Evaluating the Flutie Effect in the CFP Era

William Miller

Abstract

In this paper, I seek to estimate the impact of college football success on overall university growth. To accomplish this goal, I create a novel dataset that included information on both university football success and institutional characteristics, and then use this data to estimate a fixed effects method that regressed the natural log of total applications on total wins, playoff appearances, national championship wins. Through this investigation, I find that all three football success measures were statistically insignificant predictors of application pool growth.

Introduction

Football is a massive part of the American college experience for countless students. Campuses that would otherwise be quiet on Saturdays come alive with tailgates, watch parties at local bars and restaurants, and fans gathering in massive, colosseum-like stadiums to watch their team battle it out on the grid iron. At large state universities, like the University of Oklahoma, those fall semester Saturdays genuinely feel like holidays to many students. But, like any huge celebration, they come at a steep cost.

Every year, universities spend tens of millions of dollars on their football programs, with some schools spending upwards of $200 million some years to upgrade stadiums and construct luxury box seats for wealthy alumni (Smith, 2009). These universities justify their spending by appealing to the supposed boost their football teams give to their national brand. Schools like the aforementioned University of Oklahoma, University of Texas at Austin, University of Michigan, and the Ohio State University are arguably more well known for their football teams than their academics. In fact, former OU President George Lynn Cross was once quoted as saying he wished to “build a University our football team could be proud of” (Berkow, 1989).

As it turns out, there is some evidence for this claim. In a 1987 paper by McCormick and Tinsley, the first paper to investigate this topic, found that schools who belonged to one of the major football conferences on average received applicants with higher SAT scores than schools who did not (McCormick and Tinsley, 1987). Building on this research, Murphy and Trandel found the first lag of within-conference football win percentage to be a statistically significant predictor of number of applications to a school (Murphy and Trandel, 1994). Pope and Pope also found that winning a national championship in either football or basketball was correlated with receiving more applications that same year (Pope and Pope, 2009).

The phenomenon of schools with winning teams receiving more applicants has been dubbed the “flutie effect” (Chung, 2013). Because many of the landmark studies on this topic were conducted before the College Football Playoff format was introduced in 2014, I seek to contribute to the literature by evaluating the validity of the Flutie Effect post-2014. To do this, I rely on the existing literature to specify my model.

Informed by McCormick and Tinsley as well as Murphy and Trandel, I chose fixed effects to estimate this model. Within the model, I followed the lead of Murphy and Trandel and included a dummy variable for national championship wins, and like McCormick and Tinsley, I chose to include a measure of college football wins. Instead of their within-conference win percentage, though, I chose to include a raw measure of number of wins in a season. Finally, I included an additional dummy variable for College Football Playoff appearances, as this investigation focuses specifically on the post-CFB college football landscape. Because the work of Murphy and Trandel found same-year championship wins to be most significant, I chose only to include the same year figures and not those for lags or leads. I also chose to include same year wins based on this intuition.

Studies on this topic often include a measure of average faculty salary and cost of attendance—mine is no different (Murphy and Trandal, 1994). And while some studies choose to include a dummy variable for public/private status or a factor variable for football conference membership, I left those measures out of my model because fixed effects models cannot include time-invariant unit characteristics.

Data

To estimate the effects of football success on applications received, I constructed a novel dataset. This dataset takes institutional characteristics from the Integrated Postsecondary Education Data System (IPEDS), college football playoff information from the official College Football Playoff website and win totals from the website cfpsaturdays.com. The summary statistics for the included variables can be seen below:

Statistic	N	Mean	St. Dev.	Min	Max
LogApp	1,150	9.940	0.683	7.508	11.917
Tuition1000	1,123	15.250	13.648	4.404	61.706
Salary1000	1,150	95.715	22.353	36.459	206.400
Wins	837	6.638	3.148	0	15
Natty	846	1.011	0.103	1	2
Playoffs	846	1.963	0.188	1	2

As far as units are concerned, “Wins” should be understood as the number of times a football team won in a season. Tuition1000 and Salary1000 are expressed in thousands of dollars. Finally, Natty and Playoffs are dummy variables, taking on a value of 1 if a national championship or playoff appearance occurred, and a value of 0 if the event did not occur.

