution of higher education in the United States.[24] Thus, I can obtain data on the quality of students (SAT scores) only for the enrolled student population for each academic institution in my sample. Relying on this information along with the admission rate, I use order statistics to infer the quality of the applicants.

Schools take into account standardized test scores as well as other dimensions of quality when making their admission decisions. Thus, a typical admission rule would be a

[23] The college-going rate and college-applying rate can be different because one can apply to colleges but decide to not go, thus, the latter would be slightly higher. However, if there are no systematic differences between the two ratios across states, then the former would be a good proxy for the latter in the context of equation (6).

[24] To obtain individual-level information for applicants (SAT scores), one would need permission from each academic institution and from each student who applied to those institutions.

probabilistic function with regard to standardized test scores. If the admitted and the applicant distribution are observed, we can infer the admission rule such as

$$\Pr\left(A \mid x\right) = \frac{f\left(x \mid A\right) p\left(A\right)}{f\left(x\right)}, \tag{7}$$

where A denotes admission, thus, $f\left(x \mid A\right)$ and $f\left(x\right)$ are the probability density function of standardized test scores for admitted students and applicants, respectively, and $p\left(A\right)$ is the unconditional admission probability. Likewise, if the admitted distribution and admission rule are observed, we can back out the applicant distribution. However, because only the distribution of standardized test scores conditional on admission $f\left(x \mid A\right)$ and the unconditional admission probability $p\left(A\right)$ are observed due to privacy regulations, I have to rely on distributional assumptions to infer the applicant distribution $f\left(x\right)$. Hence, as in assumption A2, I assume that each institution stochastically chooses to admit students based on the order of their standardized test scores. Because each institution wants to attract students of higher quality, this assumption does not seem unreasonable. This assumption, however, does not mean that a school chooses to admit students based solely on standardized test scores, but instead it means that a school also takes into account other dimensions of quality not captured by standardized test scores, as explained in detail below.

Suppose that a certain institution admits $n-k+1$ out of n applicants (where $1 \leq k \leq n$). Assuming that the school stochastically chooses $n-k+1$ out of n students based on the order of their standardized test scores, we can construct an order statistics distribution from any underlying distribution.[25] Let X_i be a random variable (standardized test score) that has a probability density function $f\left(x\right)$ and cumulative distribution function $F\left(x\right)$. If one were to randomly draw n samples from this distribution and arrange them in a non-decreasing order, one would obtain the corresponding order statistics $X_{1:n}$, $X_{2:n}, \ldots,$ $X_{n:n}$. These order statistics are naturally random variables whose distribution is a function of the

[25] Interested readers can refer to Sarhan and Greenberg (1962), David (1981), Balakrishnan and Cohen (1991), Arnold et al. (1992), and Harter and Balakrishnan (1996, 1997).

underlying distribution. Specifically, the probability density function for the k-th order statistics is given as

$$f_{k:n}\left(x\right)=\frac{n!}{\left(k-1\right)!\left(n-k\right)!}f\left(x\right)\left[F\left(x\right)\right]^{k-1}\left[1-F\left(x\right)\right]^{n-k},$$

and the probability density function for the $k\sim n$ bracket of order statistics as

$$f_{(k:n):n}\left(x\right)=\frac{1}{n-k+1}\sum_{r=k}^{n}f_{r:n}\left(x\right).$$

Because the school chooses $n-k+1$ out of n applicants, the distribution of $k\sim n$ bracket of order statistics would represent the distribution of the admitted $f\left(x\mid A\right)$ in equation (7). Hence, the distribution of the admitted would be a function of the underlying applicant distribution $f\left(x\right)$ and unconditional admission probability $p\left(A\right)$ such that

$$f\left(x\mid A\right)=\frac{1}{n-k+1}\sum_{r=k}^{n}\frac{n!}{\left(r-1\right)!\left(n-r\right)!}\left[F\left(x\right)\right]^{r-1}\left[1-F\left(x\right)\right]^{n-r}f\left(x\right)=\frac{1}{p\left(A\right)}\Pr\left(A\mid x\right)f\left(x\right).$$

Because the unconditional probability of admission $p\left(A\right)$, by definition, is $\left(n-k+1\right)/n$, one would be able to obtain the admission rule such that

$$\Pr\left(A\mid x\right)=\frac{f\left(x\mid A\right)p\left(A\right)}{f\left(x\right)}=\frac{1}{n}\sum_{r=k}^{n}\frac{n!}{\left(r-1\right)!\left(n-r\right)!}\left[F\left(x\right)\right]^{k-1}\left[1-F\left(x\right)\right]^{n-k}.$$

This rule is quite intuitive. Suppose a school admits half of its applicants, thus, n=2 and k=2. Then, the admission rule is simply the cumulative distribution function $F\left(x\right)$, which is an increasing function of standardized test scores. That is, higher standardized test scores lead to higher admission probabilities. If another school admits a third of its applicants, thus, n=3 and k=3, the admission rule would be $\left[F\left(x\right)\right]^{2}$. Hence, if the two schools have identical applicant pools given by the same distribution $F\left(x\right)$, the latter school would be more selective with stricter admission rules ($\left[F\left(x\right)\right]^{2}\leq F\left(x\right)$ for all x). Overall, the order statistics distributional assumption presumes that schools' admission decisions typically take into account other dimensions of quality as well as standardized test scores, consistent with actual admission selection rules. For clarification, I provide an illustrative example with regards to assumption A2 and the use of order statistics in the online appendix.

Using the order statistics distribution, I can recover the underlying distribution of applicant quality. Specifically, assuming the SAT scores for applicants at institution j to be normally distributed with mean μ_j and variance σ_j^2, I can match the order statistics distribution that best fits the data to recover the underlying distribution of applicants.[26]

I observe the first and the third quartiles of the SAT scores for the enrolled freshmen class along with the admission rate and, hence, use this information to construct a minimum-distance estimator to recover the parameters of the underlying distribution function. For example, suppose that institution j admits 30 percent of its applicants. This would mean that three out of ten applicants based on the order of their standardized test scores are stochastically admitted. If the first and third quartiles of the SAT scores are Q_{j25} and Q_{j75}, respectively, then we can find the parameters of the underlying distribution function by minimizing the minimum distance estimator thus,

$$\left(\mu_j, \sigma_j\right) = \arg\min \left\{ \left(Q_{j25} - F_{(k:n):n}^{-1}\left(0.25;\ \mu_j, \sigma_j\right)\right)^2 + \left(Q_{j75} - F_{(k:n):n}^{-1}\left(0.75;\ \mu_j, \sigma_j\right)\right)^2 \right\},$$

where, in the current example, $k = 8$ and $n = 10$. Figure 5 graphically illustrates this procedure. Because, by A3, I am assuming that a random proportion of the admitted students decide to enroll, the SAT score distributions of the admitted and enrolled students are identical. Hence, from the distributional information of the enrolled students, I can obtain the mass of applicants via their SAT scores.