As mentioned above, all of these variables are drawn from the same year. For example, application numbers, tuition, and average faculty salary from the 2017-2018 school year correspond to the fall 2017 school year. This choice was made because, as found by Pope and Pope, students seem to make sports related decisions based primarily on recent performance. To illustrate this example, take the University of Nebraska-Lincoln. They are historically one of the most dominant football programs in the nation—ranked as the 9th best program of all time by Sports Illustrated—but their recent lackluster performance (recording 5 wins and 7 losses in 2023) undoubtedly has more influence on the football-going experience of their students today. It is not realistic to assume that the knowledge of historic success and the thrill of a concurrent successful season give the same utility to perspective applicants.

Methodology

Empirical Models

I specified 4 models in this investigation. Model 1 regresses the natural logarithm of the number of applications received by a school in that school year on the number of students who applied last year (the first lag of LogApp), the number of wins, dummies for national championship wins and playoff appearances, measures of tuition and salary (in thousands of dollars), and dummy variables for all but one year in the sample to account for time-variant idiosyncratic error.

Model 1:

$$LogApp_{it}\ \beta_0 + \beta_1 LogApp_{it-1} + \beta_2 Tuition1000_{it} + \beta_3 Salary1000_{it} + \beta_4 Wins_{it} + \beta_5 Natty_{it}$$

$$+\beta_6 Playoffs_{it} + \beta_7 Year2016 + \cdots + \beta_{i3} Year2022 + a_i \ + u_{it}$$

Model 2 regresses the natural logarithm of applications on its first lag, wins, tuition and salary (in thousands of dollars), and the year dummies.

Model 2:

$$LogApp_{it}\, \beta_0 + \beta_1 LogApp_{it-1} + \beta_2 Tuition1000_{it} + \beta_3 Salary1000_{it} + \beta_4 Wins_{it} + \beta_5 Year2016 +$$

$$\ldots + \beta_{11} Year2022 + a_i + u_{it}$$

Model 3 regresses the natural logarithm of wins on its first lag, the national championship dummy, tuition and salary (in thousands of dollars), and the year dummies.

Model 3:

$$LogApp_{it}\, \beta_0 + \beta_1 LogApp_{it-1} + \beta_2 Tuition1000_{it} + \beta_3 Salary1000_{it} + \beta_4 Natty_{it} + \beta_5 Year2016$$

$$+\beta_{11} Year2022 + a_i + u_{it}$$

Model 4 regresses the natural logarithm of wins on its first lag, the playoff appearances dummy, tuition and salary in thousands of dollars, and the year dummies.

Model 4:

$$LogApp_{it}\,\beta_0 + \beta_1 LogApp_{it-1} + \beta_2 Tuition1000_{it} + \beta_3 Salary1000_{it} + \beta_4 Playoffs_{it}$$

$$+\beta_5 Year2016 + \cdots + \beta_{11} Year2022 + a_i + u_{it}$$

All models take the functional form

$$y \;=\; e^{\beta_{1t}+\ldots+\beta_{it}+a_i+u_{it}}$$

I chose to estimate 4 models because of the concern of multicollinearity if just one model was estimated. A team cannot make the playoffs without winning most of their games, and a team cannot win the national championship without winning most of their games and making the playoffs. By separating these variables into three subsequent models, I hope to get a more accurate estimate of their partial effects on the number of applications received by a school.

This model can be classified as a first order autoregression [AR(1)] because the first lag of the dependent variable is included as an independent variable. This is done to address concerns of autocorrelation present in panel data which is being used here.

Econometric Method

In this investigation, I used a fixed effects model. Fixed effects is a demeaning transformation (where the mean of all i terms is subtracted off of each it term). This model is used widely in the field of economic research and is employed by Murphy and Trandel and McCormick and Tinsley. I believe fixed effects to be justified in this case because the number of units (128) is far greater than the number of time periods (9), making fixed effects more appropriate than first differences. Random effects was not selected because it leaves the timeinviariant unit effects (ai) in the error term, and we assume these time invariant characteristics (like public/private status or conference membership) are correlated with the number of applications a school receives, thus creating an endogeneity problem.

I made the choice to use standard errors clustered at the institution level when estimating this model (rather than traditional, robust, or HAC) for a few reasons. Clustered standard errors are most appropriate here because I am concerned about within-unit serial correlation and assume that there is no between-unit correlation. Clustered standard errors are also more efficient than HAC standard errors but still robust to heteroskedasticity, so they are appropriate to use in this case even if heteroskedasticity is present.

Because fixed effects is subject to the strict exogeneity assumption, some discussion of exogeneity is appropriate. Fixed effects itself does a lot of the heavy lifting here because it removes time-invariant unit effects from the error term. Anything considered to be time invariant, in this case factors like conference membership or public/private status, are controlled for and are not included in the idiosyncratic error term.

Despite this, there are likely a few factors in the error term that could lead to bias. First is the school's response to wins. This model assumes that wins have an independent effect on the number of applicants a school receives, but this isn't necessarily consistent with reality. In some cases, we might expect university marketing departments to make large pushes after successful seasons. Because they know that the school is now on the minds of young football fans around the country, they might opt to spend more after their winning season concludes than they otherwise would. This would bias the coefficient estimate for wins is biased upward because it is we conclude marketing is positively correlated with wins and positively correlated with the number of applications received.

Also, even though conferences are theoretically controlled for by fixed effects this model, the effect conference strength has on win totals is not accounted. A school like Clemson (ACC) or USC (PAC 12) likely has their win total inflated due to playing in a weak conference. For that reason, a school with fewer wins in the SEC (widely considered to be the best football conference) could reasonably be said to have had a better season than a team with slightly more wins in the Pac-12 (one of the weaker conferences). This would not be a concern if conference strength did not vary marginally over time. Assuming variance in conference strength over time means that the coefficient estimate on wins is biased downward because the coefficient on conference would likely be negative and wins are positively associated with LogApps.

Wins also don't mean the same to every school. For a team like Alabama (who won 3 of the 9 national championships in this sample and 3 additional championships from 2009-2012), a 14 win season or a loss in the national championship game might feel like a failure to fans and not attract new students, whereas a school like Kansas (who had 14 losing seasons in a row), going from a 0-12 season in 2015 to a 2-10 season in 2016 might feel like a massive upgrade to fans. This illustrates how different wins mean different things to different schools, and likely biases the coefficient estimate on wins downward because schools at the top of the win total list are likely to be schools who are used to winning—at least recently—and thus value wins less (giving the sign on wins a negative coefficient and assuming the correlation between wins and LogApp is positive).

Finally, the performance of schools in other sports can impact application numbers and bias the results. Schools like Duke, UNC, Kentucky and many others (collectively known as the "blue bloods") are known for their basketball programs more than their football programs, meaning basketball probably has more of an effect on their national profile than football. If

Duke, for example, wins the national championship in basketball, this would theoretically increase its number of applications received whether or not Duke football had a good season. For this reason, we can assume that the coefficient estimate on wins is positively biased if the basketball team does well (because the coefficient on basketball is positive and is positively correlated with LogApp) and negatively biased if the basketball team does poorly (here, the correlation between basketball success and LogApp is still positive, but the sign on basketball's coefficient is now negative).