Assumption A3 indicates that, after being admitted, the choice of enrollment is not a function of SAT scores. Figure 6 shows for a large, public, East Coast university, with academic characteristics similar to those of the majority of schools in the current analysis, the SAT score distributions of applied, admitted, and enrolled. As can be seen, the distributions of admitted and enrolled look quite similar. Furthermore, the average SAT scores for admitted and enrolled, 1173 and 1155, respectively, differ only slightly. This probably reflects

[26] The minimum and maximum SAT scores are 400 and 1600, respectively. Thus, in practice, the underlying distribution is assumed to come from a truncated normal distribution.

a degree of self-selection based on students' ability when making application decisions, and, thus, enrollment decisions from the subset of schools to which they have been admitted are more of a horizontal than vertical choice.[27] Interestingly, the shape of the SAT score distribution for the applied, admitted, and enrolled, is remarkably consistent with assumptions A2 as well as A3, providing empirical validity to the approach taken to recover the applicant distribution.

I observe the SAT score distribution of students in each market, and can infer (by equation (6)) the number of students from each state that applied to each school. Using this information, together with the distribution of the SAT scores of applicants for each school, I am able to construct the application shares for any ability level in each market. In practice, I construct the applicant shares by five evenly-divided segments based on the overall SAT score distribution. In constructing the application shares by ability segment, as in A4, I assume a school's SAT distribution of applicants to be identical across states. Although this assumption seems reasonable for private schools, it may be somewhat problematic for public schools. Because public institution applicants come predominantly from their home state, however, this assumption would likely not significantly bias the estimates. Figure 7 shows the probability distribution of public schools and composition of students (percentage of in-state students).[28] One can see that the student bodies of most public schools in Division 1 FBS are composed mostly of in-state students. In more than 35 percent of public schools, 90 percent or more of the students are from the home state; in only 10 percent are fewer than 70 percent, and in none fewer than 62 percent, of students from the home state.[29]

4.3 Estimation Procedure

[27] As an alternative, I tested a different selection rule that utilizes another layer of order statistics to allow for different SAT score distributions of admitted and enrolled students. Using this approach did not change the fundamental results of the current analysis.

[28] Source: "Percentage of Out-of-State at Public Universities," CollegeXpress.com.

[29] To further validate this assumption, figure 8 shows the SAT score (math) distribution for in-state and out-of-state enrolling students at an anonymous, mid-size, East Coast public institution. Roughly 10 percent of the institution's incoming freshmen class was from out-of-state. Although the out-of-state distribution seems to be skewed slightly towards the right, there is only a small difference between in-state and out-of-state. The difference in SAT scores between in-state and out-of-state students was likewise minimal, average SAT scores (math+reading) for in-state and out-of-state students being 1123 and 1139, respectively.

To estimate the model parameters, I use the generalized method of moments (GMM; Hansen, 1982), a generic method of estimating parameters in an econometric model without relying on any distributional assumptions on the statistical error structure. The GMM accommodates the use of instrumental variables to correct for the likely correlation between certain variables (e.g., price) and the unobserved errors. However, in the current structure, because the unobserved error component enters the share equation in (5) nonlinearly, it is not feasible to directly apply the instrumental variables technique. I therefore use the approach of Berry et al. (1995), which has been widely applied in the marketing literature (e.g., Sudhir, 2001; Gordon and Hartmann, 2012).[30]

For the initial value of goodwill G_{j0}^{a}, one can structure a distributional assumption and integrate over it, or, with a long enough time series in the panel and the belief that the carryover rate is relatively small, start off with some initial number. The time series of the IPEDS and College Board SAT data in my sample is for nine years (2001–2009) and that of the athletics data is for 15 years (1996–2010). Having sufficient past athletic performance data, I use the information from the entire history of athletic performance to set the initial goodwill stock as

$$G_{j0}^{a} = \frac{1}{1-\lambda^{a}} \cdot \frac{1}{T} \sum_{\ell=1}^{T} b^{a} A_{jk}$$

in the estimation procedure.

4.4 Choice of Variables and Instruments

For school characteristics, I use average faculty salary and faculty–student ratio, variables commonly used in the literature to control for quality of education. I use the distance in miles from a student's home state to an institution for school–market characteristics to take into account any psychological and monetary costs of being away from home. Furthermore, I use the annual borrowing rate to account for the opportunity cost of postsecondary education.

[30] I direct readers to Berry et al. (1995) and Nevo (2000, 2001) for details of the estimation procedure.

I use the number of football wins in a season for current athletic performance. As noted in section 2.2, because the more wins in a season, the more likely a team is to receive greater media exposure; therefore, the total number of wins in a season is a good proxy for current athletic success. The college football season ends in early January with the conclusion of the BCS National Championship game. For teams that do not qualify for post-season bowl games (teams with fewer than six regular season wins), the season ends around Thanksgiving Day with the conclusion of their main rivalry games. For teams that qualify for a bowl game, the season ends with the conclusion of the bowl game, sometime in late December or early January. Application packets, although they vary by institution and individual, are usually submitted around this time for the next academic year. So I use as a measure of current athletic performance the previous academic year's overall football wins.

The unobserved (by the econometrician, but fully observed by student and school) time-varying common component $\Delta\xi$, which represents difficult to quantify features, may be correlated with tuition. While it is merely a given fact that, with profit-maximizing firms, prices are correlated with $\Delta\xi$, this is somewhat less obvious with educational institutions. It is highly unlikely that tuition is a flexible decision variable that one can systematically change over a short period of time. Nevertheless, I use the previous two years' tuition as instruments for current tuition.