As noted above, fixed effects does a lot of heavy lifting to mitigate all of this bias, and so does the AR(1) specification, but the fact that many of these factors are time variant rather than time invariant means that the variables included in the regression (i.e. the first lag of the natural log of applications, wins, national championship wins, playoff appearances, tuition, and faculty salary) are not strictly endogenous and that omitting the hard to measure (like context-dependent marketing spending) and impossible to measure (like a fanbase's subjective value placed on football relative to other sports) undoubtedly causes some bias.

Results

The results from running the 4 regressions detailed above are as follows:

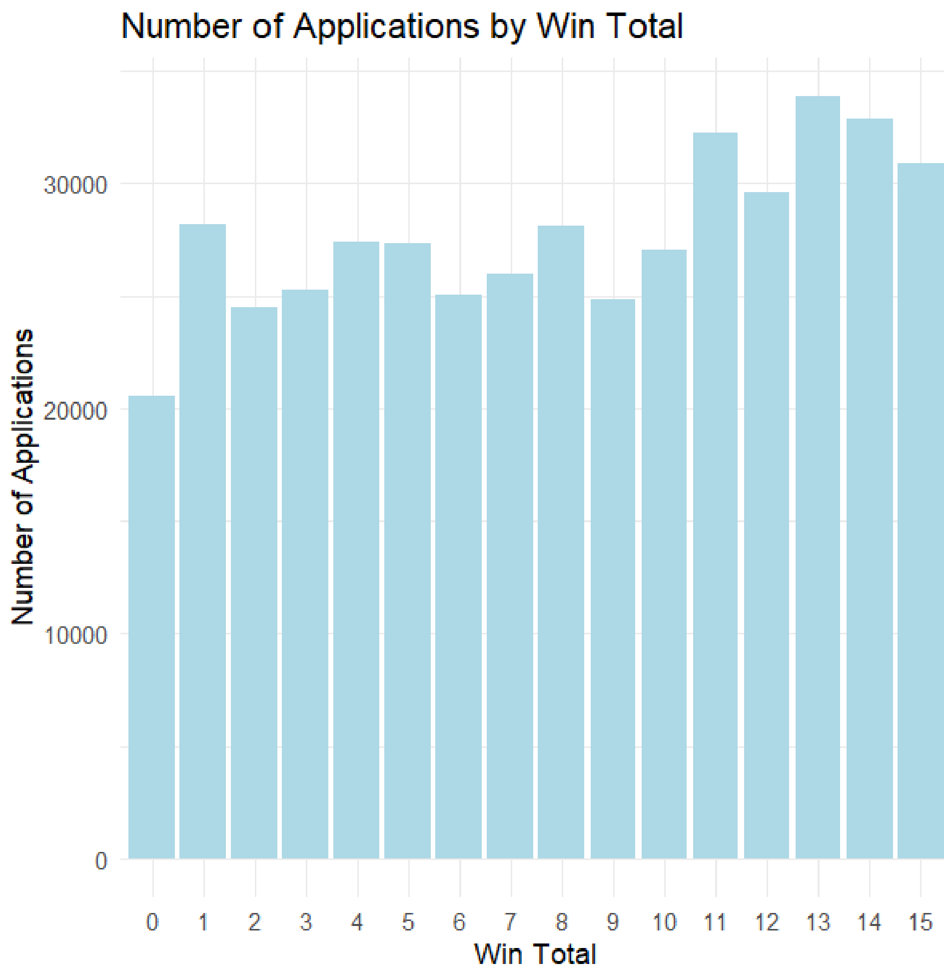
Regression Results

	Dependent variable:			
	LogApp			
	(1)	(2)	(3)	(4)
LogApp_shift_1	0.614***	0.613***	0.622***	0.622***
	(0.052)	(0.052)	(0.048)	(0.048)
Tuition1000	-0.003	-0.003	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Salary1000	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Year2016	0.014	0.014	0.010	0.010
	(0.013)	(0.013)	(0.013)	(0.013)