By using an extensive set of school fixed effects, I am able to capture omitted or unobserved characteristics of quality and, thus, partially address the endogeneity problem related to athletic success. However, $\Delta\xi$, which represents time-specific deviations, can be endogenous with athletic goodwill. To further address the endogeneity concern with regard to $\Delta\xi$ and athletic goodwill G, let us discuss the possible factors that construct the unobserved $\Delta\xi$. One can think of $\Delta\xi$ as any media exposure that is not observed in the data. A successful movie filmed on campus or special event, such as a presidential debate, would fall into this category. As such events likely occur randomly, the endogeneity problem is probably not a big concern.

The endogeneity issue is likely to be a problem if we think of $\Delta\xi$ as investments, or the maturity of investments, such as the opening of a new residence hall or academic facility. Because the goodwill stock of athletics is a function of historical athletic success, and athletic success is likely a function of past investments in athletics, there may be a chance that $\Delta\xi$ and G are correlated. This is probably not the case, though, for several reasons. First, in most of the schools in my sample, budgets for athletics and academics are separate, as indicated in the 2009 report issued by the Knight Commission on Intercollegiate Athletics, which found presidents of major universities to have limited control over athletic department budgets.[31] Second, creating a strong athletics program predominantly takes longer than building facilities. Thus, although decisions to invest in academic facilities and athletics may be correlated, due to the timing difference in the maturity of investments, the endogeneity concern is less severe, further reducing the endogeneity problem. Hence, I believe that endogeneity is not a major concern in my model specification.

5. Results

I begin by showing the results of the static model in which the carryover rate λ is set to zero, and, thus, athletic goodwill is just a linear function of current athletic performance. Table 3 shows for two specifications the results of the static model without individual heterogeneity in taste or ability. These specifications would be the same as an ordinary least squares (OLS) and two-stage least squares (2SLS) regression with the natural log of odds as the dependent variable – homogeneous aggregate logit.

The results show athletic performance to have a significantly positive effect. Average faculty salary, which acts as a proxy for the quality of faculty, is positive and significant. The faculty–student ratio is positive but insignificant, possibly due to limited variation in the size of the faculty or student body; thus, most of the effect will be absorbed by the school fixed effects. Both tuition and distance are negative and significant, implying that students receive disutility from both the monetary cost of tuition and mental cost of being away from home.

[31] Source: "Quantitative and Qualitative Research with Football Bowl Subdivision University Presidents on the Costs and Financing of Intercollegiate Athletics," Knight Commission on Intercollegiate Athletics, 2009.

The interest rate is negative and significant, suggesting that students value the opportunity cost with regard to postsecondary education.

The results of the OLS and 2SLS do not differ much. The elasticity of tuition increases slightly with the use of instrumental variables, but not as much as found in other studies in which the magnitude of increase is as much as twofold (e.g., Berry et al., 1995; Villas-Boas and Winer, 1999). This is probably because tuition may be close to being exogenous and is not as much of a flexible control variable that can be easily adjusted over a short period of time as prices are for profit maximizing firms.[32]

Table 4a shows the results of the static model with heterogeneity in both taste and ability. To allow for heterogeneity in taste for athletic success, I include a random coefficient for current athletic performance. In other words, the goodwill function in equation (1) is simply $G^a_{jt} = b^a A_{jt}$ with $\sigma^a_A A_{jt} \nu^a_{isA}$ added to allow for heterogeneity in taste for athletic performance. More specifically, the model I estimate here is

$$u^a_{isjt} = \sum_k \beta^a_k x_{sjkt} - \gamma^a p^T_{sjt} + b^a A_{jt} + \xi^a_j + \Delta\xi^a_{sjt} + \sum_k \sigma^a_k x_{sjkt} \nu^a_{isk} + \sigma^a_p p^T_{sjt} \nu^a_{isp} + \sigma^a_A A_{jt} \nu^a_{isA} + \varepsilon^a_{isjt}.$$

I further partition the student population into five evenly-divided segments based on overall SAT scores and construct applicant shares by each market segment to estimate segment level parameters. The range of SAT scores for the different segments is shown in the top row of table 4a. Athletic performance is positive and significant for all segments. Average faculty salary is also positive and significant. However, the mean utility parameter for athletic performance is greatest for students with low, and smallest for students with high, SAT scores. The magnitude is as much as three times as large for the lowest as for the highest ability segment, implying that athletic success is relatively more important to students with low academic ability. We can clearly see that the relative importance of athletic performance decreases with students' SAT scores, implying that students with higher ability, although not unappreciative of, are less enthusiastic about, the success of a school's athletic program than are lower-ability students.[33]

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[32] The results of several robustness checks to verify that tuition is exogenous are reported in the online appendix.

[33] An alternative approach to incorporate (continuous) observed heterogeneity would be to draw student quality from the observed SAT distribution and interact it with the athletic performance variable, the number of wins.

With regard to the quality of education, the relative importance of average faculty salary, which proxies for quality of faculty, increases with SAT scores, indicating that the demand for high-quality education increases with students' academic ability. The effect of the faculty–student ratio, although insignificant for all segments, dramatically increases with student ability, again implying that higher-ability students care relatively more about academics than their lower-ability counterparts do.

The coefficients on tuition and distance are all negative and highly significant. The effect of interest rate is negative and significant for all segments, with the highest-ability segment being the most sensitive. Although this result may come as a surprise, it makes intuitive sense, in that students with higher ability probably have a greater opportunity cost with regard to postsecondary education. The heterogeneity parameters are, for the most part, insignificant, except for tuition and distance for a number of segments. Even for the significant parameters the magnitude is negligibly small, showing close to no heterogeneity in taste. It is probably the case that the extensive set of school fixed effects is absorbing most of the heterogeneity. Although all students are positively affected by a school's success on the field, even, surprisingly, the highest-quality students, the relative importance is stronger for students with lower ability.

Table 5 shows the results of the dynamic model, for which I allow for heterogeneity only in student ability since the heterogeneity parameters on taste in the static model show that it is negligible. Athletic performance is again highly significant for all segments, with the lowest segment showing a much stronger preference than the higher-ability segments. The carryover rate λ is significant for only the lower-ability segments, implying that athletic goodwill from the previous years remains relevant only to students with low ability.