Year2017	0.007	0.007	0.0005	0.0004
	(0.019)	(0.019)	(0.019)	(0.020)
Year2018	0.044**	0.044**	0.037*	0.036*
	(0.020)	(0.020)	(0.021)	(0.021)
Year2019	0.064**	0.064**	0.057**	0.057**
	(0.027)	(0.027)	(0.027)	(0.027)
Year2020	0.052*	0.052*	0.045*	0.045*
	(0.027)	(0.027)	(0.027)	(0.026)
Year2021	0.121***	0.121***	0.107***	0.107***
	(0.034)	(0.034)	(0.033)	(0.033)
Year2022	0.130***	0.131***	0.123***	0.123***
	(0.040)	(0.040)	(0.039)	(0.039)
Wins_shift_1	0.003	0.003		
	(0.002)	(0.002)		
Natty_shift_1	-0.031		-0.020	
	(0.028)		(0.029)	
Playoffs_shift_1	-0.006			-0.006
	(0.018)			(0.015)
Observations	724	724	733	733
R^2	0.628	0.628	0.620	0.620
Adjusted R^2	0.566	0.567	0.558	0.558
F Statistic	80.390*** (df = 13; 619)	95.216*** (df = 11; 621)	93.358*** (df = 11; 630)	93.322*** (df = 11; 630)
Note:				*p<0.1; **p<0.05; ***p<0.01

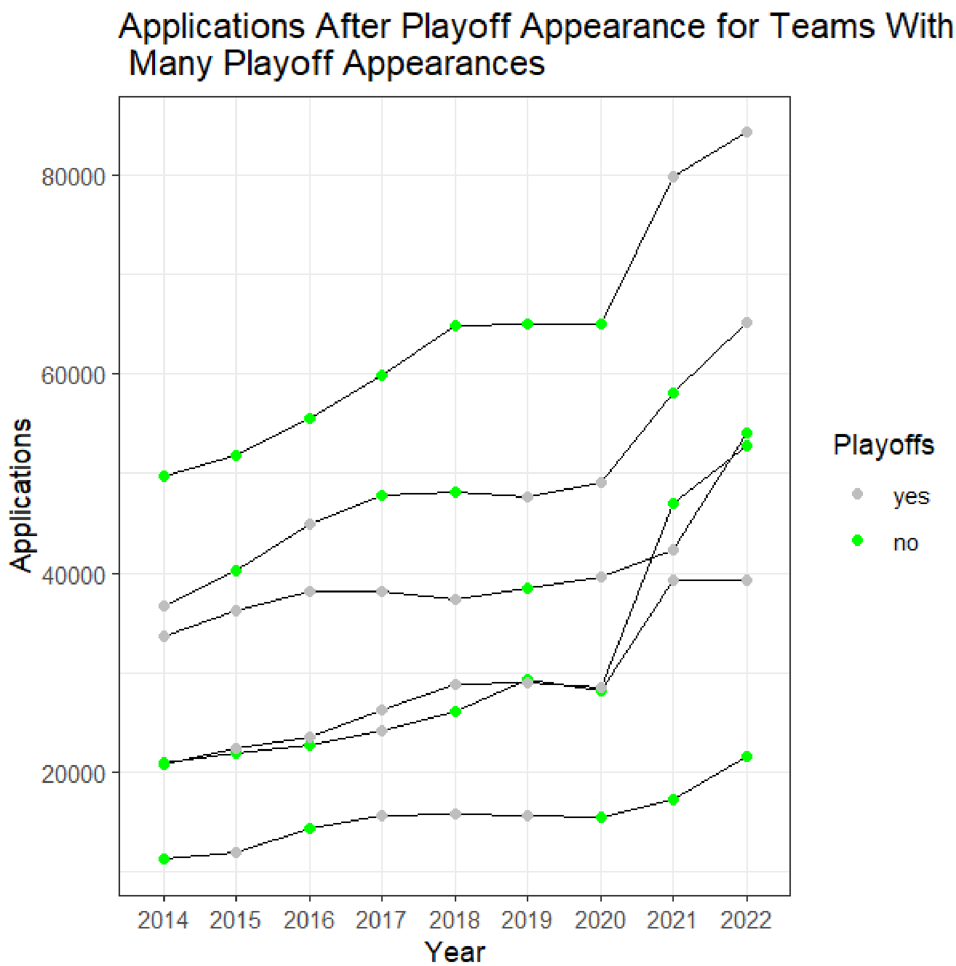
From this table, a few things are clear. First, none of the three college football success indicators (Wins, Natty, and Playoffs) are independently statistically significant. When investigating further, an F-Test of the joint significance of these three variables (where