Counterfactual analysis

The natural counterfactual to perform is to determine how significant athletic success is in attracting potential candidates to apply to a specific institution. Table 6a shows the

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The results of this model specification are reported in table 4b. The interaction term with regard to SAT scores and football success is negative and significant, consistent with the results of the model that incorporates discrete-level observed heterogeneity. I thank an anonymous reviewer for suggesting this robustness check.

‘what if’ scenario: What happens if a mid-level school that used to have a mediocre football team suddenly performs well on the field, with everything else held constant?[34] I define mediocre performance as winning only four games per season, performing well as winning ten games per season, in the previous two years. Overall, applications increase by 17.7 percent when a school has a higher level of athletic success. However, most applicants come from the lower-ability segments. To match the increase in total number of applications absent athletic success, a school would have to decrease tuition by 3.8 percent or attract better faculty who would be paid 5.1 percent more in the academic labor market. Of course, due to differences in preferences for academic quality or athletic success on the part of students of different ability, the composition of applicants will be different depending on whether the increase results from lower tuition, improved academic quality, or athletic success. Tables 6b and 6c show the percentage increase in applications by students of different ability when the quality of faculty improves and tuition falls, respectively, to equal the increase in applications from success on the field. One can see that the increase in applications is spread more evenly among segments when tuition decreases, and that improvement in the quality of faculty affects high-ability students more than low-ability students. These findings are in contrast to the effect of athletic success on different ability segments. Moreover, each additional win for a school results in an additional loss for another school. Hence, this counterfactual exercise potentially underestimates the effect of athletic success.[35]

Building upon this analysis, the next apparent counterfactual is to look at how athletic success affects the selectivity of schools. Schools care about selectivity, particularly, the admissions rate, which is used as a key evaluation criteria in determining the quality rankings of academic institutions. Table 7 show the computed admissions rates of schools in the 25th, 50th, and 75th percentiles, in accordance with their average SAT scores, with low and high athletic success, defined, respectively, as winning four and ten games per season in the previous two years.

[34] I define mid-level school as a school with median fixed effects estimates.

[35] I thank an anonymous reviewer for this comment.

In computing this counterfactual, I keep the observed (estimated via order statistics) school's admission rates, which are different for each segment, constant. The logic behind this counterfactual is that schools making admissions decisions are not basing their evaluations on SAT scores alone. Other factors go into the decision making process, such as high school grades and extracurricular activities, and the admissions rate I observe in the data for each segment corresponds with this admissions policy.[36] For example, suppose a school's admissions rate in the lowest-ability segment is 15 percent. This means that, although the students in this segment have relatively low SAT scores, 15 percent possess other dimensions of quality (mentioned above) that make them worthwhile for the school to attract. This form of admissions policy takes into account the policies of schools that are sometimes required, by state law, to admit students that surpass a certain quality level (not necessarily SAT scores).[37] Because I observe (estimated via order statistics) the SAT score distribution of applicants and admittees, I can compute the actual admissions rates for each ability (SAT) segment for each school. I compute the total admissions rates for low and high athletic success, keeping the school's segment-level admissions rates constant.

Table 7 shows that both private and public schools gain in selectivity through athletic success. For the median (in terms of average SAT scores) private school, selectivity rates improve by 1.1, for the median public school, by 2.6, percentage points.

6. Conclusion

Intercollegiate athletics has experienced exponential growth in popularity over the past several decades and now plays a large part in the lives of many people in the United States. Colleges and universities benefit from intercollegiate athletics through monetary gain from ticket and merchandise sales and lucrative television contracts as well as through advertising in the form of exposure in multimedia outlets.

[36] This admissions policy is consistent with the assumption with regard to the use of order statistics distribution to back out applicant SAT scores in Section 4.2.

[37] Texas House Bill 588, commonly referred to as the "Top 10% Rule," passed in 1997 guarantees Texas students who graduate in the top 10 percent of their high school class automatic admission to all state-funded universities.

The advertising effect of intercollegiate athletics was first speculated in the years following Boston College quarterback Doug Flutie's infamous game-winning Hail Mary touchdown pass against the University of Miami in 1984, following which Boston College witnessed a substantial increase in applications. As a result, the mass media coined the term "Flutie effect" to refer to an increase in the exposure and prominence of an academic institution due to the success of its athletics program. The Flutie effect, although conjectured to be quite large in magnitude, has surprisingly not been fully investigated in the academic literature. This study empirically investigates the Flutie effect to determine the relative importance of a school's athletic success compared to other factors that influence the choice of schools for students of different abilities.

To investigate the advertising effect of intercollegiate athletics, I apply a flexible random coefficients aggregate discrete choice model and treat athletic success and its cumulative performance as a stock of goodwill that decays over time, but augments with current performance. Unlike previous research that relies solely on aggregate data, I use market-level data to adequately control for different factors that affect a student's choice of postsecondary education at the market level. Furthermore, to overcome data limitations due to privacy regulations, I innovate and contribute to the broader line of research in discrete choice models by using an order statistics distribution to infer the quality of applicants from the observed distribution of the enrolling freshman class. This enables me to identify different preferences for students of different ability.

Overall, I find that athletic success has a significant impact on the quality and quantity of applicants to institutions of higher education in the United States. I find athletic success to be relatively more important to students of lower ability, and students of higher ability to have a stronger preference for the quality of education compared to their lower-ability counterparts. Furthermore, the carryover rate of athletic goodwill is evident only for students with low SAT scores, suggesting that students with low ability value the historical success of intercollegiate athletics over longer periods of time. Nevertheless, and surprisingly, students with high SAT scores are also significantly affected by athletic success.

I further find that when a school goes from being mediocre to being great on the football field, applications increase by 17.7 percent. To achieve similar effects, a school would have to either decrease its tuition by 3.8 percent or increase the quality of its education by recruiting higher-quality faculty who are paid 5.1 percent more in the academic labor market. I also find that schools become more selective with athletic success. For a mid-level school, in terms of average SAT scores, the admissions rate improves by 4.8 percent with high-level athletic success.

Why would athletic success have any impact on an academic institution's applications for admission? There may be several reasons. First, this effect may be due to simply an increase in awareness. There are many academic institutions in the United States and chances are that many of them are fairly unknown. So having a successful athletics program could increase the visibility of these institutions to students who have not yet decided on which school to apply to. Even for schools that are fairly well known, the buzz generated by performance on the field can lead to stories on the evening news and in the sports pages of newspapers that may further increase awareness of these schools.

One can go a bit deeper, though. Sports are a big part of American culture. It is common for people in the United States to make the sporting events of their alumni institutions the focal point of their social interactions. Students may find it appealing to take part in such social bonding over sports in order to feel as though they are a part of something special, something bigger than themselves. This can lead to a virtuous cycle of improved alumni engagement with the school that translates into donations and help with job placement for current students, all of which enhances the school's success. Although not addressed in the current analysis, the question of 'why' students value intercollegiate athletics could be an exciting venue for future research.

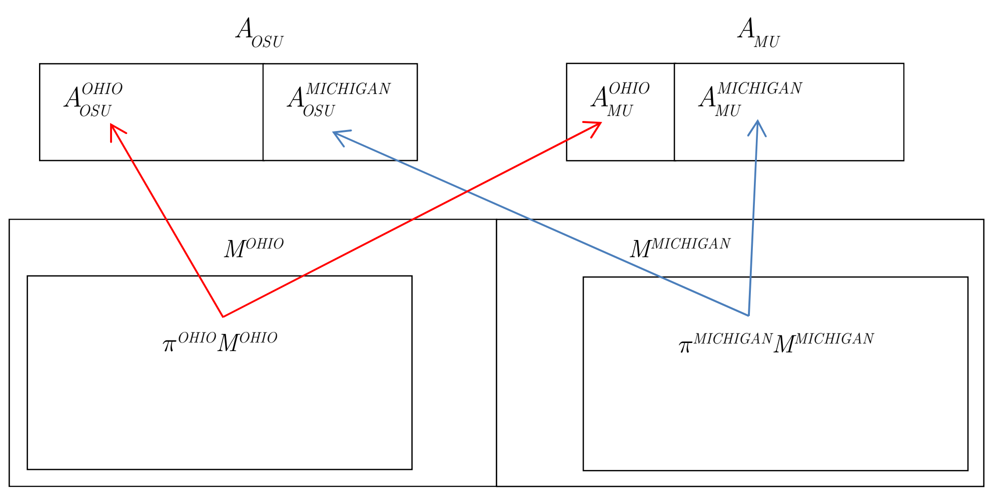
Appendix

1. Obtaining Application Shares – Illustrative Example

This section provides an illustrative example of constructing application shares in equation (6) utilizing multiple data sources. Let us assume that there are two states (Ohio and Michigan) and one school in each (OSU and MU). We observe how many SAT score reports were sent to OSU and MU from Ohio and likewise from Michigan. We also observe the total number of SAT senders from Ohio and Michigan.

The areas in figure A1 represent the number of high school seniors in each state (M^{OHIO}, $M^{MICHIGAN}$) and number of students that applied to each school from each state ($A_{OSU}^{OHIO}, A_{MU}^{OHIO}, A_{MU}^{MICHIGAN}, A_{OSU}^{MICHIGAN}$), that is, A_{OSU}^{OHIO} : number of students that applied to OSU from Ohio. π^{OHIO} and $\pi^{MICHIGAN}$ represent the college-applying rates for Ohio and Michigan, respectively. Hence, $\pi^{OHIO}M^{OHIO}$ would be the number of students in Ohio that applied to colleges, which is represented by the square area inside the area of M^{OHIO}. From the data, we only observe M^{OHIO}, $M^{MICHIGAN}$, A_{OSU}, A_{MU}, π^{OHIO}, $\pi^{MICHIGAN}$, but we want to find A_{OSU}^{OHIO} to construct our dependent variable.

Figure A1: Application Shares – Illustrative Example



We don't observe A_{OSU}^{OHIO}, but we observe the fraction of SAT scores sent to OSU from the state of Ohio,

$$\mu_{OSU}^{OHIO} = \frac{\text{Number of students in Ohio who sent SAT scores to OSU}}{\text{Total number of students in Ohio who sent SAT scores}},$$

which represents the relative popularity of OSU to Ohio students who decided to send SAT scores to any school, hence, apply to colleges. Weighing this probability by the number of high school students in Ohio that applies to colleges, $\pi^{OHIO}M^{OHIO}$, we can obtain A_{OSU}^{OHIO}, specifically,

$$A_{OSU}^{OHIO} = \frac{\mu_{OSU}^{OHIO} M^{OHIO} \pi^{OHIO}}{\mu_{OSU}^{OHIO} M^{OHIO} \pi^{OHIO} + \mu_{OSU}^{MICHIGAN} M^{MICHIGAN} \pi^{MICHIGAN}} A_{OSU}.$$

As a result, we can obtain the application share, $S_{OHIO,OSU} = \frac{\mathrm{A}_{OSU}^{OHIO}}{\mathrm{M}^{OHIO}}$. So, numerically, if the number of high school seniors in Ohio and Michigan is 120,000 and 100,000, respectively, and the number of applications that OSU received is 20,000, and μ_{OSU}^{OHIO} and $\mu_{OSU}^{MICHIGAN}$ is 0.4 and 0.1, respectively, and π^{OHIO} and $\pi^{MICHIGAN}$ are both 0.5, A_{OSU}^{OHIO} would be as follows.

$$A_{OSU}^{OHIO} = \frac{0.4 \times 120,000 \times 0.5}{0.4 \times 120,000 \times 0.5 + 0.1 \times 100,000 \times 0.5} \times 20,000 = 16,552$$

So, of the 20,000 applicants for OSU, we can infer that 16,552 would be coming from Ohio, hence, $S_{OHIO,OSU}$=16,552/120,000=0.138.

In summary, I observe the exact number of applicants for each school and decompose this number by the state from which it comes for my empirical application. In doing so, I use the information on the relative popularity of a school in each state weighted by the total number of high school students who applies to colleges for the corresponding state.