$H_0: Wins = 0 \text{ and } Natty = 0 \text{ and } Playoffs = 0, H_1: Wins \neq 0 \text{ or } Natty \neq 0 \text{ or } Playoffs \neq 0$) returns a p-value of 0.42, meaning that, not only are these variables individually insignificant, they are jointly insignificant predictors of applications received by the university in my sample.

I would argue that this insignificance is likely due to the bias described above. The marketing spending boost that comes after a good season, how individual fanbases value wins, the conference effect, and the importance of other sports relative to football (all arguably time-variant variables meaning they are not controlled by fixed effects estimation) all play a role in the resultant insignificance of the football success variables. My evidence suggests that fanbase value of wins might be the most important factor in the small and insignificant effect size of thecoefficient on wins. We established this bias as negative, meaning it would theoretically shrink the value of the wins coefficient. The plot below shows that, throughout the whole sample, winning schools receive more applicants, so it is possible that the winningest schools already get the most applicants and therefore an additional win does not buy them many more.



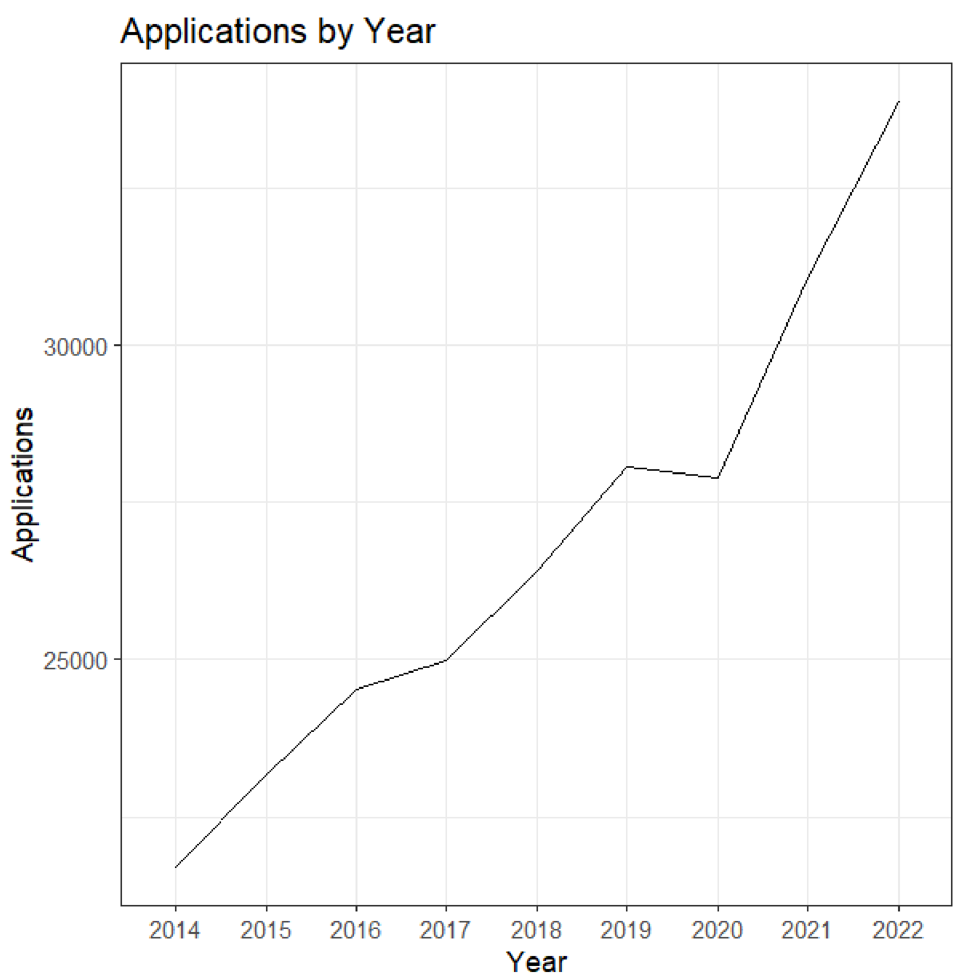
Playoffs and National championships return as insignificant for the same reason, but maybe to an even greater extent. For teams like Alabama, Clemson, and Georgia who have won almost every national championship of the last 10 years, we might expect their students to see a failure to win a national championship—or even make the playoffs—as a bust and see winning it all as the standard rather than an exceptional event. Number of applications received by schools after their teams appeared in the playoffs for teams with multiple playoff appearances can be seen below:



A second important result from this model is that the signs on tuition1000 and salary1000 have the signs we would expect; that is, raising tuition decreases the number of students who apply to a university and increasing faculty salary increases the number of students who apply to a university.

Again, though, these predictors are both independently insignificant and jointly insignificant. A joint significance F test ($H_{0:}\ Tuition100 = 0\ and\ Salary1000 = 0;\ H_1: Tuition1000 \neq 0\ or\ Salary1000 \neq 0$) returns a p-value of 0.3418, meaning that we fail to reject the null hypothesis and conclude that both the cost of attendance and the approximate quality of the faculty at a university are statistically insignificant predictors of how many students will apply.

The only results from these models that carry any statistical significance are the year dummies for 2018, 2019, 2021, and 2022. Additionally, the year dummies are jointly significant with an F-test ($H_{0:}\ Year2016\ =\ Year\ 2017\ = \ldots\ =\ Year\ 2022 = 0;\ H_1: Year2016 \neq 0\ or\ Year2017 \neq 0\ or \ldots or\ Year2022 \neq 0)\ returning\ a\ p-value\ of$ 0.00184. The number of applications all schools in this sample received are plotted over time below:



As can be seen from the coefficient estimates and the above plot, with the exception of 2020, more students apply to universities every year. As it turns out, increased participation in higher education is a global trend. This could be for a few reasons. First, like the rest of the world, the economy of the United States is becoming more specialized. According to Marginson, a college degree is increasingly seen by families to be a path to middle class comfort (Marginson, 2016). It is also possible that the increase in high school graduates observed over the last half century has created a higher demand for a university education simply because more students are now qualified (Heckman and LeFontaine, 2011). Finally, the rapid increase in college admissions since 2020 has been attributed by some scholars to the adoption of test-optional application systems, which theoretically prevent the systemic "undermatching" of students who don't apply to college because they incorrectly believe that they are unqualified (Bennett, 2021).

Conclusion

The lack of significance found in the football success variables could be due to the bias discussed above but could also be due to the limitations of this study.

The first limitation I identify in this investigation is that it only looked at the nominal change in wins by a football team; future research could incorporate measures of change in wins. This could be done with measures of deviation from the average win total of a school or deviations from the average win total of a conference to account for conference strength effects. Other researchers could also include a measure of basketball or other sport success.

The second limitation I identify has to do with other institutional characteristics. Future research could attempt to incorporate marketing spend by universities in the years after winning seasons, or it could seek to estimate the effect of athletic department spending overall or the result of changing coaches (who are responsible for both schemes and recruiting—two enormous factors in predicting college football success).