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Table 1: Descriptive Statistics

	Total		AQ		Non-AQ	
	Public	Private	Public	Private	Public	Private
No. of applications	13,797	15,184	17,139	18,971	9,841	9,907
	(8,434)	(8,298)	(8,478)	(7,436)	(6,433)	(6,319)
Size of undergraduate population	20,636	9,517	23,833	9,632	16,851	9,356
	(8,111)	(6,381)	(7,578)	(3,478)	(7,017)	(8,976)
Admission rate	0.69	0.43	0.67	0.37	0.72	0.51
	(0.18)	(0.19)	(0.17)	(0.17)	(0.20)	(0.19)
Enrollment rate	0.48	0.39	0.46	0.37	0.50	0.41
	(0.14)	(0.15)	(0.12)	(0.12)	(0.16)	(0.19)
No. of faculty	1,074	829	1370	935	723	681
	(556)	(364)	(552)	(361)	(293)	(312)
Faculty salary	70,265	86,477	75,629	89,303	63,914	82,539
	(18,407)	(18,051)	(17,385)	(20,735)	(17,542)	(12,414)
Faculty–student ratio	0.05	0.10	0.06	0.11	0.05	0.10
	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.04)
SAT scores	1,117	1,306	1,167	1,326	1,057	1,278
	(95)	(95)	(77)	(89)	(80)	(96)

Years 2001–2009, for 120 schools participating in Division 1 FBS. Standard deviation is reported in parenthesis.

Table 2: Overall Football Wins per Season – Select Schools

School/year	2000	2001	2002	2003	2004	2005	2006	2007	2008
Notre Dame	9	5	10	5	6	9	10	3	7
Penn St.	5	5	9	3	4	11	9	9	11
Texas	9	11	11	10	11	13	10	10	12
Oregon	10	11	7	8	5	10	7	9	10
West Virginia	7	3	9	8	8	11	11	11	9

Table 3: Homogeneous Aggregate Logit

	OLS	2SLS
Interest rate	-0.248***	-0.250***
	(0.021)	(0.021)
Average faculty salary	0.040***	0.041***
	(0.002)	(0.002)
Faculty-student ratio	0.762	0.790
	(1.067)	(1.067)

# Wins	0.018*** (0.004)	0.018*** (0.004)
Distance	-0.032*** (0.002)	-0.032*** (0.002)
Tuition	-0.155*** (0.002)	-0.156*** (0.002)

***: p < 0.01.

Table 4a: Parameter Estimates – Static Model

		seg1	seg2	seg3	seg4	seg5
	SAT score range	400 - 837	837 - 973	973 - 1090	1090 - 1225	1225 - 1600
θ_1	Constant	-3.225*** (0.354)	-2.392*** (0.256)	-2.198*** (0.237)	-2.171*** (0.232)	-2.752*** (0.254)
	Interest rate	-0.101*** (0.037)	-0.195*** (0.026)	-0.245*** (0.023)	-0.287*** (0.022)	-0.320*** (0.025)
	Average faculty salary	0.044*** (0.003)	0.037*** (0.002)	0.038*** (0.002)	0.039*** (0.002)	0.044*** (0.002)
	Faculty-student ratio	-1.178 (2.150)	-0.084 (1.551)	0.452 (1.342)	0.801 (1.270)	1.472 (1.334)
	# Wins	0.037*** (0.007)	0.024*** (0.005)	0.016*** (0.005)	0.012*** (0.005)	0.012*** (0.005)
	Distance	-0.028*** (0.003)	-0.031*** (0.003)	-0.035*** (0.003)	-0.036*** (0.004)	-0.040*** (0.005)
	Tuition	-0.152*** (0.004)	-0.155*** (0.003)	-0.159*** (0.003)	-0.163*** (0.003)	-0.168*** (0.003)
θ_2	Constant	0.013 (4.505)	0.012 (3.111)	0.013 (2.811)	0.012 (2.697)	0.011 (2.779)
	Interest rate	0.009 (0.442)	0.010 (0.293)	0.009 (0.269)	0.010 (0.251)	0.010 (0.250)
	Average faculty salary	0.000 (0.020)	0.000 (0.014)	0.000 (0.013)	0.000 (0.012)	0.000 (0.012)
	Faculty-student ratio	0.010 (7.458)	0.014 (5.525)	0.010 (4.832)	0.014 (4.495)	0.011 (4.489)
	# Wins	0.011 (0.024)	0.010 (0.018)	0.011 (0.016)	0.012 (0.015)	0.013 (0.015)
	Distance	0.015** (0.007)	0.011 (0.007)	0.015** (0.007)	0.011 (0.009)	0.013 (0.010)
	Tuition	0.010 (0.010)	0.011* (0.007)	0.010 (0.006)	0.011** (0.006)	0.012** (0.006)

***: p< 0 .01, **: p < 0.05, *: p < 0.1.

Table 4b: Parameter Estimates – Alternative Static Model

θ_1		θ_2	
Constant	-2.482*** (0.227)	Constant	0.010 (2.753)
Interest rate	-0.250*** (0.022)	Interest rate	0.010 (0.244)
Average faculty salary	0.040*** (0.002)	Average faculty salary	0.000 (0.010)
Faculty-student ratio	0.665 (1.302)	Faculty-student ratio	0.013 (2.986)
Wins	0.032*** (0.005)	(SAT)×(Wins)	-0.013*** (0.003)
Distance	-0.035*** (0.003)	Distance	0.011 (0.009)
Tuition	-0.158*** (0.003)	Tuition	0.012** (0.006)

***: $p < 0.01$, **: $p < 0.05$, SAT scores are scaled by 0.01, i.e., SAT score of 1,600 would be 1.6.

Table 5: Parameter Estimates – Dynamic Model

	seg1	seg2	seg3	seg4	seg5
SAT score range	400 - 837	837 - 973	973 - 1090	1090 - 1225	1225 - 1600
Interest rate	-0.100*** (0.025)	-0.193*** (0.025)	-0.244*** (0.025)	-0.286*** (0.025)	-0.320*** (0.025)
Average faculty salary	0.043*** (0.002)	0.037*** (0.002)	0.037*** (0.002)	0.039*** (0.002)	0.044*** (0.002)
Faculty-student ratio	-1.101 (1.257)	0.017 (1.257)	0.535 (1.257)	0.912 (1.257)	1.593 (1.256)
Distance	-0.023*** (0.003)	-0.028*** (0.003)	-0.030*** (0.003)	-0.033*** (0.003)	-0.036*** (0.003)
Tuition	-0.148*** (0.003)	-0.152*** (0.003)	-0.156*** (0.003)	-0.160*** (0.003)	-0.165*** (0.003)
# Wins	0.041*** (0.005)	0.026*** (0.005)	0.018*** (0.005)	0.014*** (0.005)	0.014*** (0.006)
Carry-over rate	0.289*** (0.069)	0.256** (0.111)	0.223 (0.166)	0.202 (0.250)	0.343 (0.263)

***: $p < 0.01$, **: $p < 0.05$.

Table 6: Percentage Increase in Applications by Segment

a. Four Wins per Season vs. Ten Wins per Season

	seg1	seg2	seg3	seg4	seg5
% Increase in applications	36.25	21.16	11.46	8.53	8.88

b. 5.1 Percent Increase in Mean Faculty Salary

	seg1	seg2	seg3	seg4	seg5
% Increase in applications	19.22	16.46	16.67	17.29	19.97

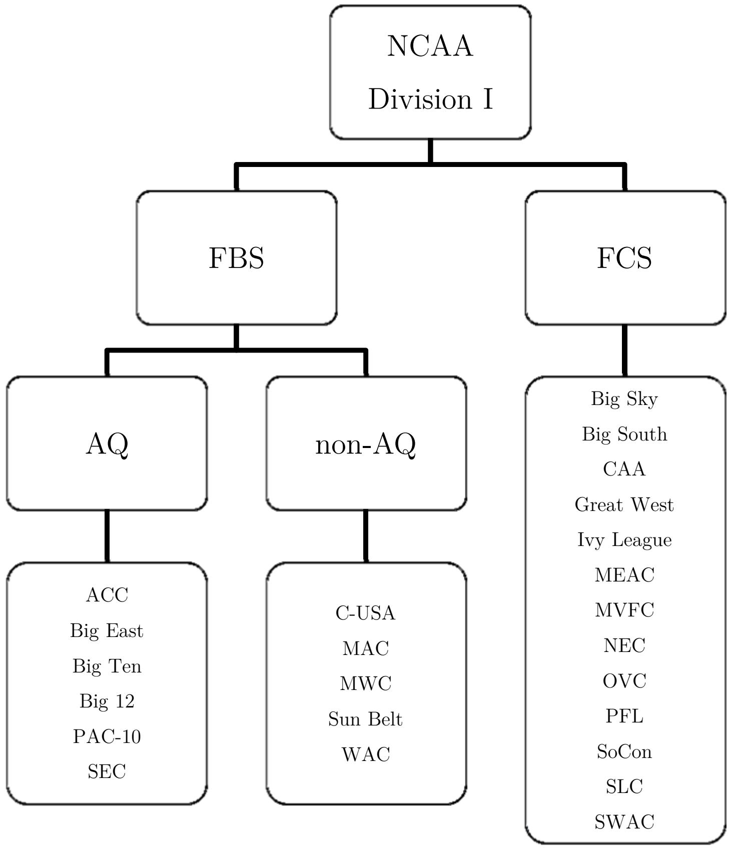
c. 3.8 Percent Decrease in Tuition

	seg1	seg2	seg3	seg4	seg5
% Increase in applications	16.81	17.20	17.79	18.26	18.93

Table 7: Selectivity (Admissions Rate), Four vs. Ten Wins per Season

School	Low-success			High-success		
	Total	Private	Public	Total	Private	Public
25^{th} percentile	76.4%	67.6%	82.4%	74.6%	66.0%	80.3%
50^{th} percentile	53.9%	37.7%	74.9%	51.4%	36.6%	72.4%
75^{th} percentile	55.2%	19.5%	62.5%	52.9%	18.2%	60.1%

Figure 1: NCAA Division I Subdivisions and Conferences



* As of December 2010.