Finally, future research ought to investigate the hedonic value of wins for different universities. It is intuitive to assume that an extra win means less to a successful football team than to an unsuccessful one, but the utility derived from a win could also reasonably be conditional on region, historical success, and other cultural factors inherent to different fan bases.

Despite not agreeing with the literature on the positive impact of college football success on university growth, my results are consistent with the literature on overall application growth throughout the 2010s and especially in the 2020s. The main takeaway from this investigation ought to be that the time effects of education (captured by the year dummy variables) were more important in this sample than football success.

This research suggests that it may be unwise to justify university spending on football with the promise that it will increase the success of the school. A better argument might be that it increases the quality of life for students already on campus or helps prepare young athletes for professional leagues, just like universities help prepare young professionals for the workforce.

It also suggests that applications to universities is on the rise, and future research should continue to seek to understand this trend as it will have a significant impact on our overall economy and labor force.

Works Cited

Bennett, Christopher T. "Untested admissions: Examining changes in application behaviors and student demographics under test-optional policies." *American Educational Research Journal*, vol. 59, no. 1, 12 Apr. 2021, pp. 180–216, https://doi.org/10.3102/00028312211003526.

Berkow, Ira. "The Grapes of Wrath at Oklahoma." *The New York Times*, The New York Times, 18 Feb. 1989, www.nytimes.com/1989/02/18/sports/sports-of-the-times-the-grapes-of-wrath-at-oklahoma.html.

Chung, Doug. "The dynamic advertising effect of collegiate athletics." *SSRN Electronic Journal*, 2013, https://doi.org/10.2139/ssrn.2345220.

"College Football Playoff History." *College Football Playoff*, collegefootballplayoff.com/sports/2019/5/22/history. Accessed 2 May 2024.

Heckman, James, and Paul LaFontaine. *The American High School Graduation Rate: Trends and Levels*, Dec. 2007, https://doi.org/10.3386/w13670.

Marginson, Simon. "The worldwide trend to high participation higher education: Dynamics of social stratification in inclusive systems." *Higher Education*, vol. 72, no. 4, 2 June 2016, pp. 413–434, https://doi.org/10.1007/s10734-016-0016-x.

McCormick, Robert E., and Maurice Tinsley. "Athletics versus Academics? Evidence from SAT Scores." *Journal of Political Economy*, vol. 95, no. 5, 1987, pp. 1103–16. *JSTOR*, http://www.jstor.org/stable/1833132. Accessed 2 May 2024.

"Most Wins by FBS Teams over Last 10 Years." *CFB Saturdays*, 12 Jan. 2023, cfbsaturdays.com/most-wins-in-fbs-over-last-10-years/.

Murphy, Robert G., and Gregory A. Trandel. "The relation between a university's football record and the size of its applicant pool." *Economics of Education Review*, vol. 13, no. 3, Sept. 1994, pp. 265–270, https://doi.org/10.1016/0272-7757(94)90014-0.

Parks, James. "Ranking College Football's 10 Best Teams All Time." *College Football HQ*, College Football HQ, 23 Feb. 2024, www.si.com/fannation/college/cfb-hq/ncaa-football-rankings/college-football-rankings-10-best-teams-all-time.

Pope, Devin G., and Jaren C. Pope. "The impact of college sports success on the quantity and quality of student applications." *Southern Economic Journal*, vol. 75, no. 3, Jan. 2009, pp. 750–780, https://doi.org/10.1002/j.2325-8012.2009.tb00930.x.

Smith, D. Randall. “College football and student quality: An advertising effect or culture and tradition?” *The American Journal of Economics and Sociology*, vol. 68, no. 2, Apr. 2009, pp. 553–579, https://doi.org/10.1111/j.1536-7150.2009.00639.x.

“Your Primary Source for Information on U.S. Colleges, Universities, and Technical and Vocational Institutions.” *IPEDS*, nces.ed.gov/ipeds/. Accessed 2 May 2024.