Figure 2: Trends for High School Graduates and Applications

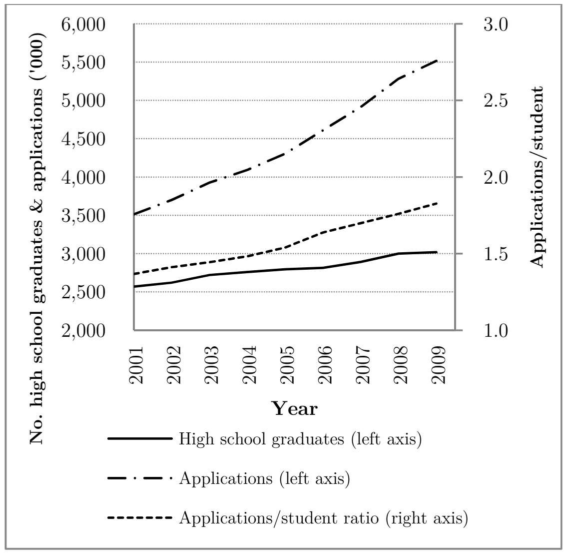


Figure 3: Trends in Applications – Select Schools

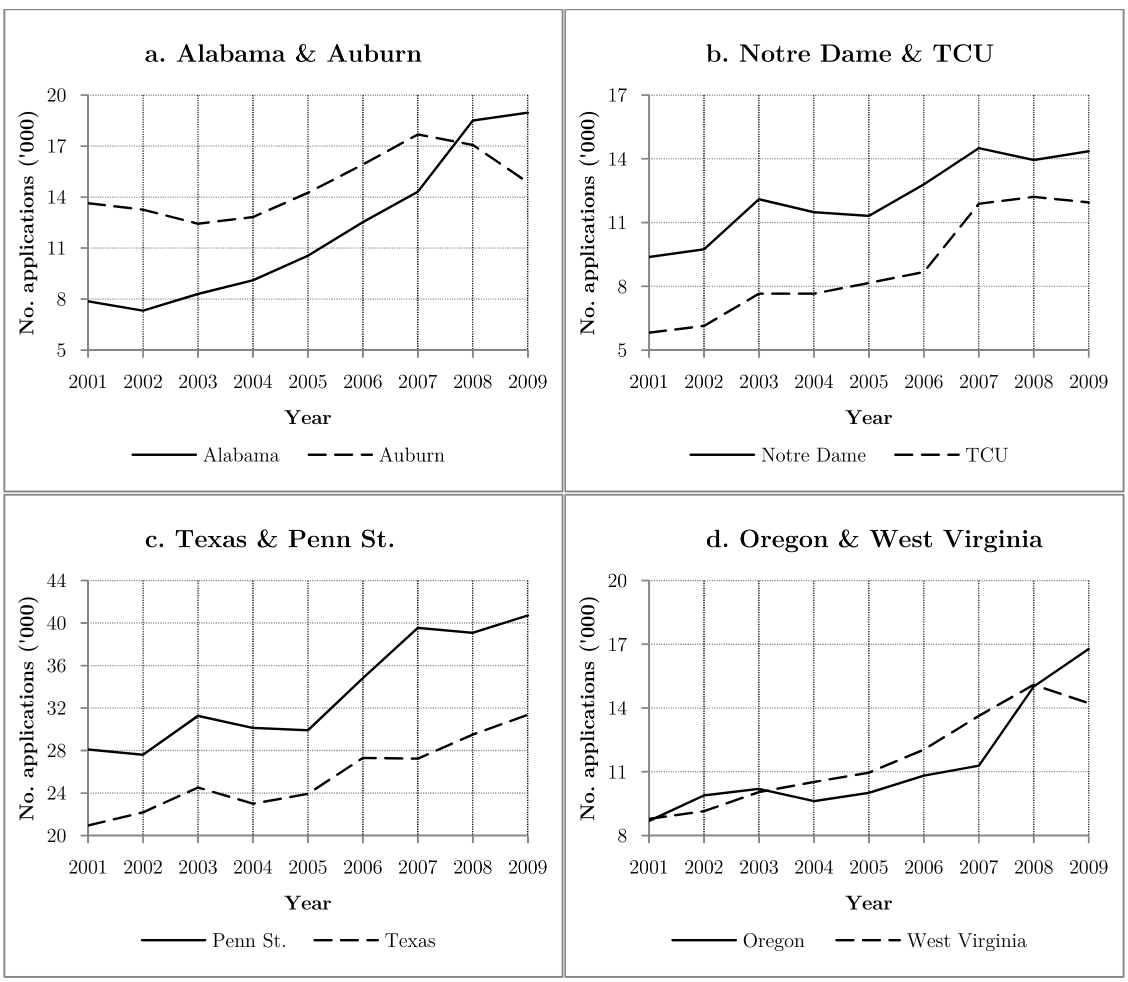


Figure 4: Increase in Applications and Changes in Number of Wins

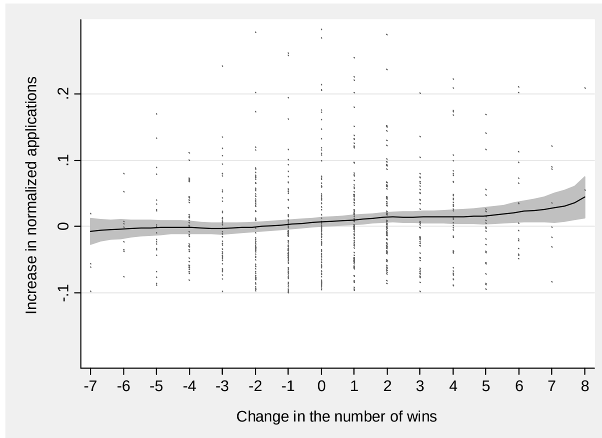


Figure 5: Distribution of SAT scores (Mass)

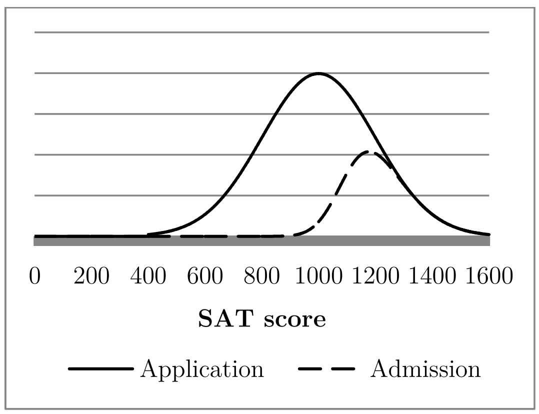


Figure 6: SAT Score Distribution of an Anonymous Public Institution

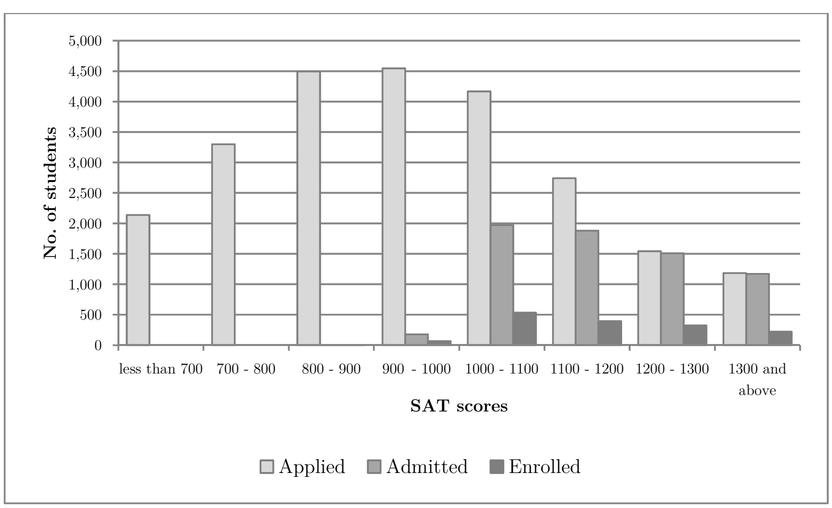


Figure 7: Distribution of the Percentage of In-State Students

for Division 1 FBS Public Schools

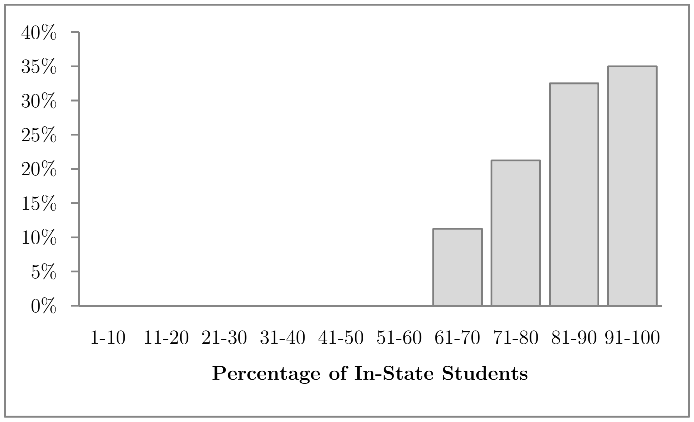


Figure 8: SAT Score (Math) Distribution of an Anonymous Public Institution for In-state and Out-of-state Enrolling Students